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ARTIFICIAL INTELLIGENCE AND THE INTERNET OF THINGS IN MICROGRIDS AND SMART GRIDS: AN ECONOMIC ANALYSIS OF PRODUCTIVITY, EFFICIENCY, AND DEMAND RESPONSE TO DYNAMIC PRICING

Ph.D. dissertation prepared under the supervision of
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STRESZCZENIE

Ekonomiczne ramy zastosowania technologii Internetu Rzeczy (IoT) i Sztucznej Inteligencji (AI) w wytwarzaniu i przesyłaniu energii w mikrosieciach i inteligentnych sieciach elektroenergetycznych

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Niniejsza dysertacja bada ekonomiczne skutki zastosowania technologii internetu rzeczy (ang. IoT) oraz sztucznej inteligencji (pol. SI, ang. AI) w sektorze energetycznym, w kontekście inteligentnych sieci (smart grids) i mikrosieci (microgrids). Analizuje ona przejście od scentralizowanych, monopolistycznych modeli rynkowych do bardziej konkurencyjnych struktur wynikających z procesu integracji dostawców energii i rozwiązań sieciowych. Badanie ocenia również, czy technologie SI i IoT zwiększają efektywność produkcyjną, zwroty z inwestycji oraz rozwój rynku mikrosieci powiązanych z inteligentnymi sieciami.

W przeprowadzonych w pracy badaniach zastosowano teoretyczne ramy neoklasycznej teorii produkcji, całkowitej produktywności czynników (TFP), wskaźników efektywności inwestycyjnej (LCOE, IRR, NPV) oraz odwołano się do ekonomii dobrobytu i ocen wynikających z analiz elastyczności popytu. Wykorzystano metodę wielokrotnego studium przypadku do weryfikacji trzech hipotez: (1) integracja AI/IoT zwiększa efektywność operacyjną i obniża koszty; (2) technologie te są kluczowe dla integracji odnawialnych źródeł energii i wspierają przejście ku konkurencyjnym rynkom; (3) zastosowanie AI/IoT poprawia efektywność inwestycji w mikrosieciach.

Analiza czterech przypadków – mikrosieci Blue Lake Rancheria, systemów energetycznych Airtel Madagascar, projektu demonstracyjnego Olympic Peninsula oraz

kalifornijskich pilotaży taryf czasowych (TOU) – dostarcza silnych dowodów empirycznych potwierdzających te hipotezy. Wyniki wskazują na znaczną poprawę efektywności operacyjnej, m.in. TFP = 4,02 w Blue Lake Rancheria i 40% redukcję LCOE dla Airtel Madagascar. Badania ujawniają również, że dynamiczne mechanizmy cenowe wspierane przez technologie smart grid skutecznie kształtują popyt, potwierdzając rolę AI i IoT w tworzeniu bardziej konkurencyjnych i efektywnych rynków energii. Dysertacja konkluduje, że integracja AI i IoT przynosi wymierne korzyści ekonomiczne, zwiększając produktywność, opłacalność inwestycji oraz efektywność rynkową, wskazując jednocześnie na potrzebę przyspieszenia inwestycji w infrastrukturę smart grid i ujednolicenia standardów interoperacyjności.

Słowa kluczowe: Sztuczna inteligencja (AI), Internet Rzeczy (IoT), inteligentne sieci energetyczne (smart grid), efektywność inwestycyjna, produktywność całkowita czynników (TFP)

Artificial Intelligence and the Internet of Things in Microgrids and Smart Grids: An Economic Analysis of Productivity, Efficiency, and Demand Response to Dynamic Pricing

Volkmar Walter Kunerth

ABSTRACT

This dissertation investigates the economic impacts of Internet of Things (IoT) and Artificial Intelligence (AI) technologies in the electricity sector, in the context of smart grids and microgrids. It examines the transition from centralized, monopolistic market models to more competitive markets due to the integration of distributed energy sources. The research further examines whether AI and IoT enhance productive efficiency and investment returns in the broader microgrid market connected to smart grids.

The theoretical frameworks applied are neoclassical production theory, Total Factor Productivity (TFP), investment efficiency metrics (LCOE, IRR, NPV), and principles of welfare economics and demand elasticity. A multi-case study methodology is employed to test three core hypotheses: (1) that AI/IoT integration enhances operational efficiency and reduces costs; (2) that these technologies are pivotal for integrating variable renewable energy sources and fostering a shift toward competitive market structures; and (3) that AI/IoT adoption improves investment efficiency in microgrids.

The analysis of four case studies—the Blue Lake Rancheria microgrid, Airtel Madagascar's remote telecom power systems, the Olympic Peninsula Demonstration Project, and the California Statewide Time-of-Use (TOU) Pricing Pilots—provides strong empirical support for these hypotheses. Key findings demonstrate significant improvements in operational efficiency, such as a TFP of 4.02 at Blue Lake Rancheria and a 40% reduction in the Levelized Cost of Energy (LCOE) for Airtel Madagascar. The studies also reveal that dynamic pricing mechanisms, enabled by smart grid technologies, that shift consumer demand, confirm the role of AI and IoT in enabling more competitive and efficient market structures.

The dissertation concludes that the integration of AI and IoT in the energy sector yields economic benefits, driving productivity, improving investment viability, and enhancing market efficiency. These findings have suggested a need for accelerated investment in smart grid infrastructure, updated regulatory frameworks, and the promotion of interoperability standards to realize the full potential of a digitized, resilient, and sustainable energy future.

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INTRODUCTION

We are currently undergoing a global energy transition from a fossil fuel-driven economy to a low-carbon energy framework, driven by the urgent need to combat climate change, strengthen energy security, and enhance the resilience of energy systems (IEA, 2025b; Nasa, 2025). Over the last hundred years, electricity has been produced centrally, relying on dispatchable, reliable fossil fuels such as gas, coal, petrol, and nuclear energy, and built on robust infrastructure and supply chains. Coal, oil, and natural gas are major sources of carbon dioxide (CO2) emissions, primarily through combustion for electricity, heat, and transportation (Nasa, 2025). Fossil fuels and nuclear plants can operate continuously, providing base-load power with high-capacity factors, and are well-integrated into existing grid infrastructure. But they are prone to geopolitical risks and extraction limitations, and they are also major contributors to climate warming and its adverse effects on the Earth (Pennstate, 2025). Electricity provided by solar and wind energy is a major driver for mitigating global climate change (Long et al., 2023). But while producing much less climate-warming gases, they are intermittent, and as such, they are not continuously available for electricity generation due to changing weather conditions, time of day, and seasonal variations (Fekete et al., 2023). Challenges with intermittency require weather forecasting abilities, grid upgrades, energy storage capacities, or hybrid energy systems that include fossil fuel generating capacity (Lafuente-Cacho et al., 2025).

At the same time, governments are responsible for maintaining economic growth by providing affordable, reliable energy, which is essential to social stability. Balancing the goals of affordability and clean energy is challenging due to the intermittency of renewable energy sources and the mismatch between electricity demand and supply, both of which affect societies and markets. Virah-Sawmy & Sturmberg (2025) point out that governments must create clear policies and incentives that foster the renewable energy transition, while also accounting for the socio-economic impacts on communities that could create social pressures. While renewable energy projects advance global climate goals, they often lead to localized environmental and economic impacts in the form of high electricity prices. In addition, they require substantial investments in new infrastructure and technologies. Electricity cannot be stored economically for long periods, and therefore, large discrepancies between electricity production and consumption at certain times pose significant economic challenges.

Since electric energy supply conditions fluctuate due to the integration of more renewable energy sources, the discipline of economics is crucial in evaluating the challenges for markets. Findings from such research can help lawmakers, policymakers, investors, and technology providers make more informed decisions and empower customers to reap greater economic benefits.

The fourth industrial revolution has introduced technologies such as artificial intelligence (AI) and the Internet of Things (IoT), which are fundamental drivers of technological and economic change, addressing challenges associated with the current energy transition. AI and IoT can help make electric energy more affordable, sustainable, and reliable by optimizing energy production and providing the infrastructure for more competitive market structures, helping to align supply and demand of electric energy better, and integrating renewable energy more efficiently in electric grids (Kumar et al., 2023a; Schwab, 2016a).

In addition, AI- and IoT-generated data provide technical and financial intelligence for making multi-billion-dollar investments in electric energy infrastructure. This data provides policymakers, utilities, economists, and investors with predictability and enhanced decision-making information. This thesis examines the economic impacts of AI- and IoT-enabled microgrids and intelligent grids, also known as smart grids. It examines how AI and IoT impact the economic frameworks of production, supply, demand, and pricing within the broader context of the electric energy sector. By applying relevant economic theories and investigating the transition from traditional monopolistic supply models to competitive, smart-grid-enabled energy market models, this research aims to provide insights into the future of electricity markets. At the core of this dissertation are three issues: optimizing renewable and distributed energy production through AI and IoT in microgrids and distributed energy assets, thereby improving financial metrics and efficiency; AI and IoT providing the technical framework for better integrating renewable energy into the grid, and demand response mechanisms using pricing schemes to better align customer demand and electricity supply from intermittent renewable energy sources resulting in more competitive market structures.

The transformative potential of AI and IoT in the electric energy sector has led to a growing body of research. A review of the existing literature reveals a fragmented landscape, divided into three distinct areas of research: technical analyses from engineering and information sciences that examine technological aspects and outcomes; research on policy frameworks; and economic studies and papers on various aspects of integrating renewable energy. Research in the field is either focused on the economic efficiency gained through the application of new technology or broadly market-oriented, examining the integration of renewable energy within the social sciences (Verdes et al., 2023). A comprehensive economic-technological framework that systematically addresses changes in economic frameworks and how they are impacted by technology is currently missing. The absence of a unified technical-economic approach represents a significant gap in understanding. This dissertation aims to fill this gap and explore how AI and IoT are reshaping economic frameworks and influencing societal dynamics in the electric energy industry.

Research by Cioara et al. (2021), Ejiyi et al. (2025), and Rajaperumal & Columbus (2025) supports the criticality of this research gap. Cioara et al. (2021), in their systematic review of digital twin technology in smart grids, point out the absence of a unified framework that bridges technical optimization with economic theories and market-level considerations. This highlights the research gap in achieving a more integrated, holistic technical-economic perspective on digital transformation in the energy sector through AI and IoT. Concurrently, Ejiyi et al.(2025) and Rajaperumal & Columbus, (2025) point out that peer-to-peer trading and AI and IoT-driven technology innovation are reshaping market structures, societies, and policy frameworks in the electric energy sector.

However, the most extensive body of existing research in the field is technical in nature. Much of the research focuses on engineering and computer science papers that detail the concepts and technical capabilities of intelligent AI and IoT-enabled energy systems at both the macro (smart grid) and micro (microgrid) levels. While they differ in scale, both smart grids and microgrids face similar technical challenges related to maintaining their physical assets and keeping their respective grids stable. A key example is the application of machine learning and sensors for predictive maintenance of individual components, such as solar panels, generators, and batteries, which is critical for ensuring reliability. Preventive maintenance and scheduling optimization in both large-scale utility grid networks and localized microgrids are essential for managing and maintaining the electric energy infrastructure and assets (Alam et al., 2025). Engineering-grounded research provides insight into how the architecture, technical capabilities, and functionality of AI and IoT enhance the reliability and efficiency of energy systems. Engineering papers, however, mostly do not translate the outcome of technical research insights into overall quantifiable economic outcomes. They treat economic outcomes as assumed rather than as a central outcome of their analysis and research. Engineering research at the microgrid level is focused on the design and implementation of localized assets and control systems. The studies explore the functionality of advanced Energy Management Systems (EMS) that enable a microgrid to operate autonomously (Eyimaya & Altin, 2023) and detail the functionality of IoT-enabled controllers and sensors for the management of a microgrid, as was done, for instance, for the Blue Lake Rancheria microgrid in California (Mohanpurkar et al., 2017). The Blue Lake Rancheria microgrid is one of the case studies in this dissertation.

The engineering and computer science research literature primarily investigates the technical, electrical, mechanical, and operational aspects of smart grid technologies. Researchers have explored the use of AI for demand and forecasting in microgrids (Andrić et al., 2017; Huang et al., 2022). Machine learning is applied to optimize predictive maintenance, dynamic pricing, and scheduling demand response programs, resulting in economic gains and a more efficient allocation of resources. Other papers offer insight into critical cost-benefit components, enabling the analysis of the economic viability of investments in smart grids and microgrids (Antonopoulos et al., 2020; Lee et al., 2015; Wazirali et al., 2023). Another important area of research focuses on the development of advanced communication architectures in microgrids and smart grids (Daki et al., 2017). Multi-layered communication frameworks, such as the Smart Grid Architecture Model (SGAM), are necessary for coordinating data exchange between millions of endpoints (Daki et al., 2017; Ghasempour, 2019), and are used to assess individual economic impacts at the customer level. The second type of research focuses on policy and regulatory frameworks through market analysis, using market statistics to provide strategic insights into macroeconomic dynamics and to support policy interventions that advance the energy transition to a low-carbon economy. At this more strategic level, institutions like the International Energy Agency (IEA) and the U.S. Department of Energy (DOE) publish extensively on the macro trends driving grid modernization and microgrids. The IEA provides data and analysis on the global shift toward renewable energy, highlighting that electricity demand is rising faster than total energy consumption (including transportation, heating, construction, and other sectors). New renewable generation is growing rapidly and is poised to meet a significant portion of the projected electric energy demand growth (IEA, 2024, 2025b). Policy research also identifies infrastructure challenges, such as managing grid instability from intermittent sources and the backlog of renewable projects in interconnection queues, signaling that the legacy grid is currently unprepared for the new volume and distributed nature of new energy sources (Fahad Saleh Al-Ismail & Salem, 2020). Policy research on microgrids and smart grids indicates that direct financial interventions, such as grants and tax credits, are crucial to making new projects economically viable, for example, by reducing the high capital expenditure associated with microgrid projects. Studies on the U.S. Investment Tax Credit (ITC), Department of Energy Smart Grid Grants, and other targeted subsidies highlight how these financial subsidies improve the financial feasibility of these projects (Ali et al., 2017; García-García et al., 2023). Government incentives lower upfront costs, mitigate financial risk, and accelerate the adoption of a distributed electric energy infrastructure, thereby leading to greater reliance on them. This is exemplified by the $5 million grant that helped fund the Blue Lake Rancheria microgrid, representing one of the case studies analyzed in the latter part of this research (*Blue Lake Rancheria Microgrid – Schatz Energy Research Center*, 2024).

The economic research applied in this thesis aims to enhance understanding of the economic conditions of these new energy projects, drawing on theoretical and applied economics, as well as business research that investigates the subject of productive efficiency. Foundational theoretical research on macroeconomic models of production theory, such as Solow (1957), who focuses on the relationship between technology and aggregate production, and Brynjolfsson & Hitt (1995a) who focus on the economic value of IT investments, provides the high-level economic concepts for understanding technological progress and IT-driven automation. Applied energy and engineering economics bridge the gap between technical specifications and financial viability. This is where many scholars, from institutions like UC Berkeley, California, and Lawrence Berkeley National Laboratory, have already made significant contributions on the intersection of engineering and economics. Their research literature focuses on developing and applying specific metrics and models to evaluate energy projects and markets. Numerous studies use Levelized Cost of Energy (LCOE) to compare the cost-competitiveness of different electric energy generation technologies (KOST et al., 2021). Other research, like the one by Borenstein, Bushnell, and Blonz, conducts deep analyses of market mechanisms, such as the impacts of time-of-use pricing and price elasticity of demand under various dynamic pricing schemes (Blonz & Blonz, 2022; Borenstein, Jaske, & Arthur Rosenfeld, 2002; Faruqui & Sergici, 2010). While these engineering economics scholars provide essential tools for project evaluation and market analysis, they often work in isolation, focusing on a single metric or specific market intervention at a time, and testing their tools against more traditional investments.

The integration of distributed renewable energy sources and the digitalization of the energy sector through AI and IoT have created a gap in understanding how this technological progress translates holistically and structurally into economic changes and impacts. These include productivity gains and the transition away from traditionally natural monopolistic market structures in the electricity industry. As noted, current research is often conducted in academic silos. Technical studies demonstrate the technical nature and impact of AI and IoT; policy research investigates what is desirable and achievable for society; and economic evaluations focus on isolated economic metrics. The central problem this dissertation addresses is the absence of a unified economic–technical framework to holistically assess the impact of AI and IoT on the electric energy sector. Existing studies often focus on a single metric (like LCOE) or a single context, failing to capture the interconnected effects on production efficiency (TFP), investment viability (IRR), and the associated market changes from monopolistic to more competitive structures. There is a lack of scientific work that systematically investigates the general technological influence of AI and IoT as distinct factors, along with their associated economic effects across the modern energy ecosystem. While Brynjolfsson & Hitt (1995a) established IT as a critical input for firm productivity; their work predates modern AI and IoT systems. While energy economists have analyzed specific market interventions, they have not yet integrated the overarching technological shift into a comprehensive economic model approach reflecting production, distribution, and market structures. This leaves critical questions unanswered: How do the efficiency gains from an AI-driven control system translate into measurable changes in a project's total productivity? How do the financial metrics like IRR and ROI of microgrid projects justify the upfront capital costs of their intelligent infrastructure? Furthermore, how do micro-level economic key performance indicators aggregate? How is the macro-level shift from regulated monopolies to competitive, transactional energy markets enabled by technology, and what are the economic outcomes? Without a framework that connects the dots, stakeholders are left making multi-billion-dollar decisions with an incomplete picture, investing in a grey zone. Separating electric energy production costs from market mechanisms does a disservice to all stakeholders, as it fails to reflect the true costs.

The central question that underlies this dissertation is to what extent Artificial Intelligence (AI) and the Internet of Things (IoT) influence the economics of electricity production, distribution, and consumer market behavior. To answer this broad question, this research breaks it down into three distinct economic frameworks, each leading to its own research question. Regarding operational and investment efficiency, the study examines how integrating AI and IoT technologies affect productive efficiency, costs, and investment returns in microgrids. This analysis explores whether data-driven optimization can deliver measurable improvements in total factor productivity (TFP) and financial performance (IRR, LCOE), addressing the core claims of Hypothesis 1. In the context of renewable integration and market structure, the research investigates the role of AI and IoT in managing and integrating variable renewable energy sources. It also explores driving the structural shift from centralized, monopolistic markets toward more competitive and resilient energy systems, as outlined in Hypothesis 2. Finally, the study examines demand-side management by analyzing how AI and IoT enable strategies, such as dynamic pricing and demand response, to optimize grid load profiles and influence consumer behavior. This approach tests the mechanisms that underpin the market evolution described in Hypothesis 3.

This dissertation proposes the following three hypotheses, which will be tested in Chapter 4 through analysis of four selected case studies.

Hypothesis 1 (H1): *The integration of AI and IoT enhances operational efficiency and reduces costs in microgrids.* The core claim is that AI and IoT enable optimization, automation, and predictive monitoring, leading to resource savings (fuel, maintenance), reduced Levelized Cost of Energy (LCOE), increased Internal Rate of Return (IRR), and improvements in Total Factor Productivity (TFP).

Hypothesis 2 (H2): *AI and IoT technologies are pivotal for integrating variable renewable energy and fostering a shift toward competitive market structures*. The core claim is that AI and IoT enable the management of renewable, dispersed energy resources, supporting grid stability and resilience services. AI and IoT enable more competitive market structures through the availability of data from IoT devices and sensorics at different points in the ecosystem.

Hypothesis 3 (H3) posits that AI and IoT augment the effectiveness of demand-side management (DSM) strategies, including demand response (DR) and time-of-use pricing, thereby facilitating more efficient allocation of electric energy from *renewable energy sources*. The central argument is that IoT devices, particularly smart meters, provide the critical data and communication infrastructure necessary for demand side management (DSM). AI-driven analytics optimize DSM programs and analyze consumer responses to pricing signals, leading to load shifting and better utilization of electric energy production.

While this dissertation does not establish a new, unified theory of energy economics, it develops a new, comprehensive analytical framework that could serve as a prerequisite for any such future theory. By applying production, investment, and market theories and demonstrating their interconnectedness through case studies, the research provides a more integrated approach for explaining the economic structure of a digitized electric energy sector. It builds upon the work of foundational economic theories and demonstrates how the integration of AI and IoT, as distinct technological factors, reshapes the technical ecosystem, thereby driving changes in economic dynamics in production efficiency, investment decisions, and changing market structures in the energy sector.

Hypothesis 1 (Efficiency) extends classical production theory, which historically was developed in classical economics. (Smith, 2000) identified capital and labor as primary inputs and was subsequently enriched by Robert Solow's concept of the "Solow residual," or Total Factor Productivity (TFP), capturing technological progress (Solow, 1957). This dissertation advances production theory further by explicitly recognizing AI and IoT as specific, measurable, and critical factors of production, building upon (Brynjolfsson & Hitt, 1995a) inclusion of information technology as a distinct input of production. Hypothesis 1 operationalizes this approach by employing TFP to quantify productivity gains attributable to AI and IoT, testing whether these digital technologies now constitute fundamental inputs to energy production. Total factor productivity (TFP) measures the output produced by all inputs in the production process, including labor, capital, and technology, representing the efficiency with which an economy utilizes its resources to generate output. (Solow, 1956). Brynjolfsson & McAfee (2014) emphasize IT can enhance productivity by optimizing resource use, reducing downtime, and improving decision-making processes. Looking at the energy sector through the lens of TFP allows for assessing productive efficiency. Economic efficiency in modern energy networks might become a critical determinant for investment selection, as AI and IoT technologies optimize energy generation, distribution, and management.

Hypothesis 1 further addresses financial metrics, exploring how return on investment (ROI), internal rate of return (IRR), and levelized cost of energy (LCOE) are fundamental financial-economic metrics for evaluating the viability and efficiency of investments in AI and IoT (IEA, 2023). Within the framework of economic theory, these metrics are integral to capital budgeting, investment analysis, and decision-making processes (IRENA, 2022). When applied to renewable energy projects, they help stakeholders assess financial performance, compare alternatives, and make informed decisions that align with both economic and environmental objectives (IEA, 2023).This thesis also aims to use ROI, IRR, and LCOE as key economic indicators to evaluate the efficiency improvements achieved through AI and IoT in microgrids and hybrid energy projects.

The research also postulates that the integration of AI and IoT into renewable energy projects can increase ROI, IRR, and reduce LCOE by enhancing operational efficiency, providing better predictive maintenance, and improving energy management. AI-driven analytics can forecast energy production more accurately, better aligning supply and demand, therefore enabling better financial planning and risk assessment. Machine learning algorithms optimize asset performance, reducing downtime and operational costs, thereby enhancing both ROI and IRR (Q. Huang et al., 2022). Predictive maintenance powered by AI minimizes downtime by reducing unexpected failures and extends the lifespan of equipment, thereby lowering LCOE (Irena, 2016). Furthermore, AI algorithms optimize energy distribution and storage, ensuring that renewable energy is utilized more efficiently. Accurate demand forecasting reduces wastage and optimizes energy storage solutions, contributing to a lower LCOE (Bošnjaković et al., 2025). ROI, IRR, and LCOE act as economic determinants of the efficiency improvements enabled by AI and IoT.

Hypothesis 2 reflects classical theories of monopoly reflected in (Brock, 2024) and competition in (Grossman & Cole, 2003), particularly neoclassical economic models that characterize market structures ranging from natural monopoly to perfect competition (Muhamed & Magdy, 2020). Historically, the electricity ecosystem exemplified a natural monopoly, justified by high fixed costs that made a single provider the most economically efficient solution. This dissertation argues that AI and IoT technologies serve as technological catalysts, enabling the transition from a natural monopoly to more competitive structures(Cretì & Fontini, 2019; Greer, 2011). They facilitate the integration, management, and coordination of distributed energy resources by providing sensorics, information gateways, and analytical tools, enabling decentralized and competitive market structures. The possibility of this transformation from a practical monopoly into a competitive market has already been predicted by several researchers (Abir et al., 2021; Eltamaly et al., 2021; Mariyaraj & Thankappan, 2024; Naga Malleswara Rao et al., 2023). Hypothesis 2 thus applies and tests theories of competition through more decentralization in the electricity sector - demonstrating how technological innovation can enable new market structures.

Hypothesis 3 touches upon theories of consumer behavior, pricing signals, and welfare economics. Consumers historically lacked both the necessary real-time information and the means to adjust their consumption patterns in response to changing supply and pricing. Hypothesis 3 posits that AI and IoT technologies are drivers for transforming the market into more price-elastic structures. IoT technologies—such as smart meters and interconnected devices—address information asymmetries through sensorics and two-way communication infrastructure, creating real-time consumption data, and enabling consumer reactions to dynamic price signaling. AI machine learning overcomes behavioral economic challenges, such as consumer inertia and cognitive load, by automating data analysis and optimizing dynamic pricing strategies. Smart thermostats enable consumers to respond immediately and automatically to price fluctuations. By testing Demand-Side Management (DSM) strategies, this research provides concrete validation for the real-world applicability of demand elasticity theory. It illustrates how AI and IoT can facilitate grid management by actively influencing demand, enhancing social welfare, reducing operational costs, and enhancing grid stability.

This dissertation is organized into four chapters, with a logical structure that guides the reader through the historical, economic, technological, and practical aspects of the research. Chapter 1 begins by establishing context, describing the roles of automation and energy across the four industrial revolutions. It argues that technology and automation have been drivers of productivity, leading to market disruption since the beginning of the first industrial revolution over 200 years ago. Chapter 1 then delves into the economic theories that underlie the analytical basis for this research, building the theoretical framework for the case studies. This includes an examination of classical and neoclassical production theory, leading to total factor productivity as a measure of efficiency. Chapter 1 also examines the concepts of investment analysis metrics (LCOE, NPV, IRR), which are applied in Chapter 4 for hypothesis testing. In addition, it explores market theories related to monopoly, competition, and consumer behavior that are important to the transformation of electricity markets. This chapter is critical as it provides the conceptual economic frameworks used to test the hypotheses in the subsequent case studies in Chapter 4. Chapter 2.1 outlines the characteristics and evolution of the modern energy sector. It discusses the fundamental role of energy as a factor of production in the global economy. It traces the historic shift from a system dominated by centralized, fossil-fuel-based power plants to one that is increasingly distributed, with renewable energy resources. This chapter examines the economic and operational challenges posed by this transition, setting the stage for the technological solutions explored later in the dissertation. Chapter 2.2 delves into the key technologies driving the transformation of the electric energy sector. This chapter defines the Internet of Things (IoT) and Artificial Intelligence (AI), explaining their core architecture and functionalities. It moves beyond general definitions to focus specifically on their application in the electric energy domain, arguing that the combination of IoT's data-gathering capabilities and AI's analytical power is a necessary precondition for managing a modern, decentralized, and competitive energy system. Chapter 3 presents the methodological framework for the case study selection. It establishes the analytical and methodological foundation for evaluating how AI and the IoT influence productivity, efficiency, and cost structures in smart grids and microgrids. It explains the research design, data sources, and case study methodology used to quantify the economic impact of IoT- and AI-enabled energy systems.

Chapter 4 is the core chapter of the dissertation, applying the theoretical frameworks from Chapters 1 and 3 to four different case studies. In this chapter, a multi-case study methodology is applied to test the three hypotheses on efficiency, market structure, and investment. The analysis of the Blue Lake Rancheria and Airtel Madagascar microgrids investigates changes in operational efficiency and investment returns after the deployment of AI and IoT. The examination of the Olympic Peninsula Demonstration Project and the California Statewide TOU Pricing Pilots examines market transformation and demand-side management (price elasticity of demand) enabled by AI and IoT. In Chapter 4, the sub-chapter "Results and Implications" synthesizes the findings from the case studies and discusses their broader significance. This chapter evaluates the evidence from the case studies against each of the three hypotheses. It then discusses the broader implications of the research for economic theory, public policy, and industry practice. It concludes by offering specific directions for future research needed to continue building upon the framework and findings established in this dissertation. To test the three hypotheses, the dissertation employs a multi-case study research methodology. This approach is well-established in economic and social science research for investigating complex, contemporary phenomena in their real-world context, particularly when the boundaries between the phenomenon and its context are unclear (Kathleen M. Eisenhardt, 1989; Yin, 2014). The subfield of the electric energy sector, especially one undergoing rapid technological change, is well-suited to analysis through the lens of case studies. Several factors drive the decision to use this method. There is a lack of comprehensive, longitudinal sectoral operational and financial data related to microgrids. This is because there are few examples of applications and they are very recent, which would be required for a large-scale econometric analysis. The novelty of the business cases means that a qualitative approach is necessary to uncover the causal mechanisms at play. In addition, the case study method allows for a holistic understanding of the subject by comparing diverse contexts to explore similarities and differences, for testing the hypotheses of this dissertation (Stake, 1995). By examining specific, documented implementations such as the Blue Lake Rancheria microgrid and the California TOU Pilots, it is possible to isolate the economic effects of technological interventions from other confounding variables. Thus, the case study approach is the most appropriate method for obtaining meaningful results and building a robust, evidence-based argument. Data collection and analysis in this dissertation rely on a mixed-methods approach, primarily involving the analysis of quantitative data drawn from publicly available, verifiable secondary sources. The data collection process was tailored to each case study to ensure a rich, contextually relevant dataset for testing the hypotheses. Data sources include official project reports from government and research institutions such as the California Energy Commission (CEC) (Carter, Saucedo, et al., 2019) and the Pacific Northwest National Laboratory (PNNL) (*Transactive Energy | PNNL*, 2024), corporate financial records and technical specifications from companies involved in the projects (Braun, 2016) , and smart meter data from large-scale utility pilots. For instance, the analysis of the Blue Lake Rancheria microgrid utilizes operational and cost data from CEC reports. At the same time, the Airtel Madagascar case draws on detailed financial and performance metrics from GSMA (*GSMA: Green Power for Mobile*, 2013) and internal company documents. The smart grid analyses leverage extensive smart meter and pricing data from the California TOU pilots and the eGRID data repository (PG&E, 2024). The data has been further enriched through interviews with key personnel from the companies involved in the investment and technology integration for the selected case studies, such as Siemens and project leaders from PNNL. In addition, interviews were conducted with scientists actively involved in developing transactive energy.

The analytical techniques proposed in Chapter 3 and applied in Chapter 4 are directly aligned with the economic frameworks established in Chapter 1. To test the hypotheses related to operational and investment efficiency in the microgrid cases, the analysis involves calculating Total Factor Productivity (TFP), Levelized Cost of Energy (LCOE), and Internal Rate of Return (IRR). To test the hypotheses related to market transformation and demand-side management in the smart grid cases, the analysis focuses on calculating the price elasticity of demand and quantifying peak load reductions. This combination of data sources and analytical methods enables an evidence-based evaluation of the economic impacts of AI and IoT across the case studies.

The scope of this research is the economic impacts of AI and IoT technologies in the energy sector. In this economics thesis, the primary lens of analysis is how these technologies affect productivity, investment viability, and market structures. The research examines two primary contexts: microgrids, where the analysis centers on operational and investment efficiency metrics like TFP, LCOE, and IRR; and smart grids, where the focus is on market dynamics and consumer behavior, analyzed through concepts like the price elasticity of demand. The thesis does not conduct a deep engineering analysis of the technologies themselves, nor does it evaluate the entire bulk power system; instead, it uses engineering data as the context for its economic investigation. Methodologically, the research is based on an in-depth analysis of four specific case studies. While this approach provides a contextualized understanding of the phenomena, the findings are not intended to, and cannot, be statistically generalized across all situations. The goal is to build and test a robust analytical framework. Furthermore, this research acknowledges that it represents a snapshot in time. The rapid and ongoing evolution of technology in energy, AI, and IoT, along with changes in their associated costs and regulatory landscapes, will continue to transform the energy sector and introduce new paradigms. This dissertation provides a foundational economic understanding of the current transition, but ongoing research will be necessary to track future developments. One future economics research approach could be to examine how systems characterized by high penetration of digital technologies (AI/IoT) approach the marginal cost of information, causing information itself, rather than generation capacity, to become the primary factor in determining market structure and allocative efficiency, like in the automated mobility solutions of Waymo and others.

CHAPTER 1 ECONOMIC THEORIES AND FRAMEWORK OF PRODUCTIVITY

1.1 The Four Industrial Revolutions and the Evolution of Energy Networks

Technological change has been associated with productivity improvements across all four industrial revolutions. The first and second industrial revolutions saw enhancements in productive efficiency through mechanization and electrification. Across four distinct industrial revolutions, from the mechanization of the 18th century to the cyber-physical systems of the present, technological innovation has remained the fundamental driver of productivity growth. The current transition to Industry 4.0, characterized by artificial intelligence and the Internet of Things, is not a departure from this historical trend but rather its latest and most transformative iteration, continuing the centuries-long link between technological advancement and the productive phase in efficiency (Mokyr & Strotz, 2000).Currently, the global economy is transitioning from the third to the fourth industrial revolution, marked by technologies such as the Internet of Things (IoT), artificial intelligence (AI), and virtual reality (VR), which are automating and improving industrial processes. The fourth industrial revolution, often referred to as Industry 4.0, exemplifies the ongoing relationship between technical improvement and productivity enhancement (Schwab, 2016b).

The first industrial revolution took place between the late 18th and early 19th centuries. During this time, manufacturing evolved from a focus on manual labor performed by humans and supported by work animals to an optimized form of labor performed by humans using water- and steam-powered engines and other types of machine tools (Britannica, 2024). Arnold Toynbee (1852-1883), a prominent English economic historian, played an important role in understanding the first industrial revolution through his economic theories and descriptions. Toynbee coined the term "Industrial Revolution" to describe the transformative economic period in Britain between 1760 and 1840, marked by rapid industrialization and technological advancements. His analytical approach, focusing on the economic and social changes of this era, provided a comprehensive framework for future scholars. Toynbee's works, such as “Lectures on the Industrial Revolution in England: Popular Addresses, Notes and Other Fragments” (1884) and “The Industrial Revolution” (1883), compiled his insights and analyses, making them accessible to a broader audience. These publications, along with his influential lectures at Oxford University, emphasized the importance of economic history as a field of study and highlighted the complex interactions between economic developments and societal changes (McCloskey, 1981). By examining the causes and effects of industrialization, including technological innovation and changes in labor patterns, Toynbee advanced the understanding of the industrial revolution's impact on the modern economic system. His emphasis on the social consequences of industrialization, particularly the conditions of the working class and the need for social reforms, added a human dimension to the economic analysis (Bair, 2022). Toynbee's contributions influenced academic discourse on economic history and theory and continue to shape contemporary research. Adam Smith (1723-1790), a Scottish economist and philosopher, is often regarded as one of the founders of contemporary economic thought. His seminal thesis, "An Inquiry into the Nature and Causes of the Wealth of Nations" (1776), explains the foundational principles of modern economics and remains a cornerstone of the discipline, marking the origin of classical economic theory (Heilbronner, 2024). Adam Smith's analytical framework introduced key concepts such as the division of labor, specialization, exchange, and the scope of the market. His pioneering insights, which built upon the historical notion of the division of labor from Plato's works, argued that specialization leads to a qualitative improvement in productivity. Smith also proposed that a nation's prosperity should be measured by total production and commerce, a concept we now call gross domestic product. Smith believed that a nation's wealth is created by the productivity of its people and the efficiency of its markets rather than by the amount of gold or silver it possesses. In "The Wealth of Nations"(A. Smith, 1979), he pointed out the importance of division of labor, specialization, and free trade in promoting economic growth and increasing wealth. Smith's ideas and concepts have significantly impacted economic thought, politics, and philosophy. His work continues to have an impact today. Adam Smith and Arnold Toynbee contributed to the understanding of the first industrial revolution, but through distinct lenses. The introduction of machinery and steam power during the first industrial revolution led to substantial improvements in efficiency and productivity in the production and manufacturing sectors. Among the pivotal innovations of this era were mechanized tools that enabled the mass production of goods at a faster pace than conventional technologies. The spinning jenny and the power loom revolutionized the textile industry, enabling cost-effective, large-scale textile manufacturing (Mantoux, 2013). Steam power emerged as a transformative force, profoundly impacting productivity across multiple sectors. With steam engines powering machinery and transportation, the fast, cost-effective movement of goods and passengers advanced, revolutionizing trade and economic growth. (Molella, 2005). This technological breakthrough led to increased trade and economic expansion, as commodities could be manufactured and distributed faster and at lower cost. However, aggregate productivity growth from the invention and usage of the steam engine did not have a major impact in the UK until after 1850, 75 years after Newcomen's and Watt's steam engines were invented (Harald Edquist et al., 2006). The principles of efficiency and productivity established during the first industrial revolution are evident in contemporary energy industries that use microgrids and smart grids. Microgrids, small-scale power grids that can operate independently or in conjunction with the primary grid, embody the legacy of the first industrial revolution's focus on optimizing energy use and technological integration. Technological integration during the first industrial revolution, through the steam engine, enhanced energy efficiency by reducing transmission losses and optimizing local energy production and consumption (Lasseter, 2002).

Many historical accounts trace the origins of modern electrical power to the early 18th century during the first industrial revolution. One of the pivotal moments was the demonstration of electric conduction by Stephen Gray, which laid the groundwork for subsequent developments (Beaty & Fink, 2012). His breakthrough led to the creation of glass friction generators in Leyden, Germany, in the 1740s. These inventions inspired Benjamin Franklin's renowned experiments with electricity (Mahon, 2003). The progression continued with Italy's Alessandro Volta, who invented the battery in 1800, an advancement in the storage and use of electrical energy (Kuhn, 1967). In 1808, Humphry Davy developed the first effective arc lamp, providing a new method of producing light (Pearce, 1987).

The adoption of electricity marked one of the most significant developments in energy production. The development of the alternating current (AC) electrical system, pioneered by Nikola Tesla and George Westinghouse, enabled more efficient electricity generation and transmission over longer distances, creating more extensive and centralized power grids (Jonnes, 2003). This advancement paved the way for the electrification of many aspects of modern life, including manufacturing, transportation, and communication. It was instrumental in promoting economic growth and social change during this period. The AC electrical system remains a vital component of modern energy production and distribution systems, with a wide range of applications across sectors of the economy (Patel et al., 2017).The widespread adoption of electricity enabled electric lighting, new electrical appliances, and machines, which were vital in boosting productivity for both industries and private households. The availability of electricity enabled powering a wide range of devices, from simple lighting fixtures to complex industrial machinery, significantly expanding the scope and efficiency of modern manufacturing and production processes (Ahuja, 2015). By 1890, the main technical challenges surrounding the development and adoption of electricity had been mostly resolved, marking a significant milestone in the history of energy production. Thereafter, a series of incremental improvements and micro-inventions emerged, which focused on enhancing the reliability, durability, and affordability of electrical devices and systems (Chandler, 1994). For instance, in 1900, the cost of an incandescent lightbulb decreased by a factor of five over the previous two decades, and its efficiency had doubled, owing to the advent of new materials, manufacturing techniques, and design innovations. These incremental improvements in the cost and performance of electrical technologies further accelerated the adoption of electricity across sectors of the economy, including manufacturing, retail, transportation, and communication. They also laid the foundation for future technological advancements in the field of electric energy production and transmission (Mokyr & Strotz, 2000). Reliable and affordable electricity boosted productivity and made investments in it profitable. The historical examples above make a point of investigating how AI and IoT contribute to affordable, reliable electricity today and what the economic impacts of these technologies are in terms of financial and welfare economics. The period of the late 19th to early 20th centuries, known as the second industrial revolution, was characterized by technological advancements and economic growth. This era witnessed significant progress in manufacturing, production, and automation, which had a strong positive impact on productivity levels. The advent of mass-production concepts, including the assembly line, bolstered productivity by streamlining manufacturing processes and optimizing the use of capital and labor (Niiler, 2023). For example, assembly-line production led to significant improvements in productivity, as goods could be produced much faster and at lower cost than before (Dassbach, 1991). Like the automation on assembly lines during the second industrial revolution, AI and IoT are the main drivers of automation in the fourth industrial revolution. The expansion of technological systems, such as telegraph and railroad networks, gas and water lines, and sewage infrastructure, was enabled by innovations and scale in the manufacturing sector. The integration of electricity for powering industrial processes increased efficiency and enhanced machine flexibility (Stearns, 2020).

The second industrial revolution was characterized by a significant increase in the use of fossil-based energy, specifically from coal and oil, which had far-reaching impacts on energy production and the economy (Ahuja, 2015). The development of the internal combustion engine, powering automobiles and other machinery, contributed to a surge in oil demand. Refining crude oil made fuels more accessible, more abundant, and cost-effective (Rogers, 2009). The expansion of railroads and steamships drove demand for more coal. Moreover, advances in processing technologies, such as the Bessemer process for steel production—the first inexpensive industrial method that enabled the mass production of steel—drove growth in construction, infrastructure, and manufacturing, accelerating the pace of industrialization. Although the increased use of fossil fuels brought about significant benefits, including enhanced productivity and economic growth, it also contributed to environmental and social consequences. The consumption of fossil fuels and the production of cars resulted in air and water pollution, and the extraction of coal and oil often led to environmental damage, worker exploitation, and societal consequences associated with it (Ahuja, 2015). Significant technological and economic advancements have often been coupled with significant negative environmental consequences coming from high fossil fuel use. The current technological revolution, driven by AI and IoT, is not only about enhancing economic productivity but also about reducing CO2 emissions and environmental damage inherited from previous industrial eras.

The impact of the increased production and use of fossil fuels during the second industrial revolution laid the foundation for subsequent industrial revolutions and the development of advanced energy production and technology, which continue to shape the modern world (Rifkin, 2011). The first microgrids were built during the second industrial revolution by Thomas Edison in New York. By 1886, Edison's firm had installed 58 direct current (DC) microgrids (Roosa, 2021). A microgrid is an integrated electrical energy system consisting of distributed energy resources and multiple electrical loads, operating as a single, autonomous grid either in parallel to or independent ("islanded") from the existing utility power grid. Its generation, storage, and use are contained within a discrete geographic area, while its energy is managed by a control system independent of the main grid. Microgrids can utilize a variety of sources for their power, including electricity from the grid, renewable energy sources like solar panels and wind turbines, and diesel generators (Eyimaya & Altin, 2023). Studying the second industrial revolution is essential for comprehending the principles of electricity, fossil fuels, and automation, all of which are vital components of modern microgrids and smart grids that utilize AI and IoT. The use of these technologies in microgrids and smart grids highlights the evolution of energy production and the continued importance of these concepts in contemporary society. In these energy systems, efficiency gains are achieved through automation. The second industrial revolution also marked the beginning of a centralized, monopolistic energy supply, in which a few large energy companies controlled electricity production and distribution. This era, spanning the late 19th to early 20th centuries, established the foundational economic and technical framework for electricity production, fossil fuel usage, and automation, which are vital to modern energy systems. The widespread application of electrical power and the development of large-scale industrial processes were key features of this period (Hughes, 1993). The centralized electricity systems laid the groundwork for today's energy landscape, which has evolved with the advent of smart grids and distributed energy resources (DERs).

The third industrial revolution began in the mid-20th century. The integration of digital technology, computers, and digital influenced automation marked the third industrial revolution from the 1950s to the late 20th century. This revolution was driven by significant advances in electronics, computing, and telecommunications, which were integrated into industrial operations, enhancing productivity, precision, and efficiency (Brynjolfsson & McAfee, 2014).The rise of IT and automated control systems, as well as the beginnings of decentralized energy generation, can be attributed to developments in this period. This era is characterized by the shift and enhancement of traditional industries toward an economy with increased output and growth, enabled by information technology and digital communication. This also fundamentally altered the way people and systems connect, communicate, and process information. Key technological advancements, such as the development of the transistor in 1947 and the rise of the internet, have played crucial roles in this transformation (Riordan et al., 1999). The third industrial revolution saw manufacturing shift from analog and mechanical systems to production processes enhanced by digital technology. One of the most important economic effects of digitally enhanced automation is reducing operational costs, increasing productivity, and streamlining processes. Automated processes reduce the need for labor-intensive tasks and enable faster decision-making driven by data insights from collected data and localized embedded computer systems, such as Programmable Logic Controllers. A Programmable Logic Controller (PLC) is an industrial digital computer explicitly designed to optimize and control manufacturing and other industrial processes.

It can automate production processes by monitoring machines and executing logic in factories and industrial production. Unlike general-purpose computers, PLCs are built to operate reliably in harsh industrial conditions—such as extreme temperatures, dust, and vibrations. They play an important role in the operational layer of the energy system, where they execute real-time control, protection, and automation of physical assets, including generators, switchgear, inverters, substations, and microgrid components.

PLCs serve as the real-time central controller in microgrids and smart grids, automating and scheduling tasks such as generator start/stop sequencing, load shedding, and voltage/frequency regulation. Their rugged design and reliable local control are supported by TCP/IP connectivity, enabling them to integrate seamlessly with higher-level SCADA and energy management systems for coordinated grid optimization (Jeremy. Rifkin, 2011). Another technological advancement was the adoption of computer-aided design (CAD) systems. CAD enabled engineers and manufacturers to create highly detailed, precise product designs, shortening the product development and R&D process. This allowed for rapid prototyping and reduced time-to-market for new products (Porter, 1990). The integration of CAD into manufacturing streamlined the entire product development process and enabled greater customization and adaptability in production lines (Groover, 2019). This influenced modern energy systems by allowing individual, less specialized companies to design their own electric power facilities and grids. Industrial robotics automates repetitive and dangerous tasks, thereby improving workers' safety and maintaining consistent product quality. The deployment of robots, initially in the automotive industry and later widespread, led to continuous, high-output production lines, reducing human error and operating costs (Maning, 2013; Groover, 2019). While the early industrial robots were not interconnected, as seen in later AI and IoT-enabled Industry 4.0 systems, they represented a significant leap toward automating complex tasks and enhancing production capabilities (Nof, 2023).The transformation driven by the third industrial revolution set the foundation for interconnected, automated, and efficient production environments that would eventually lead to the development of Industry 4.0 (Brynjolfsson & McAfee, 2014). Semiconductors were a critical component in this technological revolution, enabling the miniaturization and enhanced performance of electronic devices. They played a crucial role in the development of integrated circuits, which facilitated the deployment of digital systems in the industrial landscape (Rifkin, 2011). Nowadays, companies can automate an entire production process - without human assistance. The basics for these advancements were laid in the third industrial revolution. Examples include robots that execute programmed sequences without human intervention (Mathur, 2022). In addition to industrial automation, the third industrial revolution also had a significant impact on the energy and electricity-producing industries. The end of the third industrial revolution in the late 1990s witnessed a push towards renewable energy as awareness of environmental challenges posed by greenhouse gas emissions from fossil fuels grew. Modernizing electrical grids was crucial for the energy sector's transformation. Traditional grids, with their unidirectional flow of electricity and limited adaptability, were progressively upgraded to support dynamic, bidirectional communication and distributed energy production and distribution. This was to address the challenges posed by the intermittency of renewable energy sources such as solar and wind. The integration of automated forecasting tools and adaptive energy management systems (Denholm et al., 2010) enabled grid operators to better predict energy output and demand, allowing them to adjust operations and ensure a steadier power supply, thereby mitigating fluctuations from renewable energy sources. Smart IoT devices, such as smart meters, helped create more dynamic, competitive energy market models (Sioshansi, 2011). Utilizing real-time analytics to optimize energy production and distribution, as in manufacturing processes, has led to economic improvements in the energy sector. Another advancement brought by the introduction of digitally enabled automation was in power plant efficiency. Power plants used automated systems to manage critical components such as turbines, boilers, and generators. As the case in manufacturing plants, introducing SCADA systems marked a significant milestone in this transformation. Integrating sensors, automated control systems, and computerized monitoring has enabled operators of traditional and renewable power plants to oversee and manage complex systems effectively. These technological advancements significantly reduced human error and operational downtime (El-Shebiny et al., 2007). The outcome was more streamlined, reliable, and productive energy production capable of meeting the growing demands of industry, public institutions, and private customers. It allowed plant operators to optimize performance and reduce greenhouse gas emissions, thus meeting stricter environmental regulations and societal demands (Sayed & Gabbar, 2017). The result was generating more power with fewer resources, creating a smaller carbon footprint. Automation technology enhances safety and predictive maintenance by utilizing automated systems equipped with sensors and real-time data analytics. These facilitated predictive maintenance schedules, enabling potential issues to be identified and addressed before they escalated into major problems

(Mobley, 2002). This enhanced worker safety, reduced repair costs, and minimized unscheduled downtime, leading to more consistent and safer energy production. However, the path to automation during the third industrial revolution was challenging and costly. One significant barrier was the high cost of technology adoption. Energy companies with legacy systems often found the financial burden of upgrading to automated infrastructures daunting (Joskow, 2000). The legacy of automation technology implemented during the third industrial revolution continues to shape today's energy sector. The groundwork laid for implementing decentralized energy systems, including microgrids and distributed generation, has enabled more resilient, independent energy production. Automation's role in integrating renewable energy has expanded, supporting the integration of today's clean energy technologies and sustainable practices. The introduction of data-driven decision-making tools has enabled the optimization of energy production and distribution, which is essential for integrating distributed renewable energy sources and improving efficiency. In addition, digital automation technologies better prepare the energy industry to manage increased energy demand from electric mobility and data centers (Chartier et al., 2022). The third industrial revolution has relevance to the increased deployment of microgrids and smart grids, as advanced control systems and monitoring technologies help optimize energy production, distribution, and consumption (Ray & Biswal, 2020, p. 21). In addition, the third industrial revolution has led to advancements in renewable energy technologies, such as improved solar panels with higher yields and larger wind turbines that produce more electricity. Integrating renewable energy sources into the grid has been made possible by the improvements and invention of advanced energy storage technologies, such as lithium-ion and redox flow batteries, that can store excess electricity generated by renewables and make it available when needed later in the day and so curb fluctuations in production and demand of electricity (Kathiresh et al., 2021).

The fourth industrial revolution brought forth disruptive technologies and trends such as the Internet of Things (IoT), robotics, virtual reality (VR), and artificial intelligence (AI) (Schwab, 2016b). IoT sensor devices and AI algorithms are utilized to monitor and optimize equipment performance, facilitating data-driven decision-making and enhancing overall productivity and operational efficiency (Manyika & Chui, 2015). Robots and Cobots are deployed to automate repetitive tasks and improve precision, thereby seamlessly integrating with the human workforce to increase productivity and reduce human error (Ferreira & Fletcher, 2022, p. 172). Virtual Reality (VR) is leveraged for employee training and safety simulations, providing immersive learning experiences and reducing workplace accidents (Guerra et al., 2018, p. 16). AI is applied for predictive maintenance and quality control purposes, enabling proactive identification of potential issues and ensuring the consistent delivery of high-quality products (Amelete et al., 2021, p. 579).

The Internet of Things and artificial intelligence synergistically contribute to the development of intelligent systems, with IoT sensors facilitating the real-time collection of data from machinery and equipment conditions. At the same time, AI algorithms analyze the acquired data to predict requisite maintenance interventions, minimizing downtime, increasing equipment lifespans, and optimizing overall efficiency (Lee et al., 2015). The fourth industrial revolution augments the manufacturing landscape by incorporating digital technologies, fostering intelligent and industrial systems that adeptly navigate and automate the complexities of market dynamics, supply chains, and consumer demand (Zimmermann et al., 2021, p. 128). Within the space of microgrids and smart grids, the focus is on sophisticated systems for control, monitoring, and optimization that manage electricity production, distribution, and consumption in real time (Ramchurn et al., 2011, pp. 5–12). For instance, IoT devices play a crucial role in monitoring energy usage and identifying opportunities for energy savings and efficiency enhancements in private households and businesses (McKenna et al., 2018). IoT sensors are integrated into components of the microgrid infrastructure, including solar panels, wind turbines, batteries, and energy storage systems, to collect real-time data on energy generation and storage, and transmit this information to a centralized monitoring system and command-and-control centers (Palma-Behnke et al., 2013). Data from IoT devices within microgrids can be subjected to advanced analytics tools, such as machine learning algorithms (Saadatmand, 2017). Those facilitate the analysis of real-time data, enabling the identification of patterns and trends that optimize microgrid performance and enhance energy production efficiency (Andoni et al., 2019). These algorithms also process information from IoT sensor devices on meteorological patterns and other factors that influence microgrid performance. By analyzing this data, AI algorithms enable opportunities for energy savings, forecast energy demand, and optimize renewable energy sources, such as solar and wind power (Binyamin et al., 2024). This technology can predict renewable energy production based on weather patterns and respond to demand fluctuations (Olabi et al., 2022). By using a digital twin of a microgrid or renewable energy plant, operators can monitor and control the facility in real time and simulate different operating scenarios to optimize energy production. Using digital twin technology allows operators to be alerted to and identify potential hardware issues to perform predictive maintenance. This enables informed decision-making to manage the microgrid system, ensuring optimal uptime and performance and thereby increasing efficiency (Odhiambo, 2024).The fourth industrial revolution represents a time of fundamental shift in the way we produce goods and energy, narrowing the gap between the digital and physical worlds (Klitou, 2014).

1.2 Investment Analysis Frameworks for Energy Projects

This sub chapter explores key economic theories and frameworks relevant to energy markets, including neoclassical production theory and Total Factor Productivity (TFP), supply and demand dynamics with elasticity and pricing strategies, welfare economics concerning externalities, and investment analysis tools such as Levelized Cost of Energy (LCOE), Net Present Value (NPV), and Internal Rate of Return (IRR), which are typical decision and evaluation criteria for investments in solar, nuclear or wind energy plants (Smith & Parmenter, 2016). The complexity of the new electric energy market, with distributed energy sources and prosumers, requires an integrated understanding of interrelated economic theories and frameworks. Neoclassical production theory and Total Factor Productivity (TFP) explain how energy producers optimize their inputs to maximize output, and they touch on theories of productive efficiency (Solow, 1956). Supply and demand dynamics, along with elasticity and pricing strategies, explain market operations and the responsiveness of consumers and producers to price changes (Varian, 2014). Welfare economics underscores the importance of policy frameworks that incorporate social costs and pricing to achieve allocative efficiency (Pigou, 2019). These frameworks address the economic understanding of all critical aspects of electricity production, distribution, and markets. TFP addresses production efficiency, grounded in neoclassical production theory. Time-of-use pricing (TOP) addresses market dynamics, supply and demand, demand elasticity, and pricing strategies. In the context of AI and IoT, they can measure how investments in these technologies positively influence the whole ecosystem, enabling better asset allocation and increased societal welfare. Financial investment analysis tools such as Levelized Cost of Energy (LCOE), Net Present Value (NPV), and Internal Rate of Return (IRR) are essential for evaluating the financial viability of energy projects and guiding investment decisions (IAE, 2022). The concept of Levelized Cost of Electricity (LCOE) shares conceptual similarities with the microeconomic concept of Long-Run Average Total Cost (LRATC), as both represent average costs over an extended period that account for input flexibility or asset life spans (Kenton, 2021). NPV is associated with investment theory and the time value of money. NPV helps determine the expected profitability of an energy project by accounting for the opportunity cost of investing resources elsewhere. A positive NPV indicates that the energy project is expected to generate value over and above the cost of capital, aligning with the goal of profit maximization in neoclassical economics (Sokolov, 2023). Firms use NPV to allocate capital efficiently, ensuring investments increase firm value by accepting projects whose discounted future returns exceed their costs. This relates to the microeconomic intertemporal choice theory, which studies how agents (consumers or firms) make decisions involving trade-offs across different time periods by discounting future costs and benefits to maximize their utility or profit (Varian, 2014).

The Net Present Value formula is as presented in equation 1.

$$NPV = \sum_{t=0}^{n} \frac{R_t}{(1+r)^t} - C_0 \quad (1)$$

where: R_t = Net cash inflow during the period t; r = Discount rate; C_0 = Initial investment cost; n = Number of periods (years).

The idea of NPV is based on the understanding that each subsequent cash flow should be discounted to adjust its nominal value to the changes in real value occurring in time. Each periodical cash flow value is obtained by discounting the nominal value, which can be written down as: $\frac{R_t}{(1+r)^t}$: This term converts each future cash flow into its equivalent value today by dividing it by the discount factor $(1+r)^t$. Energy project investments require massive funding. Any expected future cash flows must be set against the initial investment cost.

A positive NPV indicates that the investment is expected to generate more value than its cost, making it a profitable choice. Negative NPV characterizes an investment that would not cover its cost and is considered unviable. NPV = 0 indicates that the project breaks even, generating exactly enough to cover its cost of capital. This formula is fundamental to financial decision-making, as it allows investors to evaluate the profitability of energy projects, such as solar plants and microgrids, by accounting for the time value of money. NPV is also a critical determinant for evaluating the economic influence of ICT technologies, including AI and IoT, on an energy project. Implementation of AI and IoT involves upfront investment costs, but their ability to enhance efficiency, reduce operating costs, and possibly generate additional revenue streams can improve a project's long-term economic performance. The Internal Rate of Return (IRR) is another key financial metric used to evaluate the profitability of potential investments. It represents the discount rate at which the present net value (NPV) of all cash flows equals zero, indicating the break-even rate of return for a project. In simpler terms, the IRR is the expected annual rate of return from an investment. If the IRR exceeds the required rate of return (hurdle rate) or the cost of capital, the investment is deemed financially viable. This makes IRR useful for comparing multiple energy projects, as it provides a standardized measure of return based on projected cash flows (Fernando, 2024). Although AI and IoT systems increase upfront costs, they can ultimately raise a project's Net Present Value (NPV). This is achieved by improving annual cash flows through lower maintenance and energy expenses, new revenue from demand-response programs, and delayed asset replacement costs. The present value of these long-term gains often outweighs the initial investment. IRR, or internal rate of return, is a metric used in financial analysis to estimate the profitability of potential investments. If the IRR exceeds the required rate of return (hurdle rate), the project is considered acceptable. This aligns with the economic principle of allocative efficiency, which holds that resources are allocated to their most productive uses (Sokolov, 2023). IRR is the discount rate that makes the NPV of all cash flows equal to zero (equation 2). It is the expected annual rate of return generated by the project. IRR is found by solving.

$$0 = \sum_{t=0}^{n} \frac{R_t}{(1 + \mathrm{IRR})^t} - C_0 \qquad (2)$$

The Internal Rate of Return (IRR) method is commonly used in the energy industry, providing an effective way to compare energy management investments with alternatives. While reducing energy use and costs are appealing, corporations and decision-makers must prioritize investments that maximize returns on available company funds. The IRR method enables a direct comparison of competing investment options, ensuring that resources are allocated to the most economically beneficial projects (Smith & Parmenter, 2015).

Net Present Value (NPV) and Internal Rate of Return (IRR) help with investment decision-making by providing additional and complementary insights. While NPV measures the absolute monetary value added by a project, IRR shows profitability as a percentage, enabling easier comparisons across projects of varying scales and durations (Brealey et al., 2020). Together, these two metrics offer a good framework for evaluating a project's financial viability, with NPV focusing on value creation and IRR serving as a benchmark for relative returns against the cost of capital (Damodaran, 2012).

Levelized Cost of Energy (LCOE) is linked to production cost theory in microeconomics, representing the average cost of producing a unit of electricity over the lifetime of an energy generation project. It accounts for all relevant costs, including capital expenditures, operation and maintenance, and fuel expenses, serving as the "per-unit production cost" of electricity generation across an asset's lifespan (DOE, 2015). LCOE is also defined as the average net present cost of electricity generation for a generator over its operational life. It is a critical metric for investment planning. It serves as a standardized tool for comparing different electricity generation methods on an equivalent basis, enabling informed decision-making in energy economics and policy. It incorporates the time value of money, a fundamental financial concept stating that money available now is worth more than the same amount in the future because it can earn interest. By discounting future costs and outputs to their present values, LCOE provides a uniform basis for comparing projects with different lifespans and cost structures (Matsuo, 2022). LCOE represents the average cost per kWh of energy produced over the system’s lifetime, accounting for both upfront costs and ongoing expenses (equation 3).

$$LCOE = \frac{\sum_{t=0}^{n} \frac{C_t}{(1+r)^t}}{\sum_{t=0}^{n} \frac{E_t}{(1+r)^t}} \quad (3)$$

where C_t is the total cost in year t, E_t is the energy produced in a year, and the discount rate is r.

The numerator is the Present Value of Costs, representing the total costs incurred in year t, including capital costs (such as construction, equipment, and installation), operational and maintenance costs, fuel costs (if applicable), and decommissioning costs at the end of the project’s life. Those costs are discounted by the factor of $(1 + r)^t$, the discount rate, which reflects the time value of money and accounts for the opportunity cost of capital or project risk. The denominator is the Present Value of Energy Produced, where E_t is the monetized market value of energy output (in kWh or MWh) generated in a year. This value must be similarly discounted with the factor of $(1 + r)^t$. LCOE allows for comparison of the cost efficiency of each power solution in terms of the cost per unit of energy generated. This is particularly useful for understanding which system produces energy at the lowest cost, making it ideal for evaluating the long-term operational affordability of renewable and hybrid power systems (Matsuo, 2022). The LCOE is a valuable tool for understanding the economic impact of ICT technologies, such as AI and IoT, in energy production projects. It captures how these technologies affect both costs and efficiency over the project lifecycle. By optimizing energy production processes, reducing downtime, and improving predictive maintenance, AI and IoT lower operational and maintenance costs, directly reducing the total discounted costs in the LCOE formula (Brealey et al., 2020).Energy efficiency is enhanced through the integration of IoT-enabled sensor data and AI-driven analytics, which increase the precision of energy generation processes. Greater operational precision translates into higher energy yields and reduced production costs per unit of energy. While the integration of AI and IoT often requires higher initial capital expenditures, LCOE helps determine whether the long-term cost savings and efficiency gains justify these upfront investments. Furthermore, ICT solutions can lead to cost reductions and operational efficiencies, allowing benefits to materialize earlier. The time value of money incorporated in LCOE calculations highlights their financial impact (Damodaran, 2012). LCOE also supports comparative analysis of projects with and without ICT integration, quantifying the economic benefits of adopting technologies and revealing potential competitive advantages. By demonstrating how AI and IoT influence costs and energy production, LCOE enables strategic decision-making, helping stakeholders identify the most cost-effective and viable energy solutions. In summary, LCOE provides a quantifiable measure of the economic impact of ICT, helping investors and policymakers evaluate cost efficiency and productivity in energy production projects.

1.3 Productivity in the Energy Sector

Productive efficiency, an economic metric rooted in microeconomics, occurs when a firm produces goods or services at the lowest possible cost using available inputs and technology, effectively utilizing human capital, financial assets, and technological infrastructure to minimize production expenditures (Sexton, 2018); (Fried et al., 2008); (Koutsoyiannis, 1975). By implementing digital technologies such as sensors and data analytics, including machine learning, manufacturers can enhance productive efficiency, reduce costs, and increase production output, thereby boosting competitiveness and offering consumers lower prices (Motlagh et al., 2020; Porter, 1985).Economic efficiency extends this concept to the broader economy by ensuring that all goods and factors of production are allocated to their most valuable uses, minimizing waste, and maximizing social welfare. This is particularly relevant in the energy sector, where optimal resource allocation achieves maximum output at minimum cost (Clarke, 2024). Operational efficiency, a subset of economic efficiency, measures how effectively a system generates, distributes, and uses energy by calculating the output-to-input ratio, thereby reducing resource waste and maintaining desired output levels (Debreu, 1951;Koopmans, 1951). In the context of microgrids—self-contained energy systems that generate, store, and distribute power locally—the integration of IoT devices and usage of AI algorithms, and its broader ICT infrastructure, enhances efficiency, productivity, and overall performance by enabling real-time monitoring, predictive maintenance, and optimized energy management (Fantana et al., 2013). Evaluating microgrid efficiency involves combining economic metrics with technical indicators such as energy efficiency, capacity factor, availability factor, load factor, and reliability indices, thereby facilitating comprehensive performance assessments and resource optimization (Lasseter, 2002;Coelli et al., 1998). Theoretical frameworks from economists like Solow (1957), along with Adam Smith's classic factors of production—land, labor, and capital—provide foundational insights for modern economic analysis, emphasizing the importance of efficient input allocation to enhance productivity and economic well-being. For the energy investment assessment, this thesis will utilize operational efficiency analysis to determine improvements in energy production within microgrids through ICT investments, such as AI and IoT equipment. The aim is to increase productivity and economic efficiency, thereby enhancing the sustainability and effectiveness of local energy systems. The production function can therefore be defined as effectively utilizing human capital (L), financial assets, and technological infrastructure (K) to minimize production expenditure:

$Y = f(K, L, N)$ (4),

where K = Stock of Capital, L = Labor force, and N = Land.

Efficiency is enhanced when companies optimize the combination of input factors—such as labor (L), capital (K), and land (N) to minimize production costs (Farrell, 1957). Conversely, using outdated technology leads to inefficiency, resulting in energy waste and suboptimal outcomes. Schurr (2003) explores the relationship between energy use and economic growth, arguing that improvements in energy efficiency driven by technological advancements can increase productivity by allowing greater output from the same energy input, thereby fostering economic growth without a corresponding rise in energy consumption. Schurr's study of the period between 1920 and 1981 identified that technological progress significantly boosted total factor productivity (TFP), which measures economic performance by comparing output to combined inputs of labor, capital, energy, and materials. He observed that the ratio of total energy usage to worker hours more than doubled between 1920 and 1973 and increased by around 50% relative to capital in the U.S. economy. This increase in TFP was primarily due to reductions in energy intensity and productivity improvements, influenced by technological innovation. Integrating Internet of Things (IoT) and Industry technology can further enhance TFP by streamlining production processes, minimizing waste and downtime, and improving the quality of goods and services (Kowalska et al., 2023). Consequently, technological innovation plays a crucial role in total production efficiency, enabling output to grow more rapidly than energy consumption and contributing to overall economic well-being.

TABLE 1 *RATIO OF ENERGY USE TO CAPITAL AND LABOR INPUTS FOR SELECTED YEARS, 1899-1981 (INDEX: 1973=100)*

	Private business economy			Manufacturing		
Year	Energy to labor inputs	Energy to capital inputs	Energy to capital plus labor	Energy to labor inputs	Energy to capital inputs	Energy to capital plus labor
1899	22.0	45.5	27.5	25.1	73.8	31.1
1910	33.6	66.0	41.5	39.1	86.1	46.9
1913	35.4	68.5	43.5	43.8	83.7	51.2
1918	40.1	74.3	48.6	45.7	86.7	53.3
1920	39.7	68.7	47.2	44.2	75.3	50.4
1923	41.2	72.2	49.1	47.0	73.4	52.5
1926	40.8	69.3	48.1	48.3	71.0	53.1
1929	41.9	67.5	48.8	49.2	73.4	54.1
1937	45.8	68.9	52.5	52.6	82.0	58.6
1944	49.7	89.5	59.3	47.2	118.8	58.3
1948	53.5	85.2	61.9	55.9	94.5	63.7
1953	57.3	81.1	64.3	60.1	93.9	67.3
1957	63.7	81.3	69.2	66.8	88.3	71.9
1960	69.5	83.2	74.0	72.3	89.8	76.5
1969	91.2	96.2	92.8	88.0	96.3	90.3
1973	100.0	100.0	100.0	100.0	100.0	100.0
1979	94.7	88.0	92.4	98.4	82.7	93.9
1981	88.6	77.7	84.9	92.3	66.3	84.7

Source: Schurr (2003).

Schurr's findings that improvements in energy efficiency driven by technological advancements increase productivity pertain to the pre-modern era of electronics. However, the observed trends are more universal and are supported by more recent data. Despite the overall decline in manufacturing employment, the manufacturing sector became more energy-efficient and productive between 1970 and 2014. PNNL's (2017) energy indicators show that the economy-wide energy intensity index declined by approximately 16 percent from 1985 to 2014, reflecting improved energy efficiency and more significantly in the manufacturing sector (Belzer et al., 2017).

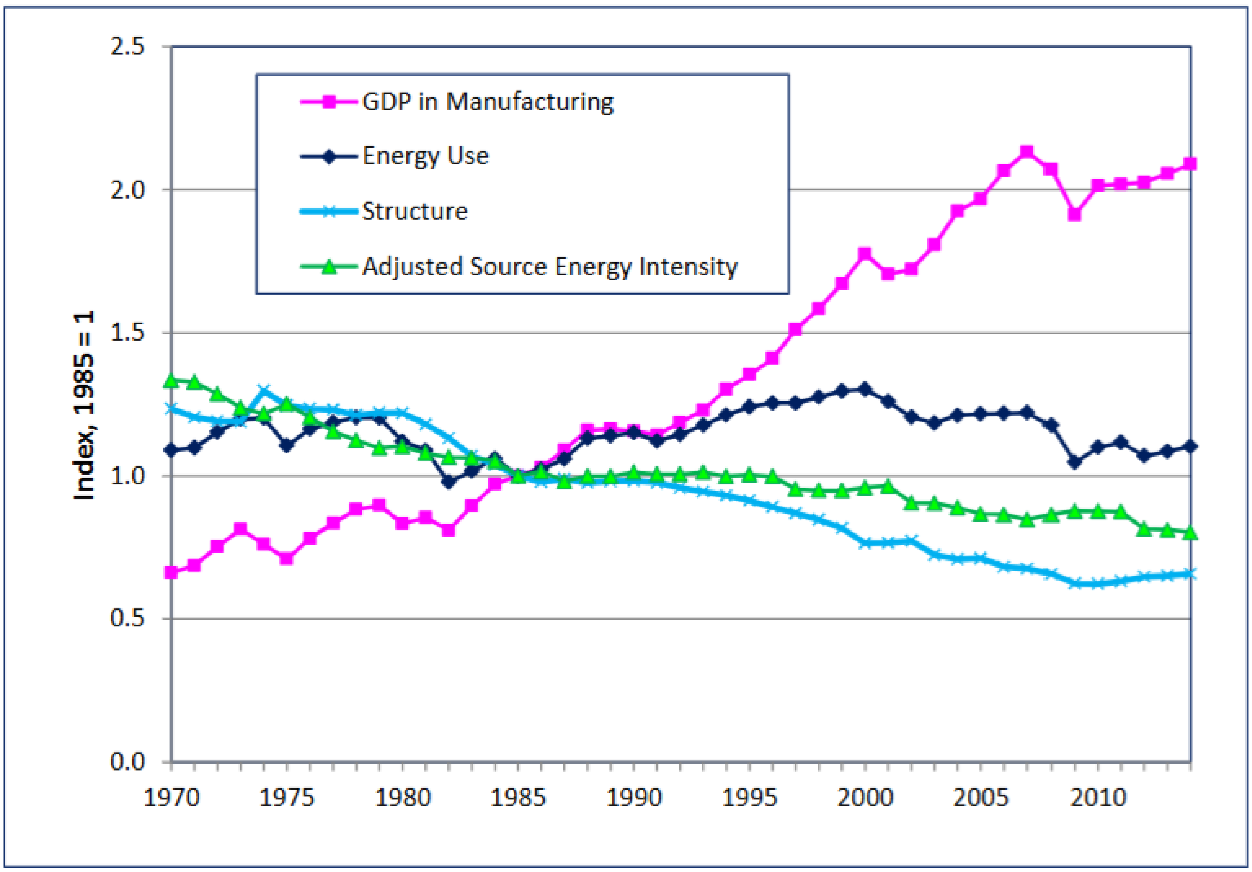


FIGURE 1 ENERGY INTENSITY AND RELATED INDICES FOR MANUFACTURING, 1970-2014

Source: (Belzer et al., 2017).

Figure 1 shows that manufacturing GDP grew strongly after the mid-1980s, more than doubling by 2014, while total energy use remained roughly constant over the same period. At the same time, the sector's structure shifted away from energy-intensive industries, with the index declining from about 1.2 in 1970 to 0.6 in 2014. As a result, adjusted source energy intensity fell from around 1.3 to 0.8, indicating that U.S. manufacturing became significantly more energy-efficient, producing more output with less energy per unit. Energy intensity in manufacturing has declined due to technological improvements enabled by increased IT spending, leading to efficiency gains and structural shifts. The green line in the graph indicates that energy is becoming a smaller complementary factor in the production function. Relative to labor and capital, energy's part in producing value has declined. The decline in energy-to-labor and energy-to-capital ratios reflects this. Between 1987 and 2020, energy's cost share in U.S. manufacturing declined from about 5–6% to below 3% (Federal Reserve Bank of St. Louis, 2024), representing a significant reduction in its relative importance to labor and capital. Labor costs continued to account for the largest share at roughly 55–60%, declining modestly with the use of automation (U.S. Bureau of Labor Statistics, 2020), while capital's share rose slightly as IT and advanced equipment became more prominent (Garner et al., 2022). As a result, the energy-to-labor ratio fell sharply, as higher labor productivity and declining energy intensity meant less energy was used per unit of labor. The energy-to-capital ratio declined as the capital share increased, while energy input costs remained flat or decreased.

TABLE 2 ENERGY INTENSITY INDICATORS (MANUFACTURING, 1970–2014)

Year	GDP in Manufacturing (Index 1985=1)	Energy Use (Index 1985=1)	Structure (Index 1985=1)	Adjusted Source Energy Intensity (Index 1985=1)
1970	0.6	1	1.2	1.3
1975	0.7	1.05	1.15	1.2
1980	0.8	1	1.1	1.1
1985	0.9	1	1	1
1990	1	1	1	1
1995	1.2	1.1	0.9	0.95
2000	1.5	1.05	0.8	0.9
2005	1.8	1	0.7	0.85
2010	2	0.95	0.65	0.8
2014	2.1	1	0.6	0.8

Sources: Author's own and (Belzer et al., 2017).

The table was constructed by approximating values directly from Figure 1 in the PNNL report. (Belzer et al., 2017). This chart plots manufacturing GDP, energy use, structure, and adjusted source energy intensity, indexed to 1985 = 1. It identified the reference years on the x-axis (1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010, 2014) and visually estimated the corresponding y-axis values for each series, rounding to two decimal places for consistency. These approximations were digitized from the graph and serve as illustrative indicators of long-term trends: GDP more than doubling, energy use remaining flat, the structure shifting away from energy-intensive industries, and adjusted energy intensity falling by about 40% over the period. Interestingly, the energy intensity use calculations have been largely abandoned in official US and World Bank statistics from the mid-1980s, focusing more on renewable energy and emissions instead of energy-growth factors.

Therefore for the last decade, the above picture could be only supplemented by regional research. Santos et al. (2021) investigated the long-term relationship between total factor productivity (TFP) and aggregate final-to-useful exergy efficiency in Portugal from 1960 to 2014. They conclude that improvements in energy efficiency, measured in exergy terms, significantly explain TFP variations by effectively capturing the contributions of capital and labor to economic growth. Production efficiency is evaluated by examining the relationship between outputs and key inputs such as labor, capital, technology, and energy (Sickles & Zelenyuk, 2019); (Chou et al., 2014).This framework is particularly relevant in the context of renewable energy generation, where it serves as a more precise indicator of productivity impacts than aggregate measures of economic growth (Ayres et al., 2002). Technological advancements, including the integration of AI and IoT, enhance TFP by streamlining energy production processes, minimizing waste, and reducing downtime through digital technologies like microcontroller-enabled automation, machine learning, and data analytics (Kowalska et al., 2023). One AI example is Long Short-Term Memory (LSTM) networks, a type of recurrent neural network designed for sequence data, which have been utilized to forecast load, solar, and wind generation with significant accuracy improvements. Shering et al.(2024) report that using LSTM models reduced the Mean Absolute Scaled Error (MASE) for load forecasting by 24% and improved solar generation predictions by up to 22% when incorporating temperature as an external variable. Furthermore, ICT-enabled microgrid controllers enhance TFP by monitoring real-time energy supply and demand, optimizing energy storage and distribution, prioritizing energy usage based on availability and load priority, and detecting and addressing issues such as equipment failures or power outages, thereby reducing downtime and repair costs (Alsaidan et al., 2017). Total factor productivity in energy production can therefore be effectively calculated by considering the inputs of capital, labor, technology, ICT (including AI and IoT), and energy. This highlights that technological innovation is central to improving economic outcomes and operational efficiency in microgrids as well as in larger energy systems (Kahouli et al., 2022). The calculation can be defined as follows:

$$\text{TFP} = \frac{Y}{f(K,L,N,\text{ICT},E)} \quad (5),$$

where: Y= "Output" represents the total production output of energy, C= "Capital" represents the amount of physical capital invested in the energy production process, L= "Labor" represents the amount of labor used, T= "Technology" represents the use of machinery in the production process, ICT= "ICT" or “IoT” represents the use of Information and Communication Technology, and E= "Energy" represents the energy consumption used in the production process of energy production.

This formula calculates the efficiency of energy production by dividing the total production output by the total inputs used in the energy production process. TFP captures the impact of technology, ICT (AI and IoT), and other intangible factors on energy production efficiency. Including energy as an input in the TFP calculation helps evaluate how energy use affects production efficiency, an essential factor for sustainable energy generation. Studying the link between TFP and its inputs also shows how IoT can improve efficiency. To calculate electricity production efficiency in Microgrids and Smart Grids, the Total Factor Productivity (TFP) metric is defined as the ratio of Energy Output to the combined inputs of Capital, Labor, Technology, ICT, and Energy Input. The formula for TFP is expressed as:

$$\text{TFP} = \frac{\text{Energy Output}}{\text{Capital} \times \text{Labor} \times \text{Technology} \times \text{ICT} \times \text{Energy Input}} \quad (6).$$

Energy Output refers to the total energy produced, measured in kilowatt-hours (kWh) multiplied by the cost per kWh in monetary units. Capital encompasses all financial investments in the project, including costs for project planning, land development, import duties, and transportation. Labor accounts for the expenses associated with human resources involved in the construction, erection, and maintenance of energy assets, such as solar panels, batteries, and diesel generators. Technology represents the costs of machinery and technological assets used in the production process, including diesel gensets, solar cells, batteries, and other hard technology assets. ICT covers the use and costs of Information and Communication Technology, which includes sensors, servers, software, and sensorics (AI and IoT), cloud storage, cables, and transmission equipment. Energy Input denotes the energy consumed during production, including diesel fuel or gas, transportation costs, waste or theft, and expenditures for solar energy.

Technical efficiency fosters more efficient energy production, which subsequently reduces the cost of goods production, thereby decreasing capital requirements (Solow, 1957). Consequently, energy efficiency becomes a component of capital.

Productive efficiency is closely related to the concept of technical efficiency. A firm is technically efficient when it combines the optimal combination of labor and capital to produce goods. i.e., cannot produce more of a good without more input. In this case, technical efficiency is the most efficient way of producing energy utilizing technology (Erena et al., 2021). The phenomena underscore the concept of total factor productivity, as explained by the Cobb-Douglas Function. The Cobb-Douglas Production Function was first introduced by Paul Douglas and Charles Cobb in their influential 1928 paper, "A Theory of Production," presented at the American Economic Association meetings in 1927 (Cobb & Douglas, 1928). This function provides a mathematical representation of the relationship between capital and labor, illustrating how these inputs combine to produce output. While the Cobb-Douglas function was a key component of their work, the paper's primary innovation lay in their approach to modeling production rather than the function itself. Since its inception, the Cobb-Douglas Production Function (CDPF) has become a fundamental tool in economics for analyzing total factor productivity. The CDPF allows economists to separate the effects of changes in capital and labor from those of technological advancements and efficiency improvements, thereby quantifying their respective contributions to economic growth. (Biddle 2012) provides a detailed analysis of how Paul Douglas developed the function by examining U.S. industrial data from 1899 to 1922. Douglas based his formulation on indices of total fixed capital adjusted for fluctuations in capital goods costs (C), the total number of wage earners in manufacturing (L), and measures of physical production. The CDPF is commonly applied to describe how goods and services are produced by linking output with the use of capital and labor. According to (Cottrell 2019), it integrates the quantities of input required to generate output, enabling a comprehensive analysis of production processes. Felipe and Adams (2005) note that the Cobb–Douglas production function is still the most commonly applied framework for examining productivity and economic growth in both theory and practice. Much of the research on growth, technological development, productivity, and labor focuses on estimating the parameters of aggregate production functions. In macroeconomics, empirical estimates of these functions are essential analytical tools grounded in theoretical concepts such as potential output, technological change, and labor demand.

The Cobb-Douglas equation is given by:

Y = A x Kα x Lβ (7)

where: Y = Total product, A = Total factor productivity (TFP), K = Available capital, L = Labor (human resources), B = Elasticity of human resources.

Energy plays no role in the standard Cobb-Douglas Production Function. Recognizing that the standard Cobb–Douglas formulation omits energy, researchers such as Keen et al. (2019) have proposed augmented models that explicitly relate output (Q) to labor (L), capital (K), and energy (E). Keen et al. (2019) describe the function relating a single measure of output (Q) to single inputs of Labor (L), Capital (K), and Energy (E) — in which energy plays an essential role, and to follow through the consequences of this function at the level of aggregate inputs and output. This approach treats energy as an independent input to labor and capital that enables them to produce output and could be given by equation 8:

$Q = F\big(L(E), K(E)\big)$ (8)

where: Q = Output, F= Function, L= Labor, E= Energy, K = Capital.

Again, energy is not introduced into a production process function independently of labor and capital; instead, it is directed by these factors to perform useful work. Without energy input, neither labor nor capital can generate productive output. Incorporating energy into the Cobb-Douglas Production Function results in the Energy-Based Cobb-Douglas Production Function (EBCDPF), which highlights the essential role of energy in production. This adaptation redefines production as the utilization of energy to generate useful work (Dufo-López et al., 2019). The EBCDPF asserts that a specific amount of energy is necessary to achieve a given level of output, underscoring energy's critical role as a factor of production. Consequently, any changes in energy usage can significantly affect the production process (Keen et al., 2019). Using the EBCDPF is advantageous for assessing the effectiveness and efficiency of energy utilization within production. By examining the relationship between energy input and output, the model offers valuable insights for optimizing energy use, enhancing efficiency, and reducing costs. Additionally, it helps identify areas for improvement to minimize energy waste and promote sustainability (Dixon & Jorgenson, 2012). The coefficients in the EBCDPF, representing the output elasticity with respect to energy and other inputs, can be estimated using econometric methods such as regression analysis. By quantifying these relationships, the EBCDPF facilitates the examination of how energy consumption influences economic output and growth, providing insights into efficiency and productivity. The underlying graph (Figure 2) is based on the formula (Keen et al., 2019) below:

$Q = C \cdot (E_x^K)^{\alpha} \cdot K^{\alpha} \cdot L^{1-\alpha}, \alpha = \frac{2}{3}$ β =1/3 (9),

where: C= Consumption, Q = Output, F= Function, L= Labor, E= Energy, K = Capital, α and β = input shares of capital and labor such that α + β = 1.

With these values, the marginal impact of varying inputs, either the exergy per machine or the number of machines, is very close to linear (as depicted in Table 3). Increases in three different types of inputs—Exergy Per Machine Input, Capital Input, and Labor Input—impact GDP, each measured as a percentage of its base level (100%). A 1% increase in either factor causes a 0.67% increase in output, compared to a 0.33% increase in output for a 1% increase in labor. Conversely, a 40% decrease in either capital or exergy per unit of capital results in a 30% decrease in output (see Figure 2).

TABLE 3 RELATION OF ENERGY AND OTHER PRODUCTIVITY FACTORS

% Input	Exergy (Red)	Capital (Blue)	Labor (Black)
0	0	0	0
10	8	7	25
20	19	18	44
30	30	30	59
40	41	41	70
50	53	53	78
60	63	64	85

70	74	75	90
80	85	87	95
90	96	98	99
100	106	110	102
110	117	121	106
120	128	132	110
130	139	143	113
140	150	155	115
150	161	166	117

Source: (Keen et al.2019).

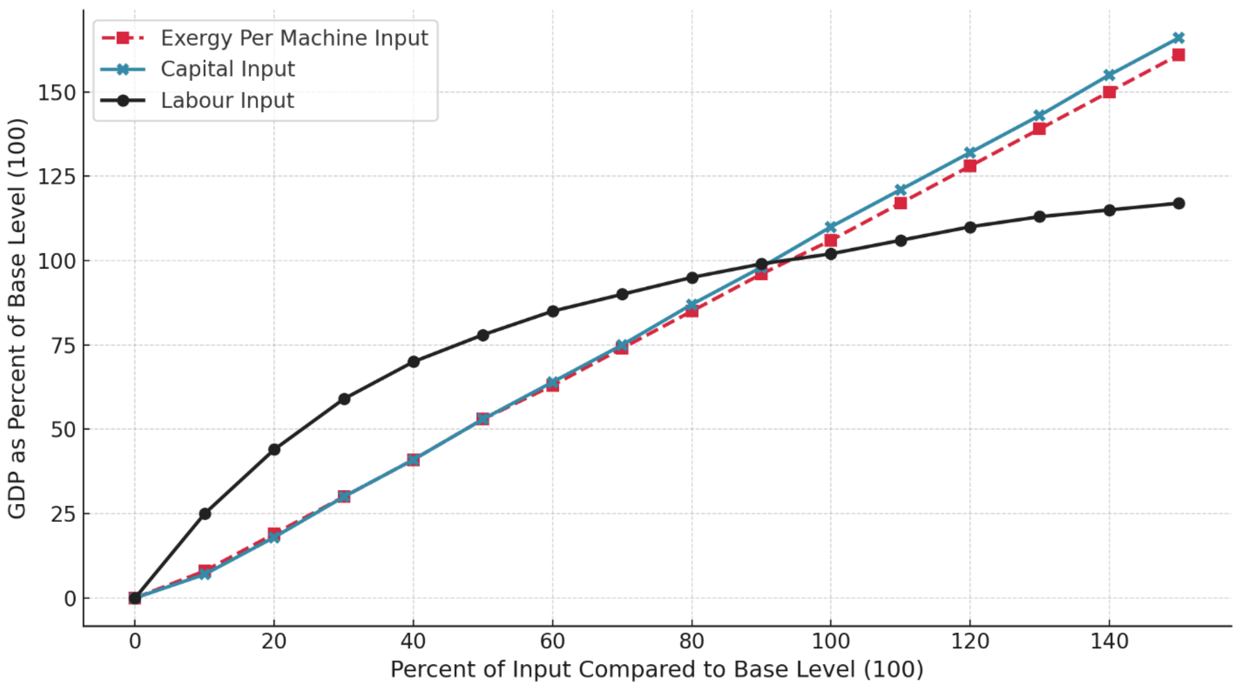


FIGURE 2 OUTPUT LEVEL GIVEN CHANGE IN FACTOR INPUT - LABOR, ENERGY, AND CAPITAL

Source: (Keen et al.2019).

Table 3 and Figure 2 display how "Exergy Per Machine Input", "Labor Input”, and "Capital Input" converge at the point where both input and GDP are at 100% of their base levels, indicating that at the base input level, the GDP is also at its base level for all three factors. Beyond this point, "Exergy Per Machine Input" and "Capital Input" have a more substantial impact on GDP growth compared to "Labor Input”. As previously stated, the traditional view of productivity factors was limited to land, labor, and capital. Over time, however, this perspective has expanded to include energy, technology, knowledge, and other factors as essential contributors to productivity. Technology has strongly influenced the production and delivery of goods and services, significantly enhancing efficiency and competitiveness. By integrating technology into their operations, companies automate routine tasks, improve accuracy, accelerate processes, and reduce costs. Research into the impact of information technology (IT) on productivity began in the 1980s and 1990s. A seminal study in this area by Brynjolfsson & Hitt (1995) argues that IT should be recognized as a distinct factor of production, alongside land, labor, and capital. To support their claim, the authors analyzed IT investment data collected from surveys of information systems (IS) departments in firms listed in the top half by sales of both the Fortune 500 Manufacturing and Fortune 500 Service categories. These annual surveys, conducted from 1988 to 1992, gathered information on annual IS budgets, the number of desktop machines (such as PCs and terminals), and overall IT spending. Their findings demonstrated that the elasticity of IT is both positive and statistically significant, indicating that IT investments are strongly associated with increases in productivity and output. This evidence underscores the critical role of IT in enhancing productivity across various industries. They investigated the effect of three inputs: Computer Capital and Labor (C), Non-computer Capital (K), and Non-computer Labor (L). Their production function can therefore be defined as:

$Q=F(C, K, L; j,t)$ (10)

Where: Q = the output of a firm (i.e., its productivity), C = the amount of capital available to the firm (IT/computer capital) K = non-computer capital, L = the amount of labor available to the firm, j = the level of investment in research and development, and t = the level of technology available to the firm.

C captures the impact of IT investments—hardware, software, networks. K captures other forms of physical capital, such as machinery, buildings, and equipment. According to this equation, productivity is a function of multiple inputs, including technology, technological expertise, R&D expenditure, money, knowledge, labor, and the pricing of these inputs. Moreover, the relationship between these inputs and productivity is interrelated, and changes in one input can considerably impact output levels. Brynjolfsson and Hitt consider three extensions of the basic framework. The first is allowing the production function to vary across firms rather than across industries. The authors further acknowledge that while the data is insufficient to allow all the parameters to vary across firms, they were able to allow the intercept term (often called multifactor productivity) to vary at the firm level (Brynjolfsson & Hitt, 1995b). Incorporating exogenous effects where management capabilities vary across the firm allows for the reformulation of the production function into:

$$\log Q_{it} = \sum_{j=1} \delta_j J_j + \sum_t \gamma_t T_t + \beta_1 \log C_{it} + \beta_2 \log K_{it} + \beta_3 \log L_{it} + \beta_4 M_i + \varepsilon_{it} \quad (12),$$

where: Q_{it} = The inflation-adjusted value-added or revenue of firm i at time t, Cit = IT Capital Stock, Kit = the amount of knowledge available to the firm, Lit = Total labor costs or number of employees for firm *i* at time *t*., ε_{it} = random error terms capturing all other factors that affect production but are not explicitly included in the model, J_j = R&D Investment, t = An index for each time period (t), pi= A parameter capturing the return to scale of computer capital, β2=A parameter capturing the return to scale of non-computer capital, β3= A parameter capturing the return to scale of non-computer labor, and M denotes the management skill.

The equation captures the relationship between the inputs (computer capital, non-computer capital, and non-computer labor) and output. It also explains how the returns to each input vary. Using logarithmic transformations in this equation allows estimation of elasticities, which measure the percentage change in output for a given percentage change in an input. The coefficients on the independent variables represent the estimated elasticities, and the interaction terms capture the effects of the interaction between inputs on output. This equation examines the relationship between various inputs, such as the level of technology and technological knowledge, and the firm's output level. It estimates the effects of changes in these inputs on productivity.

IoT investment is a specific subset of ICT investment within the production function, encompassing technologies such as computers, mobile devices, internet connectivity, telecommunications, and software applications (Huth et al., 2017). Within this broader category, IoT refers to networks of physical devices and appliances embedded with sensors, software, and connectivity that enable data exchange with other devices and systems, either via the internet or through local edge infrastructures (Laylaec, 2019). Espinoza et al. (2020) utilize the growth accounting framework to assess how IoT affects productivity. The authors identify a modest positive impact of IoT on productivity and provide projections under various scenarios. To perform this analysis, the researchers adopted the growth accounting approach developed by Jorgenson.

Growth accounting is a method used to determine the factors driving economic growth within a specific country or region by examining the contributions of inputs such as labor, capital, and technological advancements (Jorgenson, 2024). By comparing the growth rates of these inputs to the overall output growth rate, growth accounting quantifies the individual contributions of each factor to economic expansion. Also referred to as the Solow-Swan growth model, growth accounting breaks down an economy's total growth rate into distinct contributions from capital, labor, and technology. This decomposition provides a clear understanding of the sources behind long-term economic growth (Dieffenbach, 2014). The study leverages Jorgenson's growth accounting framework to highlight the positive role of IoT in enhancing productivity, offering valuable insights into the technological drivers of economic growth in Europe. In growth accounting, when information technology is included, Total Factor Productivity (TFP) measures the impact of technological progress on economic growth. TFP reflects how efficiently an economy utilizes its inputs—capital and labor—to produce output. Specifically, the TFP growth rate indicates the pace of technological advancement and is calculated as the residual growth in the economy after accounting for the contributions of capital and labor (Chou et al., 2014).An economy's total productivity increases only when it generates more output from the same amount of input. Technological improvements are a primary driver of TFP growth, encompassing all technological advancements, including ICT. Under the assumptions of competitive factor markets, full input utilization, and constant returns to scale, growth accounting decomposes growth in value added into contributions from different inputs—labor, ICT capital, and non-ICT capital—and a residual term known as TFP. This can be expressed with the following equation:

$Y_T = v_L \cdot L_T + v_{ICT} \cdot K_{ICT} + v_N \cdot K_N + TFP_T$ (13),

where: Y_T = Value-added growth, L_T = Labor growth represents the increase in the labor force, v_{ICT}= ICT capital growth, K_{ICT} = measures the growth rate of ICT investments, $v_{ICT} \cdot K_{ICT}$ = quantifies the impact of ICT capital growth on the overall economic growth and reflects growth in capital specifically related to Information and Communications Technology, v_N= assigns a weight to the growth rate of non-ICT capital K_N, and quantifies how much of the economic output is attributable to investments in non-ICT capital, $v_N \cdot K_N$= Shares of labor, ICT capital, and non-ICT capital in nominal value added, TFP_T = Growth in Total Factor Productivity.

TFP_Tmeasures the efficiency with which capital and labor are used to produce output. It captures the effects of technological progress and innovation. This equation enables scientists and policymakers to evaluate how different inputs contribute to an economy's overall growth rate, thereby identifying the primary sources of economic expansion. By quantifying each input's contribution, decision-makers can identify the key drivers of growth and formulate policies and investments that promote sustainable economic development. Behavioral economics, the empirical economic observations of human behavior, reveals that individuals often deviate from the "rational" or "optimal" decision-making models proposed by neoclassical economists, even when they possess the necessary information and tools. For example, investments in energy efficiency are typically subject to uncertainty. Under such conditions, businesses and households frequently exhibit loss aversion, a key concept in behavioral economics that describes the tendency to prefer avoiding losses over acquiring equivalent gains. Loss aversion can deter companies and households from investing in energy-efficient technologies. Heutel (2019), and Keen et al. (2019), claim that providing information led to reductions in both electricity and natural gas consumption lasting between 7 and 12 months. Additionally, Ferraro & Price (2011) found that information leveraging social comparisons was more effective in reducing water consumption than purely technical information or messages encouraging savings (Heutel, 2019). The energy market could also be analyzed through prospect theory, a behavioral economics theory that explains how people make decisions under uncertainty, risk, and probability. It was proposed by psychologists Daniel Kahneman and Amos Tversky. Prospect theory, which forms the foundation of loss aversion, not only accounts for behaviors that traditional decision theories like expected utility theory and rank-dependent utility theory struggle to explain but also integrates the explanatory power of these theories. At the individual decision-making level, loss aversion leads to a preference for technologies that are already established in the market. These established technologies are likely perceived as subjective reference points by consumers, making them more attractive than newer, less familiar options (Knobloch et al., 2019). The significance of loss aversion is further highlighted by Kahneman and Tversky's 1992 study, which showed that losses are perceived as approximately 2.25 times more painful than equivalent gains are pleasurable (Tversky & Kahneman, 1992). This heightened sensitivity to losses explains why households and businesses may reduce their electricity and gas usage in response to significant price increases.

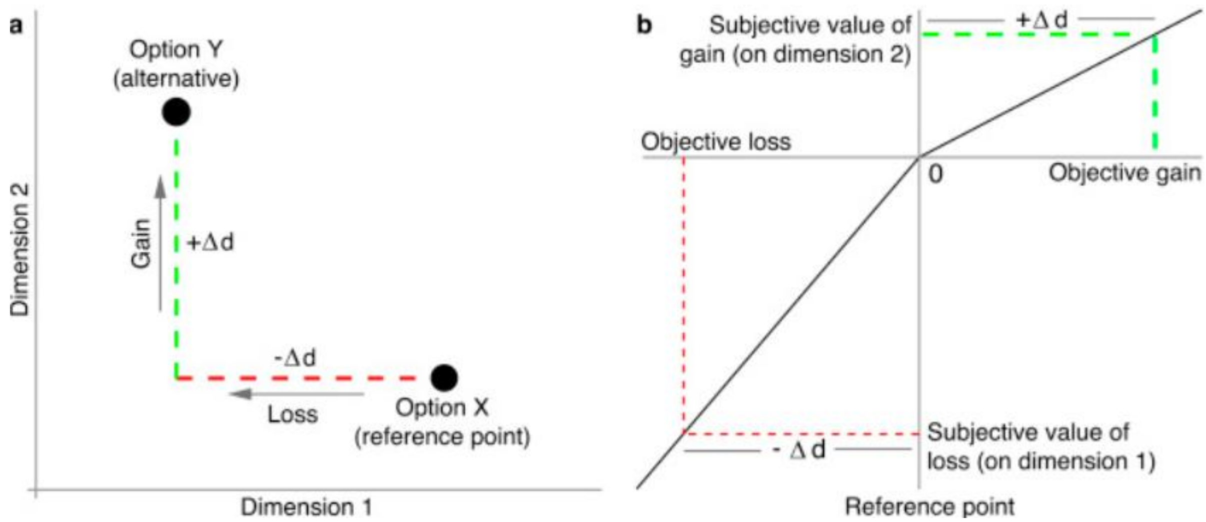


FIGURE 3 REFERENCE DEPENDENCE AND LOSS AVERSION IN PRODUCT CHOICE

Notes: a) In a riskless choice between two consumption goods (options X and Y), losses and gains correspond to differences in their individual attributes, b) Losses and gains are evaluated according to the empirically derived Prospect Theory value function. In the case of loss aversion, losses are assigned a larger subjective decision value than gains.

Source: *(Knobloch et al., 2019).*

The principles of behavioral economics, particularly loss aversion, can be relevant to price-finding mechanisms in smart grids and transactive energy ecosystems, where consumer behavior is critical. Boom & Schwenen (2021) assert that loss aversion, the tendency for individuals to prefer avoiding losses over acquiring equivalent gains, plays a role in how consumers respond to dynamic pricing within these systems. In smart grids, which enable price signals to balance supply and demand, it is essential to understand that consumers may be more sensitive to price increases (perceived as losses) than to potential savings (perceived as gains). This sensitivity can be leveraged to design pricing models that incentivize consumers to shift their energy usage to off-peak times or to reduce overall consumption. Time-of-Use (TOU) pricing is a strategy enabled by smart grid technology that leverages the principles of demand elasticity to adjust energy usage during peak demand times. TOU pricing involves varying electricity prices at different times of the day or year to reflect the changing costs of energy production (Enrich et al., 2024). During peak demand periods, when energy demand is higher, higher prices are charged, encouraging consumers to reduce usage or shift their consumption to off-peak times. Conversely, lower prices during off-peak hours incentivize increased energy use or energy storage when the grid is under less strain. This pricing mechanism can effectively smooth out supply and demand fluctuations, enhance grid stability, and help maximize the efficiency of electric energy distribution systems (Carvallo & Schwartz, 2023). By integrating elasticity of demand theories with TOU pricing, energy providers can create more efficient energy markets and systems. Smart grids, enabled by AI and IoT infrastructure, can provide signals and information to drive pricing signals that lead to market adjustments, optimizing energy distribution and energy storage infrastructure in real time. This not only improves efficiency by reducing energy waste and lowering operational costs, but also supports sustainable economic growth by aligning energy consumption with resource availability, thereby reducing CO2 emissions. Enrich et al. (2024) suggest that the effect of a time-of-use pricing program introduced in Spain on residential electricity consumption is at least 1-2%. Their study suggests that a predetermined pricing program can effectively raise consumer awareness and increase household price elasticity. This could make it a valuable policy tool for reducing peak electricity demand and enhancing market efficiency, thereby better matching demand and supply. TOU pricing and the economic theory of elasticity of demand are linked through their mutual focus on consumer responsiveness to price changes. Marshall (1920) states that the elasticity of demand measures how the quantity demanded of a good or service responds to changes in its price. When demand is elastic, consumers alter their consumption in response to price fluctuations, whereas inelastic demand indicates minimal changes in consumption despite price variations. When electricity prices rise during peak hours, consumers with elastic demand are more likely to reduce their usage or shift it to cheaper, off-peak times. This helps flatten the demand curve, reduce strain on the grid, and lower the overall cost of energy distribution (Palensky & Dietrich, 2011). For instance, Pacific Gas and Electric (PG&E), like many utilities in the western USA, has adopted dynamic pricing models that include Time-of-Use (TOU) rates and Peak Day Pricing (PDP) to incentivize consumers to shift their energy usage to off-peak times or reduce their overall consumption during peak demand periods (PG&E Demand Response Programs, 2024). These pricing models capitalize on the concept that consumers are more likely to respond to potential losses (e.g., higher electricity rates during peak periods) than to equivalent gains (e.g., savings from off-peak usage). The uncertainty associated with energy prices, especially in markets that rely heavily on renewable energy sources, can potentially heighten loss aversion (Trabish, 2017). For instance, studies have shown that consumers under PG&E's TOU rates exhibit significant reductions in peak-period energy consumption, indicating that the fear of incurring high costs effectively drives behavior change (Borenstein & Holland, 2005; Faruqui & Sergici, 2010). However, the uncertainty and variability in TOU pricing also led some consumer groups to hesitate to participate in these dynamic pricing markets, particularly risk-averse consumers or those with higher household incomes. As these households are less economically affected by price increases, they are less likely to participate in these pricing schemes (Borenstein et al., 2002). To mitigate this, PG&E and other utilities need to refine their dynamic pricing models by incorporating insights from behavioral economics, such as offering more predictable, less volatile pricing structures, providing clear, comparative information to help consumers make informed decisions, and automating adjustments. By doing so, utilities encourage greater participation in demand-side management programs, contributing to effective load balancing and increased integration of renewable energy (Faruqui & Sergici, 2010). Furthermore, TOU pricing touches on other economic theories of consumer and producer surplus. TOU pricing, which varies prices according to supply and demand, has the potential to increase consumer surplus during off-peak hours. Consumers can realize savings by shifting their energy use to periods of lower prices. However, higher prices during peak periods can diminish producer surplus if consumers cannot sufficiently reduce their demand, leading to higher marginal costs (Borenstein & Holland, 2005). By encouraging consumers to adjust their consumption patterns, TOU pricing can improve resource allocation, decrease the need for additional generation capacity, and mitigate the environmental effects associated with peak energy production.

1.4 Economic Market Structures in the Energy Sector: Monopoly vs. Competition

In the competitive market, according to the general equilibrium model, the supply side of the market could be explained by the following formula:

$$c_s = \sum_{i=1}^{N} (c_i \cdot E_i) \qquad (14),$$

where: c_s = Total supply cost and is the overall cost that all suppliers incur to generate and supply energy to the market; c_i =Cost of generation for the supplier. This is the cost incurred by each individual supplier to produce a unit of energy. It can include factors like fuel costs, operational costs, and maintenance costs. E_i =The amount of energy supplied by the i'th supplier. This is the quantity of energy that each supplier contributes to the market.

The formula adds up the product of the generation cost and the amount of energy supplied for each supplier. For each supplier i, the cost of generating energy c_i is multiplied by the amount of energy they supply, E_i . By summing these products across all suppliers, the formula provides the total cost of supplying the entire market with energy.

The formula $\sum_{i=1}^{N}(c_i \cdot E_i)$ is grounded in fundamental economic principles drawn from microeconomic and production theory and it follows the general market equilibrium model as formulated by Alfred Marshall, Paul Samuelson, Hal Varian, and William Baumol. It follows the understanding of production factors as laid down firstly by Marshall's *Principles of Economics (Marshall,1890)* and furthered by Samuelson's analysis of production functions and cost theory, illustrating how inputs like capital and labor combine to influence total production costs (Samuelson, 1947). Varian's *Microeconomic Analysis* provided a detailed examination of cost functions and optimization, emphasizing the role of marginal costs and efficiencies in production decisions (Varian, 1992). Additionally, Baumol's insights into cost theory and externalities highlight the importance of understanding cost structures in economic analysis (Baumol & Oates,1993).These contributions establish a robust theoretical foundation for the formula, illustrating how principles of microeconomic and production theory converge to inform our understanding of aggregate production costs. What is important in the context of energy markets is that, regardless of sectoral specifics, they could be analyzed following this general economic theory. Varian (1987) explores various production costs, including fixed and variable costs, influencing the cost function. The idea that total demand could be viewed as a willingness to pay applies to the energy sales and could be presented as:

$C_d = \Sigma_{J=1}^{M}\left(w_j \cdot D_j\right)$ (15),

where: C_d = Total demand cost (willingness to pay), w_j = Willingness to pay for the jth consumer, D_j = the amount of energy demanded by the jth consumer, M = Total number of consumers.

This formula, applied to the energy market, calculates the total demand cost, or total willingness to pay (WTP), for energy by summing up the individual willingness to pay for each consumer for the energy they demand. Willingness to pay is linked to consumer surplus, the difference between what consumers are willing to pay for a good or service and what they actually pay. This reflects the marginal utility theory, where the willingness to pay corresponds to the additional satisfaction or utility derived from consuming an extra unit of energy. The formula aggregates individual WTP values, illustrating energy market demand as the sum of individual consumer demands. Utility theory further explains that consumers aim to maximize their utility given budget constraints, and their WTP for energy is influenced by the utility they derive from its consumption compared to other goods. In energy economics, this formula is crucial for understanding the total economic value consumers place on energy, informing pricing, policymaking, and investment decisions. The total demand, C sub d, is the aggregate economic measure that guides the efficient allocation of resources and infrastructure investments, as it represents the market demand curve for energy.

Market structures—monopoly, oligopoly, monopolistic competition, and perfect competition—categorize markets by their competitive intensity and concentration of power, which is vital for understanding economic behavior, consumer welfare, and regulation (Mankiw, 2020). A natural monopoly arises when one firm can supply goods most efficiently due to high fixed costs and economies of scale, like in electricity production and transmission (Douglas et al., 2009). While efficient, natural monopolies require careful regulation to prevent market power abuse (Carlton & Perloff, 2015). A monopoly features a single seller with significant market power, setting prices to maximize profits (Varian, 1991). While potentially offering economies of scale and innovation, monopolies can lead to higher prices, limited consumer choice, and inefficiency (CFI Team, 2023).

However, since the beginning of the XXI century, the energy sector has been shifting away from traditional monopolies toward more competitive market structures due to the need to integrate distributed energy resources, such as renewable energy and digital technologies.

An oligopoly involves a few large, interdependent firms whose decisions affect competitors (Muhamed & Magdy, 2020), often characterized by high entry barriers and non-price competition (Tirole, 1988); (Samuelson & Nordhaus, 2009). Monopolistic competition involves many firms selling similar yet differentiated products, allowing them some pricing power through strategies like advertising (The Investopedia Team, 2024). This encourages innovation and variety despite potential marketing inefficiencies (Varian, 2014). Perfect competition is a theoretical model where numerous firms sell identical products with no market power, acting as price takers with free entry/exit and perfect information (Pindyck & Rubinfeld, 2017; Mankiw, 2020) though it is rarely seen. Understanding various market structures—monopoly, oligopoly, monopolistic competition, perfect competition, and natural monopoly—is crucial for analyzing economic behavior and designing effective regulatory policies for electricity production, distribution, and consumption. Each structure presents unique dynamics that influence competition, efficiency, and consumer welfare. While monopolies and oligopolies can lead to higher prices and limited consumer choice, they also offer benefits such as economies of scale and innovation incentives. Monopolistic competition and perfect competition promote consumer choice and efficiency, but may face challenges such as excessive fragmentation or unrealistic assumptions about perfect information. Natural monopolies, particularly in sectors with high fixed costs like energy transmission, require careful regulatory oversight to balance efficiency with fair pricing and access. A comprehensive understanding of these structures enables policymakers and economists to develop strategies that foster competitive, efficient, and consumer-friendly markets. The high fixed costs and low variable costs mean that a single provider can supply electricity more efficiently than multiple competing firms, justifying the existence of a natural monopoly. In such cases, the monopoly can lead to lower prices for consumers due to the efficient spreading of fixed costs over many units sold. However, to prevent abuse of monopoly power, these companies are often regulated by government agencies to ensure fair pricing and reliability. In a monopolistic electric energy market, control is concentrated in the hands of a single entity or a few entities, enabling them to dictate the supply and price of energy. This centralized control allows monopolistic firms to set prices without facing competition, often resulting in higher prices and potentially lower quality of service (Joskow, 2008). Natural monopolies, such as utilities, set prices based on their costs and desired profit margins rather than competitive market forces. This frequently leads to inefficient pricing structures and services that do not accurately reflect actual supply and demand dynamics (Borenstein & Bushnell, 2015). In contrast, competitive markets create prices to more accurately reflect the true economic value of goods and services through the interplay of supply and demand (Stoft, 2010). A competitive market is characterized by many sellers and buyers, where no single entity can influence prices. In this model, prices are determined by supply and demand, which may lead to more efficient resource allocation, innovation, and consumer benefits. Firms in competitive markets are driven to minimize costs and enhance product offerings to attract customers (Stigler, 1957). Understanding price mechanisms in competitive markets is essential for designing tariffs and incentives for consumers, ensuring that these prices accurately reflect true supply-demand dynamics (Bohn et al., 1984). The decentralization of energy production, facilitated by the rise of prosumers, individuals or entities that both produce and consume electric energy (Toffler, 2022), changes the centralized control typical of monopolistic electric energy markets. This shift fosters a more distributed model of energy production and distribution, challenging traditional monopolistic structures, leading to a more competitive market environment. As more prosumers enter the market, competition with traditional utilities increases, which can lead to lower energy prices, and greater innovation within the energy sector (Parag & Sovacool, 2016). Recent research highlights the potential of decentralizing energy production enabled by smart grids, which changes the economics of the energy sector. For instance, a study by Zhang et al. (2018) explores the integration of AI and machine learning into smart grids, emphasizing their roles in predictive maintenance, load forecasting, and energy distribution optimization. Peer-to-Peer (P2P) energy trading encourages multidirectional trading within a local geographical area, allowing consumers to buy and sell energy directly among themselves (Chen et al., 2021). Trials of P2P energy trading have been conducted globally, such as Open Utility "Piclo" (Johnston, 2017) in the UK, Vandebron (Damawan, 2019) in the Netherlands, and Sonnen Community (Muhr, 2019) in Germany. These trials have primarily focused on offering incentive tariffs to electricity customers from the perspective of energy suppliers, aiming to enhance customer engagement and optimize energy distribution. Many utilities have been transitioning from fixed-rate energy billing models to a combination of demand charges and time-of-use (TOU) charges. The demand charge is typically based on the highest rate of consumption ($/kW) during the billing period (e.g., one month). With demand charges, even brief spikes in demand can significantly increase the electricity bill. TOU charges involve assigning different rates to different times of the day, reflecting varying levels of demand and supply (Assad et al., 2022).

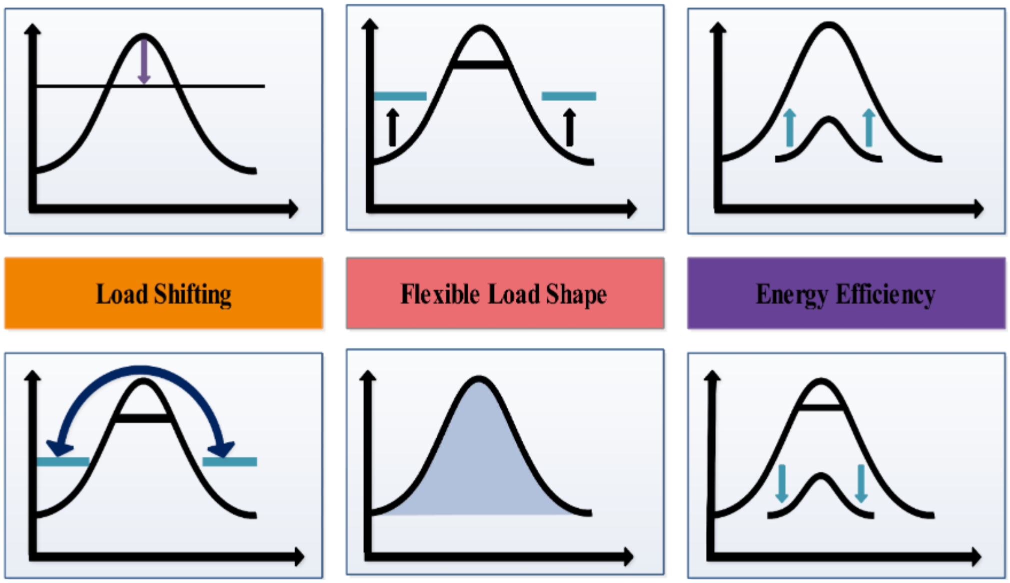


FIGURE 4 TIME OF USE CHARGES FOR DIFFERENT LEVELS OF DEMAND AND SUPPLY

Source*: Assad et al. (2022).*

Figure 4 visualizes three strategies: the first, load shifting, involves shifting consumption from periods of high demand (peaks) to periods of lower demand (off-peak), without altering the total energy consumed. This helps to flatten the overall load curve, reducing strain on the grid during critical times. The second strategy, flexible load shape, involves actively increasing demand during off-peak hours (valley filling) or decreasing it during peak hours (peak curtailment). This is often done in response to price signals or grid needs, thereby increasing energy usage adaptability. Energy efficiency focuses on reducing energy consumption. Energy efficiency measures permanently lower total electricity consumption across all periods by improving the performance of appliances, systems, or buildings, thereby reducing overall demand. These strategies balance electricity supply and demand, help integrate renewable energy, and enhance the overall resilience of the power system. Price-based programs offer different electricity prices at different times, such as (ToU) pricing, Critical Peak Pricing (CPP), Real-Time Pricing (RTP), and Inclining Block Rates (IBR), encouraging users to shift consumption to off-peak times (Faruqui & Sergici, 2010). PG&E, Northern California's premier utility, has adopted TOU plans as a shift towards more dynamic electricity pricing. By incentivizing off-peak usage, TOU plans help balance demand, reduce costs, and promote environmental sustainability (PG&E, 2024). Effective regulation is crucial to ensure fair competition and prevent market abuses, requiring policymakers to balance DER integration with maintaining grid reliability and affordability (Joskow, 2000). Transitioning to a more competitive energy market requires significant investment in smart grids and energy storage, which need to be addressed by policymakers and stakeholders to realize the benefits of DERs (Borenstein & Bushnell, 2015). Ensuring equitable access to electric energy is essential, with policymakers needing to consider support mechanisms for low-income households and communities that face barriers to adopting new pricing and market schemes (Lesser & Su, 2008).

1.5 Transactive Energy Framework and Welfare

The electricity grid was designed for electricity to flow from centralized bulk generation sources to end users at the periphery of distribution grids. However, the growing incorporation of distributed energy resources (DERs) is changing this traditional flow pattern, leading to operational challenges, especially as DER penetration reaches critical thresholds (Next-Generation Grid Technologies, 2021). With DERs now being implemented not only at the edges but also at various intermediate points within the grid, power flows in multiple directions, creating loop flows within distribution circuits. The current generation of grid control systems was not built for that, creating challenges for distribution system operators. In the modern energy markets, this simple price-demand elasticity law can be viewed through the Transactive Energy (TE) concept. TE is a framework that addresses the challenges posed by the increased use of intermittent renewable resources, such as wind and solar power (The GridWise Architecture Council, 2019). The variability of these generation resources has made it increasingly difficult to continue using the traditional load-following operational model (Ela et al., 2011). Transactive energy systems (TES) are a way to address challenges associated with the increasing use of DERs and renewable energy. Transactive energy is an intelligent, multi-level communications method that coordinates energy generation, consumption, and delivery. The concept was formalized by the GridWise Architecture Council (GWAC) in 2004, as part of the US Department of Energy's broader GridWise initiative. PNNL's GridWise Demonstration Projects on the Olympic Peninsula in Washington State, depicted in one of the case studies in chapter 4, pioneered the transactive approach, demonstrating the use of information technologies to improve grid efficiency and flexibility. TES uses smart grid technology, equipped with AI and IoT, to enable dynamic and decentralized transactions between energy producers, consumers, and prosumers (Zhou et al., 2023). Prosumers are entities that both produce and consume energy. TES facilitates peer-to-peer energy transactions, enabling consumers and prosumers to buy and sell energy in response to real-time price signals across the entire grid or localized (Zhou et al., 2023). In that new ecosystem, TES enables real-time market dynamics and economic transactions, while DERs provide local and grid electricity (Zhou et al., 2023). In TES, DERs and local markets also help utilities with reducing peak loads, utilizing a double-sided auction market model simulation (El-Baz et al., 2019). Double auctions are mechanisms involving both buyers and sellers, who simultaneously participate in the bidding process and are allocated individual shares of the resource (Faqiry & Das, 2016). This approach involves real-time, two-way communication between electricity suppliers, energy markets, the power grid, homes, commercial buildings, and other distributed energy resources (DERs). The TES approach allows for harmonization of energy availability, consumer needs, cost preferences, and real-time price finding, enhancing overall energy system efficiency and creating social welfare (Kadry et al., 2022). In TES, consumers are incentivized to modify their energy usage based on real-time pricing signals, like demand response programs. By aligning consumer behavior with grid conditions through price signals, transactive energy systems enhance grid stability, integrate renewable energy sources more effectively, and improve overall efficiency (Kabiri-Renani et al., 2022). TE enables predicting how power demand and ramp rate will respond to price fluctuations based on short-term elasticity. This understanding aids in effective energy management and planning. Demand response programs leverage this knowledge by encouraging consumers to adjust their energy use in response to price signals, ensuring that price changes prompt the desired consumption adjustments (Nizami et al., 2022). Transactive energy and pricing involve creating a framework that enables seamless, efficient energy transactions among various entities—consumers, prosumers, and energy providers—within a microgrid or a larger grid (The GridWise Architecture Council, 2019). The formula for transactive energy and pricing generally includes elements reflecting supply and demand dynamics, the cost of generation, and the willingness to pay or sell (Kok & Widergren, 2016). This approach calculates the total cost of supplying energy by summing up the individual costs incurred by each supplier (e.g., power plants, solar panel owners) for generating the energy they provide (Hammerstrom et al., 2007)

Welfare economics is a branch of economics that assesses how the allocation of resources impacts the well-being of individuals within a society (Varian, 1991). Central to welfare economics are the concepts of consumer surplus and producer surplus, which together constitute the total surplus, a fundamental measure of economic welfare. Consumer surplus represents the difference between what consumers are willing to pay for a good or service and what they pay, thereby capturing the additional utility consumers receive from market transactions (Marshall, 1920). For example, if a consumer is willing to pay $100 for a concert ticket but purchases it for $70, the consumer surplus is $30. Conversely, producer surplus measures the difference between the price producers receive and the minimum price at which they are willing to sell, reflecting the additional benefit producers gain from selling at a price higher than their minimum acceptable level (Stigler, 1957). For instance, if a producer is willing to sell a widget for $20 but sells it for $50, the producer surplus is $30. The aggregation of consumer and producer surplus forms the total surplus, which serves as a key indicator in welfare economics for assessing the overall economic well-being generated by market activities (Varian, 2014). Allocative efficiency, another concept of welfare economics, occurs when resources are distributed in a manner that maximizes total surplus, ensuring that the marginal benefit equals the marginal cost (MB = MC) (Samuelson, 1947). This condition implies that resources are utilized in the most valued manner by society, and no further gains in total surplus are possible without diminishing another party's surplus.

Welfare economics not only focuses on maximizing total surplus but also considers the equitable distribution of resources, recognizing that both fairness and efficiency are essential for societal well-being (Sen, 2001). Policymakers utilize these concepts to evaluate the impact of various interventions, such as taxes, subsidies, and regulations, on total surplus and allocative efficiency. For example, imposing a tax can create deadweight loss by distorting market prices and reducing total surplus, whereas removing such distortions can help restore allocative efficiency (Varian, 2014). Additionally, welfare economics provides the framework for cost-benefit analyses, market regulation, and the optimal provision of public goods, which are non-excludable and non-rivalrous (Samuelson, 1954). Understanding consumer surplus, producer surplus, total surplus, and allocative efficiency from the contributions of economists like Oskar Lange and John Hicks is essential for analyzing how different resource allocations affect societal welfare, offering valuable insights for creating conditions that maximize total surplus and ensure resources are used most effectively, which plays an important role in modern fragmented energy production models (Stiglitz & Rosengard, 2015).

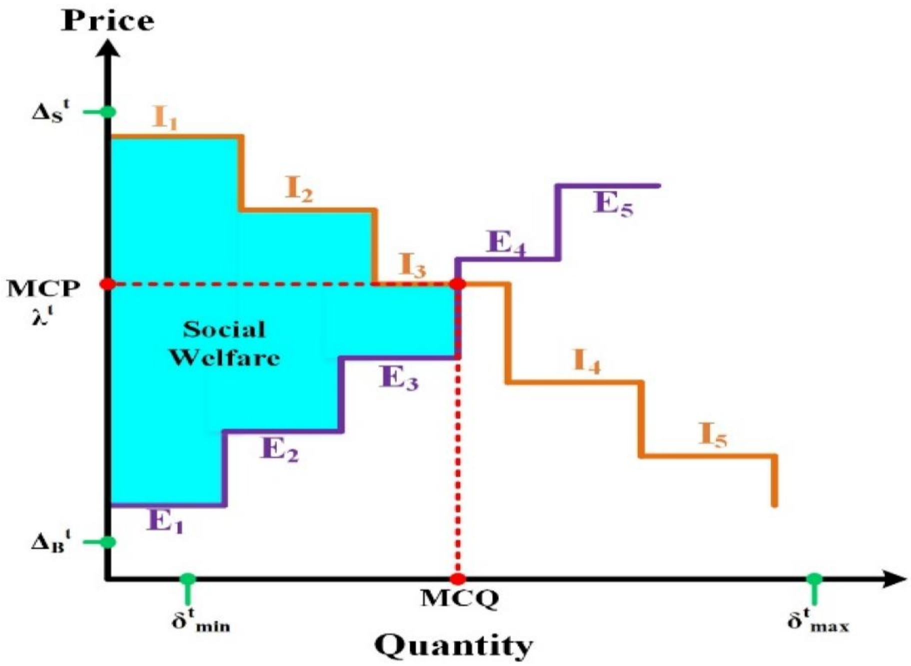


FIGURE 5 SOCIAL WELFARE IN THE TRANSACTIVE ENERGY MARKET

Source: *(Loganathan et al., 2022).*

Figure 5 illustrates the concept of social welfare within a transactive energy market for peer-to-peer (P2P) energy transactions. The x-axis represents quantity, and the y-axis represents price. "E" represents the energy producers' marginal cost steps (the supply curve), while "I" represents the consumers' willingness to pay steps (the demand curve). The Market Clearing Quantity (MCQ), where the E and I curves meet, is the corresponding volume of energy transacted at this equilibrium price (MCP). The shaded cyan area labeled "Social Welfare" is the sum of consumer surplus (the benefit consumers receive by paying less than their maximum willingness to pay) and producer surplus (the benefit producers receive by selling for more than their minimum willingness to accept). The diagram visually demonstrates how a transactive energy market efficiently determines a price and quantity that maximize the total economic benefit for all participants—buyers and sellers—in P2P energy exchanges, thereby leading to an optimal allocation of energy resources. TES facilitates real-time pricing and dynamic transactions between energy producers, consumers, and prosumers. This allows for more accurate reflection of supply and demand conditions, promoting economic efficiency (Caramanis, 2016).

Transactive energy systems enable more responsive and efficient energy markets, where consumers are incentivized to adjust their demand in response to real-time price signals. Since electricity needs to be consumed at the time of production, this leads to a better utilization of resources and increases welfare. On the consumer site, TES is based on the understanding of price elasticity of demand. It relies on the concept that consumers will adjust their electricity usage in response to price signals. The price elasticity of demand measures how responsive the quantity demanded of electricity is to a change in price. Competitive market-based pricing increases prices during peak demand and lowers them during off-peak demand times. This can incentivize consumers to shift their consumption patterns, thereby better allocating demand to supply, creating more efficient outcomes (Eid et al., 2016a). Price elasticity of demand can be categorized into elastic, inelastic, or unitary elastic. Elastic demand means that a slight change in price leads to a significant change in quantity demanded. In contrast, inelastic demand indicates that quantity demanded is relatively unresponsive to price changes. Unitary elasticity refers to proportional changes in price and quantity demanded. The formula for Price Elasticity of Demand (PED) is:

$$e_D = \frac{\%\text{change in quantity demanded}}{\%\text{change in price}} \text{ or} e_D = \frac{\frac{\Delta Q}{Q}}{\frac{\Delta P}{P}} \text{ (16),}$$

where: ΔQ is the change in quantity demanded, Q is the initial quantity demanded, ΔP is the price change, and P is the initial price.

Using this formula, if the PED value is greater than 1, the demand is considered elastic (responsive to price changes). If the PED value is less than 1, the demand is inelastic (not very responsive to price changes). If the PED value is exactly 1, the demand is unitary elastic, meaning the percentage change in quantity demanded is equal to the percentage change in price. In the context of energy consumption, demand response to fluctuating prices can be analyzed using the concept of elasticity, a microeconomic principle that quantifies consumer responsiveness to price changes. Energy consumption q(p,t), which varies with both price (p) and time (t), illustrates how consumers adjust their usage based on real-time price signals (Borenstein et al., 2002). Short-term elasticity of demand (η_q) , is defined as the percentage change in energy consumption relative to a percentage change in price. It is assumed to remain constant over brief periods (less than an hour) because consumers have limited time to adjust (Faruqui et al., 2007). This assumption allows for the derivation of related elasticities: power demand elasticity (η_P) and ramp rate elasticity

(η_R), which describe the responsiveness of instantaneous power demand and its rate of change, respectively. These elasticities are shown to be equivalent $(\eta_q = \eta_P = \eta_R)$, revealing a critical relationship for designing demand response programs (Faruqui et al., 2007). By leveraging these insights, real-time pricing (RTP) strategies can incentivize consumers to shift demand away from peak periods, enhancing grid stability and reducing reliance on costly peak-generation resources (Albadi & El-Saadany, 2008). This approach underpins effective energy management, aligning consumer behavior with grid efficiency and sustainability goals. Energy usage tends to decrease when prices are high and increase when prices are low, a behavior explained by the economic concept of elasticity. Elasticity measures the responsiveness of quantity demanded to a change in price: demand is "elastic" if a small price change leads to a significant change in quantity demanded, and "inelastic" if a large price change results in a minor change in quantity demanded. One example is the dynamics of energy consumption within residential and commercial settings, where the amount of energy used fluctuates based on its price and the time of day.

Blonz (2022) examines the economic effects of peak pricing in electricity for commercial and industrial establishments in the U.S., specifically within the Pacific Gas & Electric (PG&E) service area in Northern California. This pricing model (a form of time-of-use (TOU) pricing) aims to reduce peak electricity consumption by raising prices during high-demand periods up to 15 times annually. This approach aims to manage overconsumption during peak periods and reduce the need for additional costly capacity. The study found that peak pricing reduced peak electricity usage by 13.5% in inland areas, indicating that targeted price increases can effectively curb demand during high-demand periods. This approach achieves 44% of the welfare benefits of ideal real-time pricing, which would dynamically adjust rates based on short-term supply costs. The paper suggests that further improvements, such as reducing the number of events while increasing prices during those times, could capture up to 83% of the welfare gains possible with real-time pricing. He concludes that, although real-time pricing remains politically challenging, optimized time-of-use (TOU) programs still hold considerable potential to enhance welfare by better aligning peak consumption with supply constraints (Blonz & Blonz, 2022).

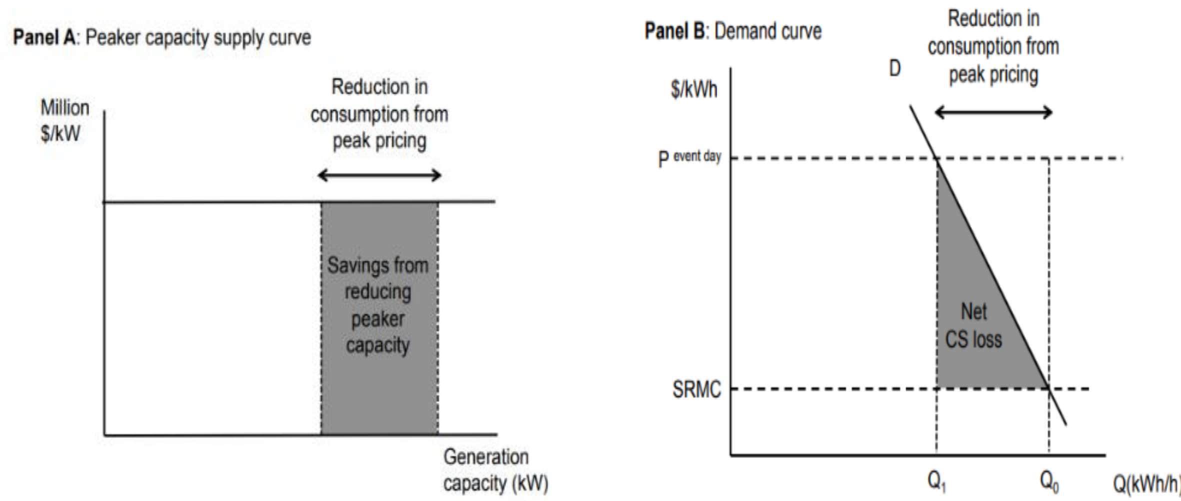


FIGURE 6 COST SAVINGS FROM REDUCTION OF PEAKER CAPACITY

Source: Blonz & Blonz (2022).

Panel A shows the supply-side impact of reducing peaker capacity (generation used only during peak demand). The shaded area represents the savings achieved by reducing the need for expensive peaker plants. In countries like the USA or Germany, traditionally, gas plants are typically used during peak demand periods and have high operational costs. In countries like Poland, coal plants are predominant with high environmental costs. Reduction in consumption refers to the decrease in energy demand resulting from higher peak prices or demand response programs. By lowering demand, the system can avoid utilizing peaker plants, resulting in cost savings. Panel B shows the demand-side effect of peak pricing on consumer behavior. The Demand Curve (D) represents the relationship between the price of electricity and the quantity demanded. As prices increase, demand decreases. Reduction in consumption from peak pricing could be observed: This change in electricity usage from Q1 (baseline quantity) to Q0 (reduced quantity) is due to higher peak prices. Net Consumer Loss (CS) is represented by the shaded triangle, which reflects the economic benefit loss to consumers from consuming less electricity when prices are high. SRMC (Short-Run Marginal Cost) stands for the cost of producing one additional unit of electricity and is typically lower than the peak price

The shift from traditional centralized energy distribution systems to smart grids represents a significant transformation in how energy is produced, distributed, and consumed. Traditional macro-level theoretical approaches based solely on productivity are less useful than applying the principles of welfare economics. It is marginal-cost pricing and transactional economics that provide a more comprehensive framework for evaluating their impact on societal well-being, resource allocation, and economic efficiency in the modern, fragmented, and smart-grid-based energy production. The integration of renewable distributed energy sources into smart grid ecosystems also addresses externalities associated with fossil fuel consumption, such as environmental degradation and greenhouse gas emissions. By internalizing these external costs, smart grids promote sustainable resource use and align with the welfare economics objective of maximizing societal well-being (Söderholm & Sundqvist, 2003). Recent studies have demonstrated that smart grid technologies enable more efficient integration of intermittent renewable energy sources, such as wind and solar, thereby reducing reliance on fossil fuels and minimizing associated environmental impacts (Hassan et al., 2024). Additionally, smart grids facilitate real-time monitoring and management of energy flows, thereby enhancing the ability to mitigate emissions and optimize energy use, further supporting sustainable, economically optimal energy production (Fang et al., 2012). These advancements ensure that energy systems become more resilient and efficient while also contributing to environmental sustainability and economic welfare (Lund et al., 2012).

CHAPTER 2 THE ENERGY SECTOR AND IOT

2.1 The changing energy sector landscape

The global electricity system is undergoing a technological-physical transformation driven by two drivers: decarbonization of electric energy production and the electrification of end-use sectors. This is forcing electric utilities to integrate increasing shares of variable and distributed renewable energy sources while maintaining high levels of reliability and affordability. This chapter aims to articulate a new economic framework for electric energy that is influenced by the changing technical, regulatory, and physical nature of energy production and distribution. The new paradigm is influencing economic principles of resource production and allocation, operationalized through digitalization via the Internet of Things and Artificial Intelligence. At the core of energy systems lie physical laws that determine what is technologically and operationally feasible. Thermodynamic efficiency, energy density, the intermittency of renewable energy sources, and the physical characteristics of electricity and flows in networked infrastructures are parameters that shape both grid architecture and the associated economic models and realities. These constraints define the feasible space within which innovation, investment, and system operations can occur. Any attempt to modernize or optimize electricity systems must therefore begin with an understanding of these realities.

Economics, on the other hand, helps with allocating scarce resources such as energy, capital, and infrastructure. Electricity markets, influenced by regulatory and pricing mechanisms, are shaped by several factors. Electricity can only be stored for a short time in lower quantities. With new "green energy" requirements, achieving supply-demand optimization is necessary, given the variability and intermittency of renewable energy sources in a system traditionally based on base-load energy sources like coal and nuclear power. Economics is not a detached discipline but is influenced by the physics, business, and regulatory components of the system it seeks to understand and shape. Another pillar of this new integrated framework is digitalization. AI and IoT provide the intelligent infrastructure to optimize physical states that shape economic frameworks, leading to optimized economic outcomes. Advanced metering infrastructure, distributed sensors, and automated control systems generate data on consumption patterns, generation profiles, and network conditions. The data is processed via edge or cloud-based computing, enabling forecasting, anomaly detection, predictive maintenance, and optimization of supply and demand patterns and pricing. The goal is to maximize the value added by improved decisions relative to the cost of sensing, transmitting, storing, and analyzing data. This should lead to enhanced system efficiency within those constraints. This shifting paradigm of energy sector operations is depicted in Figure 7.

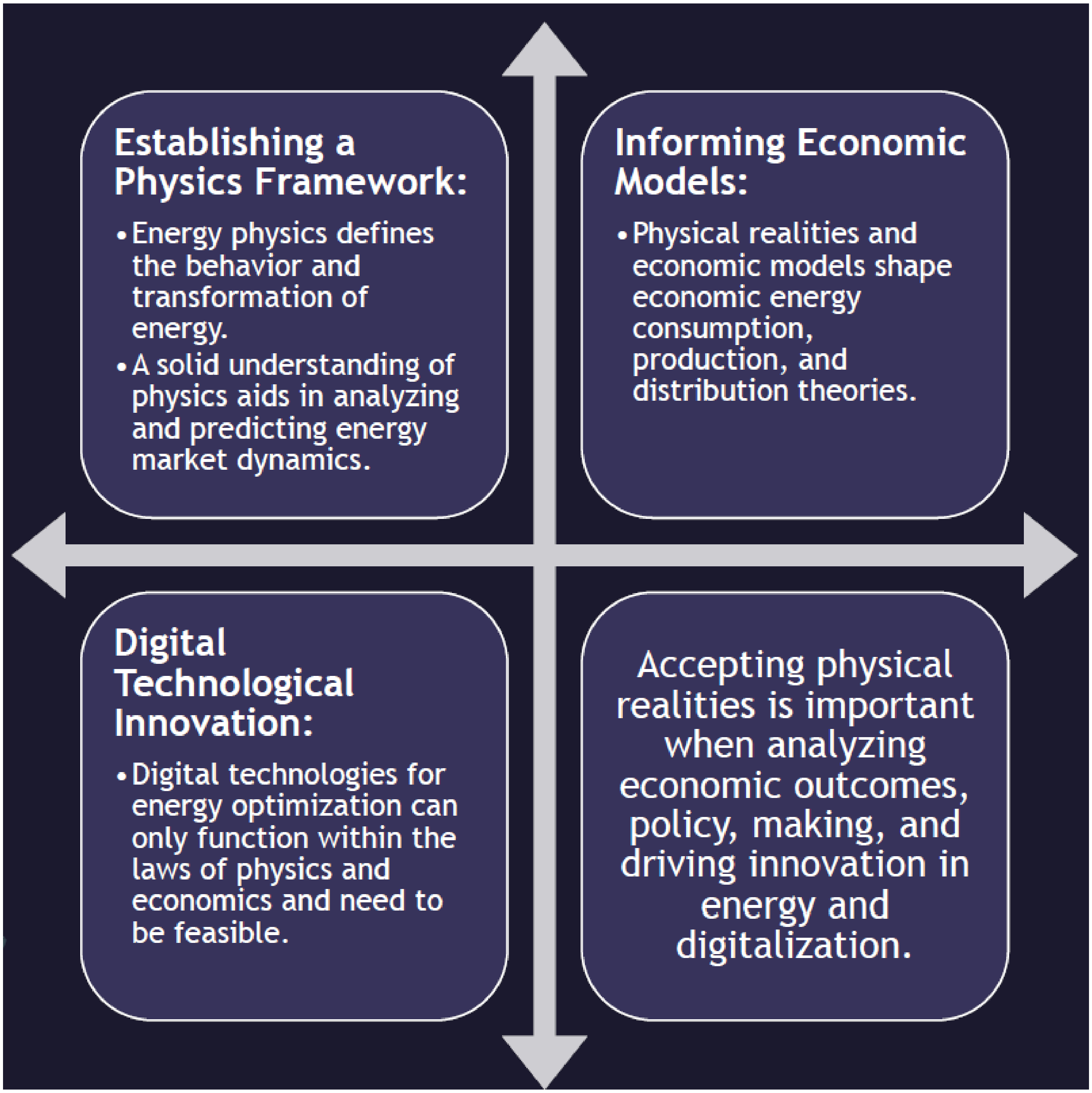


FIGURE 7 DIGITAL APPROACH TO PHYSICAL–ECONOMIC CONSTRAINED ENERGY SYSTEMS

Source: *(Kunerth, 2025).*

This framework—comprising energy, regulation, business, economics, and digitalization—shapes understanding of the evolving ecosystem of electricity production and distribution. The energy layer is determined and constrained by the laws of physics. The business-economics layer is responsible for the allocation of resources and coordination of actors. Data collected from the digital layer enables decision-making across increasingly decentralized and complex infrastructures. Digital technologies create value by serving economically rational objectives, and physical innovations require both economic viability and digital operability to scale. This integrated view becomes important when examining the structural changes in the electricity sector. Historically, centralized generation—predominantly fossil-fueled—offered high reliability and energy density, supporting vertically integrated utility monopolies. However, the rise of renewable energy has introduced a high degree of variability and decentralization, driving architectural changes. New technological ecosystems, such as smart grids and microgrids, have emerged to integrate distributed energy resources and energy storage. AI and IoT enable demand response adjustments. These decentralized structures aim not only to maintain system stability and efficiency but also to facilitate a shift toward more open, competitive, and consumer-centric models. In these architectures, digital platforms serve as the coordinating layer, ensuring synchronization between diverse resources and enabling market-based interactions, including dynamic pricing, aggregator-led demand response, and prosumer participation. The Smart Grid Architecture Model (SGAM) exemplifies this layered structure by linking physical components, communication protocols, data exchange standards, functional roles, and business processes. It provides a reference architecture for managing the complexity of modern electricity systems while ensuring interoperability across domains. Within this model, digital intelligence and automated control are not peripheral enhancements but integral to system functionality. The transformation of the electricity sector cannot be understood through the lens of any single discipline. A successful transition toward sustainable, reliable, and affordable energy systems requires an integrated approach—anchored in physics, structured by economics, and executed through digitalization. The physical sciences define what is possible; economics determines what is desirable and efficient within those boundaries; and digital technologies make what would otherwise be unmanageable at scale. This chapter's goal is to establish the conceptual foundation for such an approach, laying the groundwork for subsequent discussions on how these principles materialize in practice through specific technological, regulatory, and market developments.

2.2. The role of the energy sector

In economics, energy is the capacity for doing work. It may exist in potential, kinetic, thermal, electrical, chemical, nuclear, or other forms (Thomson William, 2024). In economics, alongside land, labor, and capital, energy is a fundamental input required to produce goods and services. Coal and petroleum, alongside natural gas, hydroelectric power, and nuclear energy, have been instrumental in elevating living standards, post the commencement of the industrial revolution. Electric energy demand is still poised to grow in the US (currently the top consumer) and globally. Power generated from water movement, wood fire, and wind has been used for thousands of years. An important concept in energy economics is energy intensity, which measures the amount of energy consumed per unit of economic output, measured in energy consumed per dollar of GDP. Research has shown a decreasing trend in the amount of energy consumed for every unit of economic output across economies. One reason for the decrease in energy intensity is the degree of automation. Automation reduces energy intensity by optimizing production processes, decreasing energy waste, and enhancing overall efficiency, thereby using less energy per unit of output (Zhang et al., 2022). At the same time, there seems to be a close relationship between energy consumption and GDP growth (Stern & Cleveland, 2004). More complex societies require a greater amount of energy per capita. The process of increasing complexity necessitates greater energy production, creating a positive feedback cycle (Timmons et al., 2014). Research shows a positive correlation between energy consumption and economic growth, suggesting a correlation between energy consumption and GDP growth. Between 1990 and 2015, global energy intensity—defined as energy consumption per unit of GDP—declined by nearly one-third. This trend was observed across almost all regions, including OECD and non-OECD economies (Deichmann et al., 2018). Energy intensity is a key metric for measuring energy efficiency. It is the ratio of energy consumption to Gross Domestic Product, where energy intensity is equal to energy consumption divided by GDP. A lower energy intensity indicates greater energy efficiency—it takes less energy to produce a dollar of economic output. A higher number means the economy is less efficient. Variations in energy intensity across countries are influenced by factors such as economic structure, climate, and geography (Wei et al., 2022). Economies centered on manufacturing typically consume more energy per unit of GDP than those dominated by services. However, advanced economies have also seen a significant decrease in energy intensity. Regions with more extreme temperature ranges require more energy for heating and cooling. The layout of cities and the transportation infrastructure also determine how much energy is used for moving people and goods. The phenomenon of reduced energy intensity can be seen across economies worldwide. Many advanced economies have been transitioning from energy-intensive manufacturing toward service-oriented industries, which require less energy input per unit of economic output. Developed economies, such as the U.S., Germany, and Japan, have experienced deindustrialization since the 1990s, with a growing share of GDP now derived from sectors like finance, information technology, healthcare, and education, which are inherently less energy-intensive (Van Marel, 2025). At the same time, the deployment of energy-efficient technologies in manufacturing and transportation has reduced the energy input required to produce the same level of output. Governments have implemented energy efficiency standards and incentives for clean technologies, which have accelerated the shift toward lower energy intensity. Technological, structural, and policy-driven changes contribute to the worldwide decline in energy intensity. AI and IoT help reduce energy intensity—the amount of energy used per dollar of economic output—by making energy systems smarter and more efficient. Better weather forecasting for renewable energy installations and forecasting electricity demand helps reduce the run times of gas power plants and reduces waste. Smart grid controls enable voltage optimization and automated monitoring reducing losses. Smart building and industrial analytics platforms identify inefficiencies and streamline operations. For example, energy management systems in buildings cut unnecessary energy use and optimize energy usage (Darby, 2010; Rojek et al., 2025).

Figure 8 shows that global energy intensity, a measure of energy waste, declined by 32% between 1990 and 2015 as the world's energy production and use became more efficient. Although developed (OECD) nations remained more efficient overall, developing (non-OECD) nations improved at a much faster rate, narrowing the global efficiency gap. The highest improvement occurred from roughly 2002 to 2008, but the initial phase, from 1990 to 1997, was the most significant.

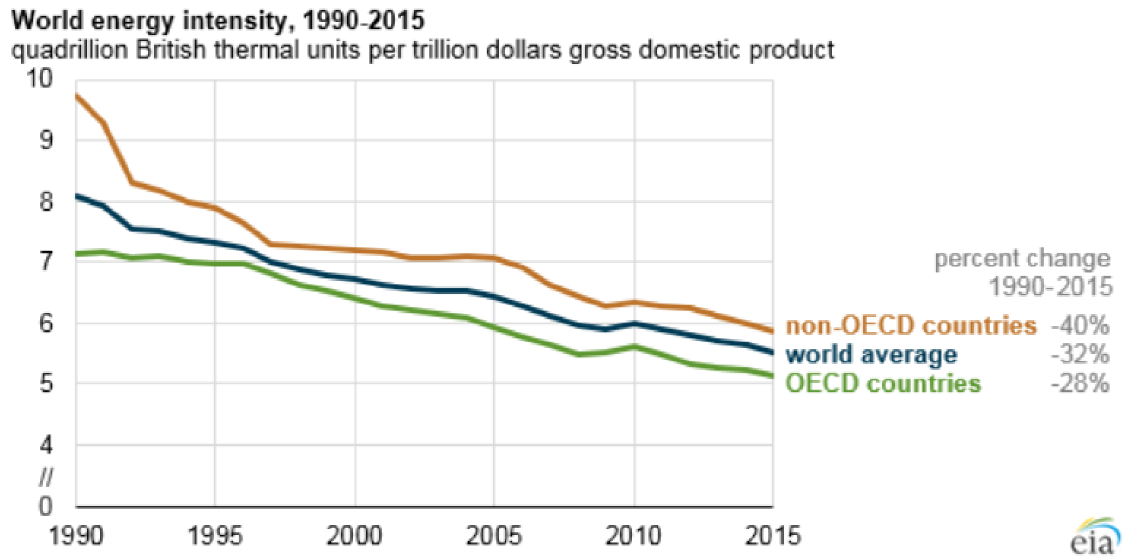


Figure 8 World Energy Intensity Index

*Source: (EIA, 2016).*The changes after 2015 are even more striking.

Table 4 Energy intensity world changes from 2015 to 2024.

Period	Avg Annual Improvement (%)	Number of Years	Cumulative Change (%)
2015-2019	2	5	-9.61
2020-2023	1.6	4	-6.29
2024	1	1	-1
2015-2024 Total	---	10	-16.15

Source:(IAE efficiency analysis, 2024).

Table 4 displays how the decade began with steady annual improvements in energy intensity of 2.0% from 2015 to 2019, driven by policy implementation. While initially volatile, the 2020-2023 period saw an acceleration in efficiency as the global energy crisis forced rapid adjustments. A slowdown to 1.0% in 2024 suggests the gains between 2020 and 2023 were driven mainly by external crises rather than by sustained momentum. The high prices caused by a reduced energy supply acted as a strong incentive to eliminate energy waste. In advanced economies, energy intensity gains have slowed after several years of rapid progress between 2015 and 2019. The projected lower 1% energy intensity improvement for 2024 is due to easing energy prices as supply increased again and waning policy urgency (IAE efficiency analysis, 2024).

As depicted in Table 4 the slope in Figure 9 graphically displays the rate of improvement in efficiency, which was steep and steady from 2015 to 2019 due to consistent energy-saving policies and flattened around 2020 amid economic disruption from the COVID-19 pandemic, as seen in Figure 9. The slope steepens again in 2022 as the global energy crisis, caused by the Ukraine war, forcing efficiency gains.

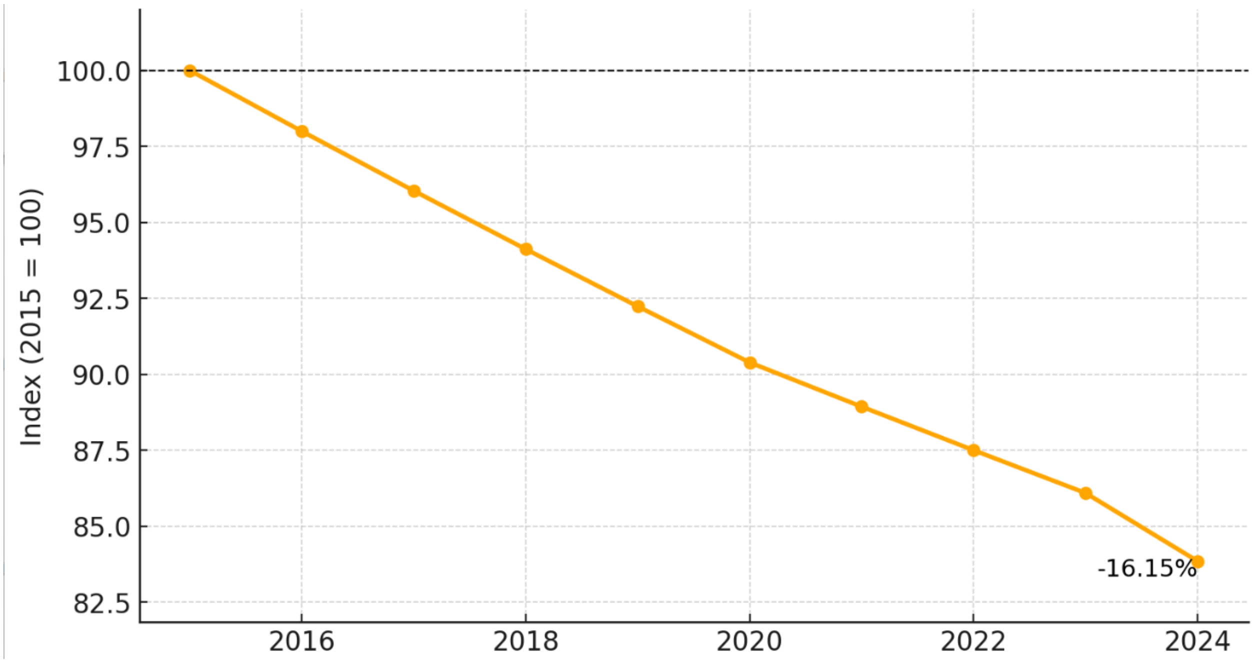


FIGURE 9 WORLD ENERGY INDEX 2015 TO 2024

Source: (IAE efficiency analysis, 2024).

Figure 10 below shows energy productivity trends across selected countries and regions between 1990 and 2024 based on EIA (2016), (IEA, 2025) and (World Bank, 2025) data. When a country's energy productivity increases, its energy intensity decreases. While most OECD economies, such as the United States (+92%) and those in OECD Europe (+70%), improved their energy productivity moderately, China achieved a substantial (+233%) increase in energy productivity despite rapid industrialization and economic expansion. This means that for each unit of energy consumed, the economic output more than doubled, corresponding to a significant decrease in their energy intensity. Many factors drove this shift (Crossley & Xuan, 2015; Zhu et al., 2020). Some regions, such as the Middle East (+1%) and Brazil (+1%), very small gains, reflecting less efficient energy use in relation to economic growth.

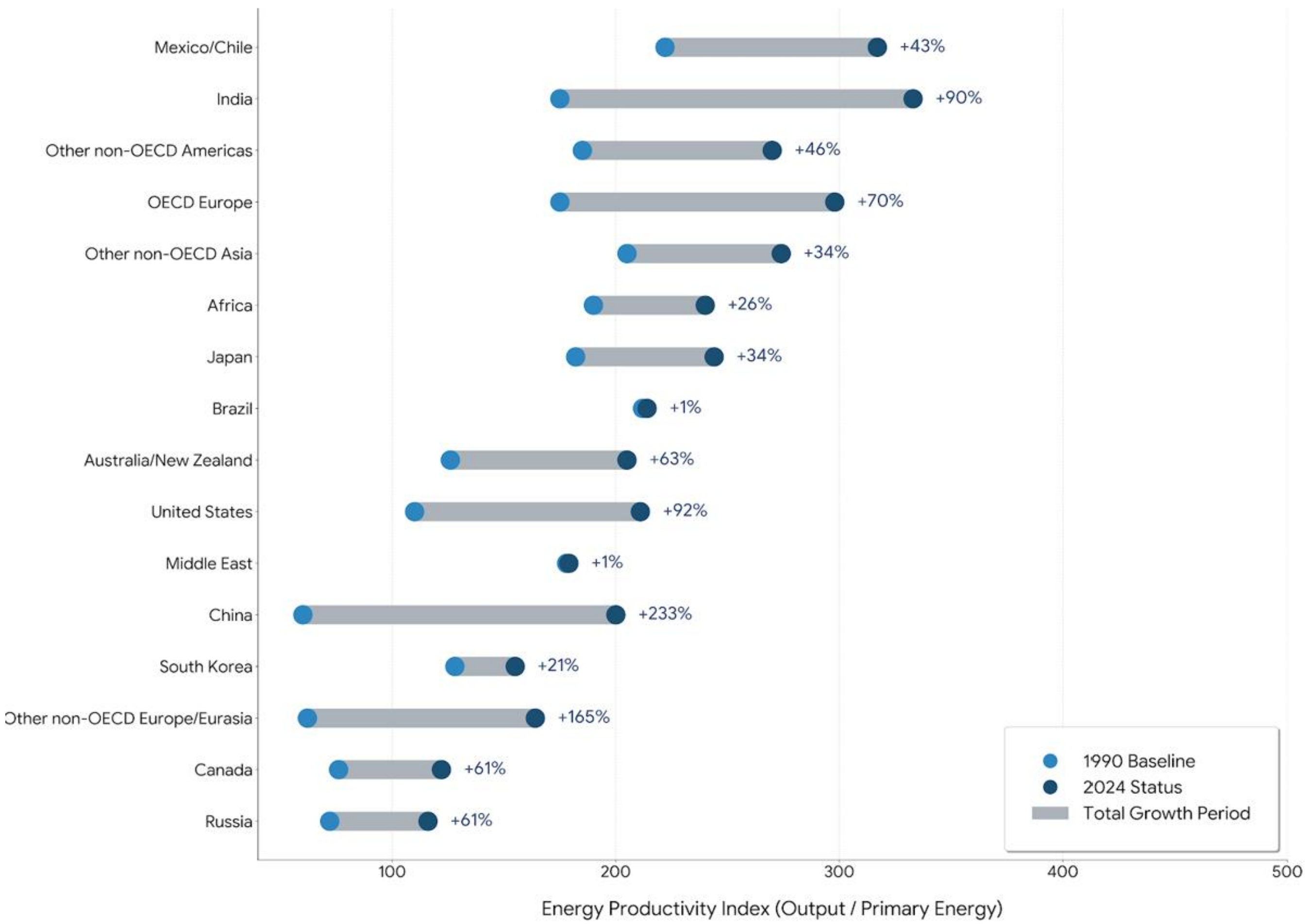


FIGURE 10 ENERGY PRODUCTIVITY IN SELECTED COUNTRIES AND REGIONS FROM 1990 TO 2024

Source: (EIA, 2016), (IEA, 2025; World Bank, 2025)

China has achieved a 233% improvement in energy efficiency, mainly due to the central government setting ambitious performance targets for its energy, transportation, and building sectors. This top-down approach is more aggressive than that of other countries. For example, in China's electricity sector, the National Development and Reform Commission (NDRC) launched a trial compliance evaluation scheme in 2011 for utilities, known as the Energy Efficiency Obligation (EEO), which was updated in 2014. A core requirement was the deployment of load-monitoring IoT equipment that covered at least 70% of the peak load. This digital infrastructure generated high-frequency operational data, which, when combined with AI-driven analytics, enabled more accurate measurement, verification, and optimization of energy-efficiency projects and demand-side programs. The improved data visibility enabled grid companies not only to track consumption in real-time but also to intervene proactively, thereby boosting both cost savings and system reliability. As a result, from 2012 to 2014, every grid company exceeded its mandated EEO targets for energy savings and peak-demand reduction. Complementing these efforts, the Chinese national ESCO program helped customers save an additional 6 TWh of electricity between 2010 and 2013 by promoting energy-saving technologies and digital solutions. In 2013 alone, first-year savings reached 16.2 TWh, accompanied by a 3.44 GW reduction in peak load. In 2014, savings were still substantial, at 13.1 TWh and 2.95 GW of peak reduction. While it is unclear to what extent AI and IoT contributed to these positive outcomes, embedding IoT sensors and AI analytics into grid operations enabled efficient, data-driven optimization systems that drive measurable economic and environmental benefits (Crossley & Xuan, 2015; Zhu et al., 2020). In continuation of its long-term energy strategy, the Chinese government set a target to reduce national energy intensity by 15% during the 13th Five-Year Plan (2016–2020). This policy has been continued into the 14th Five-Year Plan (2021–2025), which mandates an additional 13.5% reduction. While official data on achieving these latest targets is not yet widely available, research indicates that these goals have been a primary driver of China's reduction in energy intensity since 2006. However, the rate of improvement slowed over time (Huang et al., 2025). The development of energy intensity during the COVID period presented a mixed picture. A slowdown in the growth of total energy consumption was noticeable between 2018 and 2020, likely due to the adverse effects of the COVID-19 pandemic on economic activity. Pandemic-related restrictions on travel and logistics resulted in an estimated 28% reduction in CO_2 emissions from China's transport system, indicating a significant decrease in energy use in this sector. However, there was also a structural slowdown in targeted energy intensity improvements (Li & Loo, 2024; Li et al., 2025). While China is not the geographical focus of this work, it exemplifies what is generally possible in optimizing the electricity sector with AI and IoT through a centralized, strategic approach. However, not all progress is due to the implementation of AI and IoT. This approach can serve as a model for other advanced economies.

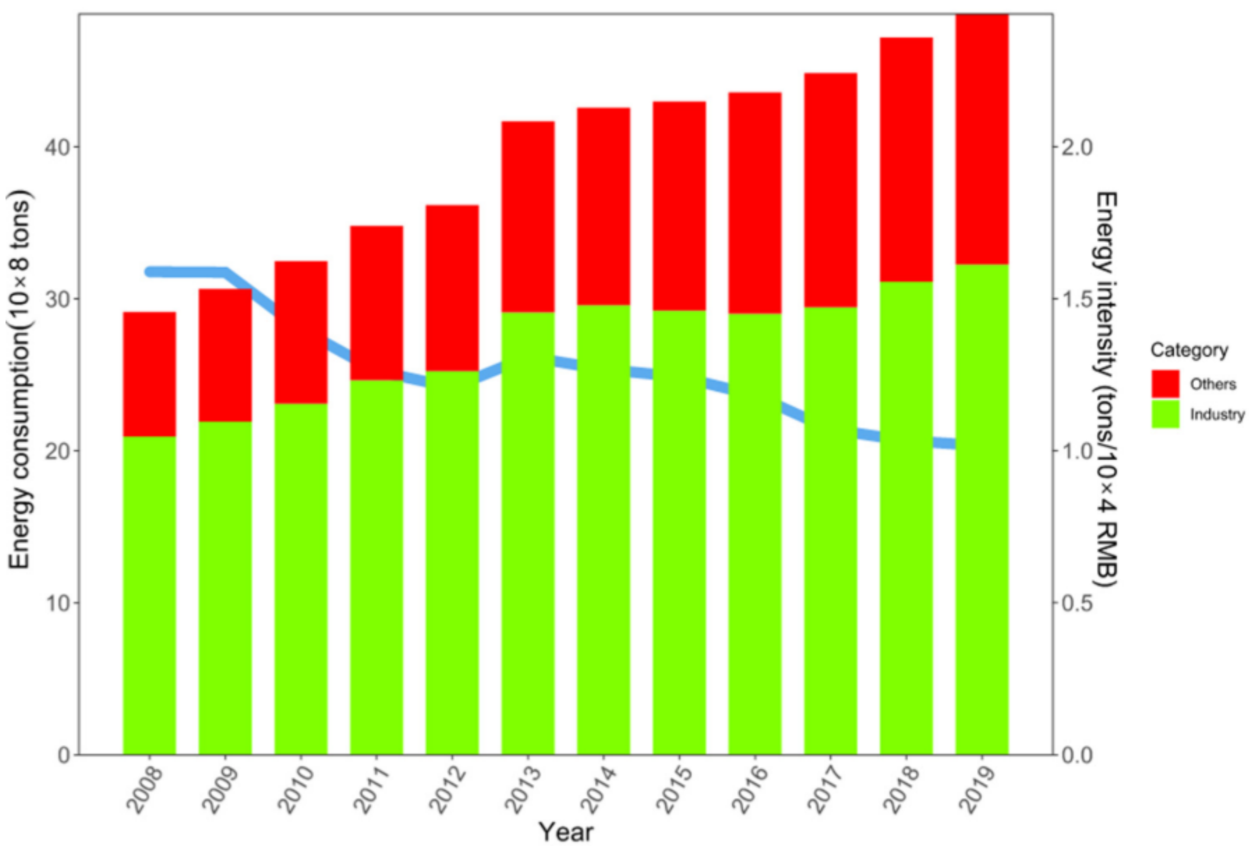


FIGURE 11 CHINA'S INDUSTRIAL ENERGY CONSUMPTION AND ENERGY INTENSITY FROM 2008 TO 2019

Source: (X.; Zhang et al., 2022).

Figure 11 illustrates that China's total energy consumption increased steadily from 2008 to 2019, with both the industrial and other sectors contributing to this rise. At the same time, the blue line indicates that energy intensity (energy used per unit of economic output) steadily decreased during the same period. This means that China's industries became more energy-efficient, even as overall energy use increased. Technological advancements support changes in energy use patterns. New technologies help economies derive more value from every unit of energy produced. In distributed electric energy production, advanced forecasting and dispatch tools ensure that energy is used when it is most valuable. AI and IoT provide advanced weather-forecasting technology to predict energy supply from sources like windmills and solar plants and to help predict consumer demand. Guided by this data, intelligent dispatch tools route the most cost-effective and efficient load to where it is needed at the optimal time. This dynamic matching of supply with demand ensures that energy is used when and where it is most economically beneficial, maximizing the value of every unit produced. This intelligence enables smart charging systems for electric vehicles and grid-scale batteries to shift charging to peak production and low electricity demand times. This reduces consumers' charging costs and enhances the overall system's efficiency by economically using the infrastructure. Electricity from grid-scale batteries can be discharged during peak demand periods and charged during periods of heightened electric energy supply (Eid et al., 2016b; Mohseni et al., 2023; Palensky & Dietrich, 2011). Research by the IEA, IPCC, and IRENA indicates that this combination of hardware and software enhances flexibility and facilitates the more efficient integration of renewables, leading to increased energy productivity (IEA, 2022; IEA, 2017; IRENA, 2022). As a result, electric utilities can power factories, homes, and businesses at a lower cost. The efficiency gains enable the economy to produce more goods and services per unit of energy consumed, creating more economic value from the same amount of electricity produced.

Szustak et al. (2022) suggest that 1% increase in energy consumption is associated with a 0.314% increase in real GDP, showing the economic benefits of energy use. The use of renewable energy sources is shown to promote sustainable economic growth: a 1% increase in renewable energy consumption leads to a 0.12% rise in real GDP, underscoring the potential for economic growth through their adoption. In agriculture, the use of fossil-fuel-based industrial fertilizers and machinery has eliminated limitations on soil nutrients, transforming modern farming practices and increasing yields. Over the past fifty years, global crop production has tripled, mainly due to increased yields per unit of cultivated land. This rise in production is associated with increased energy consumption, which is linked to essential inputs such as machinery, fuel, and fertilizers, which are derived to a large degree from oil. Energy availability has improved longevity, health, and wealth worldwide. Energy is a cornerstone of a modern industrial economy. It is the lifeblood of contemporary civilization, powering industries, homes, transportation, healthcare, and nearly every aspect of human life (Smil, 2018). This makes energy resources fundamental to modern development. As Smil notes, energy has powered industrialization, enabled mass production, and fueled technological innovation. Reliable energy supplies underpin economic growth, strong institutions, and the efficient functioning of the global economy (IAE, 2022). Energy acts as a critical input into the production function of goods and services, directly influencing productivity and output levels (Stern, 2011). It powers industries by driving machinery and manufacturing processes, supports transportation networks essential for the movement of goods and labor, and fuels the digital infrastructure that underpins communication and commerce in today's information age (Masanet et al., 2020). Data centers, servers, and network devices that fuel automation through AI and IoT consume substantial amounts of electricity to process, store, and transmit data. As digital technologies like cloud computing, artificial intelligence, and the IoT expand, energy demand in the information and communications technology (ICT) sector grows accordingly. (Masanet et al., (2020) estimated that data centers accounted for about 1% of global electricity use in 2018, a figure that will increase substantially without efficiency improvements. Energy consumption in the ICT sector affects operational costs for businesses, pricing for digital services, and the efficiency of electronic commerce, which has become a significant component of the global economy. Fluctuations in energy availability or prices can have significant impacts on economic growth, affecting everything from operational costs and supply chain efficiency to consumer prices and international trade competitiveness (Hamilton, 2009). Access to reliable and affordable energy is a key determinant of economic growth, poverty alleviation, and improved quality of life. As the global population grows and economies expand, energy demand has been steadily increasing, posing significant challenges for sustainable development and global climate change (IAE, 2022). An approximate assessment of the correlation between energy and well-being can be obtained by graphing the Human Development Index (HDI) against annual per capita energy consumption (from both commercial and non-commercial sources) for a large sample of nations (Goldemberg, 2001). Fossil fuels, including oil and natural gas, still account for approximately 82% of the world's total primary energy consumption.

This figure encompasses all forms of energy use, including electricity generation, transportation, heating, and industrial processes. According to the IEA's "World Energy Outlook 2022", fossil fuels—coal, natural gas, and oil—still accounted for approximately 61% of global electricity generation in 2022 (IAE, 2022) but are going down steadily.

Fossil fuels’ dominance is not only due to historically established infrastructure; it is also due to the physics of energy conversion processes that make them exceptionally reliable sources of electricity. The high energy density and controllable combustion of fossil fuels enable consistent, adjustable power output, which is essential for meeting fluctuating electricity demands (Çengel et al., 2024). This reliability has profound economic implications, particularly for sectors such as transportation and industry that rely on a consistent and stable energy supply. Fossil fuels remain the dominant source of energy in global production due to their high reliability and substantial energy density. The combustion of hydrocarbons releases stored chemical energy, which is then converted to thermal energy. This thermal energy is used to produce steam, which powers turbines linked to generators, generating electricity through electromagnetic induction, as described by Faraday's Law. The process ensures efficient energy conversion, which is essential for sustaining large-scale power production necessary for economic activities (Jaffe & Taylor, 2019). Reliable energy ensures uninterrupted operations, reduces downtime costs, and supports economic growth by enabling businesses and services to function efficiently (Stern, 2011). While energy consumption drives technological advancement and enables economies of scale, it also poses challenges to environmental sustainability, as overreliance on fossil fuel energy sources can lead to resource depletion, environmental degradation, and contribute to climate change. Environmental costs, such as greenhouse gas emissions that drive climate change and finite resource depletion, pose both economic and ecological challenges, requiring increased focus on alternative, sustainable energy sources to balance economic benefits with long-term planetary health (Huo & Peng, 2023). Renewable energy sources, such as solar and wind power, offer sustainable alternatives to fossil fuels but are intermittent due to their dependence on weather conditions and the time of day. Intermittency poses significant challenges to energy supply reliability and grid stability, requiring efficient energy management strategies and smart grid planning. Solar and wind energy generation fluctuates based on environmental and physical factors—solar power is unavailable at night and less steady during cloudy weather. In contrast, wind power depends on wind speed and patterns. These variations can lead to supply-demand mismatches in the energy grid (Lund et al., 2012).

Efficient energy management becomes crucial for balancing the load and ensuring a consistent energy supply. Smart grids, which utilize advanced information and communication technologies, can dynamically adjust to these fluctuations by optimizing energy distribution and incorporating energy storage solutions (Fang et al., 2012). Real-time monitoring and data collection are essential for managing modern energy grids, particularly those incorporating renewable energy sources. IoT devices, such as sensors and smart meters, gather data on energy consumption patterns, generation outputs, and grid conditions. Real-time data collected is analyzed by AI algorithms to inform decisions on energy distribution and management, enhancing the efficiency and reliability of the power grid (Güngör et al., 2011). Machine learning, a subfield of AI, can predict energy generation from renewable sources using weather forecasts and historical data. Accurate forecasting enables grid operators to anticipate fluctuations and adjust the energy supply, thus maintaining grid stability (Wu et al., 2024). Combining multiple renewable energy sources can mitigate the intermittency of individual sources. Hassan et al., (2023) investigated the optimization of a hybrid solar-wind power generation system to address the issue of intermittency. By leveraging the complementary nature of solar and wind resources—where the availability of one may offset the lack of the other- the hybrid system enhances overall energy reliability. Their review explores hybrid renewable energy systems integrating solar and wind technologies, emphasizing their current challenges, potential opportunities, and the impact of relevant policies. Although solar and wind energy each have their own advantages, their inconsistent availability and location-specific restrictions have driven research in hybrid approaches that enhance efficiency and reliability through combined systems. An extensive analysis of the current literature reveals that hybrid systems mitigate issues related to energy intermittency, enhance grid stability, and can be more economically viable due to shared infrastructure (Hassan et al., 2023). Solar energy relies on the physics of photon-matter interactions, primarily through the photovoltaic (PV) effect and solar thermal processes. The photovoltaic effect, first observed by Alexandre-Edmond Becquerel in 1839, is the foundation of solar panel technology and involves converting sunlight directly into electricity. When photons from the sunlight strike the semiconducting material in PV cells, their energy excites electrons, allowing them to break free from atoms and generate an electric current. This process depends on the properties of the semiconductor, often silicon, which has an energy bandgap optimized for efficient electron excitation.

Electric energy, commonly known as electricity, is a form of energy that results from the movement of charged particles, primarily electrons, through a conductor (Griths, 2014.). Electricity serves as a key factor of production for almost all industries. Its availability, reliability, and affordability directly impact on a firm's productivity and overall output. When electricity is unavailable or unreliable, it can severely constrain economic activity (Vogt, 2017). The electrification of households and manufacturing in Europe and North America began in major cities in the early 20th century. During this period of electrification, early electric utility companies competed for the same customers, sometimes even constructing duplicate distribution systems. This competition was more prevalent in urban areas, where it was cheaper to compete and wealthy customers were more likely to use electricity (Warwick, 2002). The electrification of households and manufacturing facilities in major cities and regions served by electric railways in Europe and

North America began during the early 1900s and experienced rapid growth until approximately 1930. By that time, 70% of U.S. households had been electrified. Electric energy has rapidly come to be considered a public good. Following the power crisis of 1918, the United States' national goal was to consolidate the power supply. The Public Utility Holding Company Act of 1934 officially recognized electric utilities as crucial public goods alongside gas, water, and telephone companies and established limitations and regulatory oversight for their operations (Mazer, 2007). From the 1930s to the present, competition in the electricity sector has been characterized by monopolistic structures, with a single or a few large companies holding exclusive control over the production, distribution, and pricing of electricity in certain geographic areas and markets (Joskow, 2024).In a regulated wholesale market, utilities are vertically integrated monopolies. They are solely responsible for generating, transmitting, and distributing electricity to their customer (EPA, 2024). Initially, and to this day, the market is dominated by vertically integrated utilities controlling the entire supply chain, resulting in public and regional monopolies. These monopolistic structures are beneficial for centralized management and system stability, which is crucial during the early stages of the electricity market's development, ensuring the consistent delivery of power to consumers (Sharifzadeh, 2022). The initial investment refers to the substantial fixed costs associated with power generation equipment and power line infrastructure. Once the initial investments are recovered, producing each additional unit of electricity is relatively inexpensive (Grossman & Cole, 2003). As more electricity is sold, fixed costs can be more evenly distributed, resulting in a fairer price for consumers. If two separate electric companies were to divide electricity production, each with its own power source and power lines, the cost would likely be almost twice as much (Stoft, 2010). In recent years, there has been a shift toward greater competition in the electricity sector, driven by the emergence of distributed and alternative sources, such as solar and wind energy, leading to the entry of new firms and increased competition. Market-based reforms from 1999 to 2012, technological improvements, and economies of scale significantly decreased the costs of producing electricity through solar and wind power in the United States and around the world from 2002 onward (Cicala, 2022). Microgrids are localized clusters of electricity sources and loads that can operate both independently and in conjunction with the traditional centralized electrical grid. Microgrids can represent a transformative force in the electricity sector, promoting decentralization, enhancing market competition, and enabling innovative energy trading models, as shown above. While challenges remain in regulation and technical integration, the continued advancement and adoption of microgrids are poised to shift energy market structures from monopolistic to more competitive, consumer-centric models. This evolution promises greater efficiency, reliability, and sustainability in energy production and distribution, ultimately benefiting both consumers and the broader energy landscape. Microgrids integrate several energy sources, including solar panels, wind turbines, battery storage systems, and conventional generators, to deliver reliable, efficient power to local customers. Microgrids enhance power supply resilience, meeting both immediate and future energy needs. A key feature of microgrids is their advanced control systems, which manage the generation, distribution, and consumption of energy to ensure optimal performance and stability (Eyimaya & Altin, 2023). The control mechanisms enable microgrids to switch between grid-connected and island modes, maintaining consistent power quality and supply during disruptions to the main grid. This flexibility safeguards consumers against outages while also maximizing energy efficiency within the microgrid. The emergence of microgrids presents an opportunity to transform market structures in the electricity production and distribution sectors by localizing energy production and consumption. Microgrids can foster increased market competition, drive technological advancements, and enhance overall market efficiency (Chavin, 2022). One feature of microgrids is their ability to decentralize electricity generation and distribution. Large utilities still have significant market power and coverage. However, microgrids promote the participation of diverse, smaller energy producers in the market and can provide electricity in regions with limited grid infrastructure. The decentralization of energy sources challenges the dominance of major utilities, reducing their market influence and creating more opportunities for smaller players and consumers to engage in the energy market. Consequently, consumers can gain greater choice over their energy sources and pricing, fostering a more equitable and competitive market environment (Sioshansi, 2011). Despite these advantages, the widespread adoption of microgrids faces several challenges. Regulatory barriers, technical complexities, and coordination issues impede the widespread integration and scale of microgrids. This requires the development of new regulatory frameworks and technology infrastructures that accommodate decentralized energy systems and support their seamless operation and integration alongside and with traditional grids (Ajaz & Bernell, 2021). Addressing these challenges is important for realizing the full potential of microgrids in transforming energy markets. As microgrids achieve higher market penetration, they can operate locally as parallel and competitive distribution grids, extending the existing electric power distribution systems. Smart grids are advanced electricity networks that use digital technologies and two-way communication to monitor, control, and optimize the flow of electricity. They efficiently balance electricity supply and demand in real-time, integrating diverse energy sources, including renewables, and microgrids to enhance reliability, resilience, and sustainability (Khalid, 2024). The increased adoption of microgrids and distributed solar and wind energy within a smart grid ecosystem has the potential to shift market structures from monopolistic to more competitive-based models, thereby enhancing overall market efficiency and consumer choice. An important innovation enabled by microgrids and smart grids is peer-to-peer (P2P) energy trading among prosumers—individuals or entities that both produce and consume energy. Through peer-to-peer (P2P) trading, prosumers can sell their excess energy generation to other customers or to the grid operator, creating a more interactive and responsive energy marketplace (NRG Energy, 2018). This capability empowers consumers to actively participate in the energy market, reduces costs, and fosters a more sustainable and resilient energy ecosystem. Peer-to-peer (P2P) energy trading platforms automate the buying and selling of electricity directly between users. P2P systems rely on automated processes that begin with real-time data from smart meters. Energy producers, also known as "prosumers," submit offers to sell their excess power, while consumers bid to purchase it. An algorithm, often based on a double auction mechanism, then clears the market by matching buyers and sellers. This structure ensures a direct, verifiable link between physical electricity flows and corresponding monetary exchanges, often secured by blockchain-based smart contracts to minimize counterparty and reconciliation risks. Despite these technological advancements, P2P energy trading remains in its early stages of development, influenced by regulatory uncertainty, scalability limitations, and market integration complexities (Islam, 2024). Key challenges to scaling peer-to-peer (P2P) energy sharing within electricity markets include regulatory, technical, and market-design barriers (Tushar et al., 2021).

While P2P systems emphasize local autonomy, bilateral transactions, and consumer-driven preferences, they differ from transactive energy (TE) models, which are designed around system-level coordination and grid-wide optimization. Transactive energy refers to a decentralized, market-based control framework in which DERs, flexible loads, and utility assets interact through dynamic price signals to balance supply and demand (Loganathan et al., 2022). TE systems rely on real-time communication, advanced metering, and autonomous agents that respond to fluctuating prices, often structured hierarchically and mediated by system operators or aggregators

(Kok & Widergren, 2016, 2023; Nizami et al., 2022; Zhou et al., 2023c). The Pacific Northwest National Laboratory (PNNL) has been instrumental in demonstrating the viability of transactive energy, particularly through projects such as the Olympic Peninsula Demonstration, one of the case studies in this dissertation, and gridSMART, which showcased how price-responsive devices can enhance grid reliability and economic efficiency in distribution networks (Hammerstrom et al., 2007). Unlike peer-to-peer or transactive energy models, which emphasize decentralized decision-making and localized energy exchange, virtual power plants (VPPs) are typically managed by a central aggregator or operator. A VPP is a centrally coordinated aggregation of distributed energy resources DERs that can include solar PV, wind turbines, battery storage, and flexible loads—that can be managed collectively as a single, dispatchable entity to deliver grid services like a traditional power plant (Ruan et al., 2024).

Virtual Power Plants integrate decentralized end users and are aggregator-led, optimized for participation in wholesale electricity and ancillary services markets, and offer capacity reserves, frequency regulation, and load-shifting solutions. Instead of a single large central power station, a VPP uses a cloud-based platform to network and control a fleet of smaller, independent distributed resources, such as power plants, solar installations, batteries, smart thermostats, and electric vehicle chargers. VPPs are operated by a central entity, often referred to as an aggregator, which manages bidding, dispatch, and financial settlements for all participating resources. The dynamic pricing aspect arises from the VPP responding to real-time market price signals. At the same time, end-users are typically compensated through fixed payments, bill credits, or other incentives, rather than directly exposed to wholesale prices. VPPs enhance operational flexibility by coordinating DER dispatch to respond to market or system operator signals, improving grid stability and economic efficiency (Kaiss et al., 2025).

Real-world examples include Tesla's Virtual Power Plant in Australia—aggregating residential batteries for grid support— Next Kraftwerke in Germany, and various aggregator-led platforms in Europe that connect numerous small-scale producers through centralized market mechanisms (ElMaamoun, 2021).

Energy models, such as P2P trading, Transactive Energy, and Virtual Power Plants, utilize a combination of IoT devices —including advanced meters, smart thermostats, smart appliances, controllable battery storage, and EV chargers — to gather data and employ AI algorithms to make optimized decisions. The primary difference between them lies in the respective AI's objective: acting as a local matchmaker for P2P, a network of decentralized agents for TE, or a central commander for VPPs. This determines whether the system prioritizes direct peer-to-peer exchange, dynamic grid-wide balancing, or aggregated participation in wholesale energy markets (Neska & Kowalska-Pyzalska, 2022).

TABLE 5 DER TRADING PLATFORMS

Model	Key Attributes	Control Structure	Market Type	Example
P2P	Bilateral trade, prosumer autonomy	Decentralized	Local, informal, or formal	Power Ledger
TE	Real-time price signals, dynamic optimization	Semi-distributed	System-coordinated	PNNL/Olympic Peninsula
VPP	Aggregated DER dispatch	Centralized aggregator	Wholesale, ancillary	Next Kraftwerke Tesla (Australia)

Source: author's own based on (ElMaamoun, 2021; Kaiss et al., 2025; Neska & Kowalska-Pyzalska, 2022; Ruan et al., 2024).

In 1900, global electricity generation was about 66.4 terawatt-hours (TWh). By 2022, it had surged to 29,165 TWh. Over that same period, electricity's share of global primary energy rose from just 0.1% to 22% - far outpacing the growth in total energy consumption.

Electricity demand is rising much more rapidly than total energy demand, driven by established uses—especially cooling—and by emerging applications such as electric vehicles and data centers. Renewables such as wind and solar electricity are driving growth in electricity generation and can already meet the overall increase in demand (IEA, 2024). Global electricity generation has grown substantially over the past decade. According to the International Energy Agency (IEA), global electricity generation increased from approximately 23,000 terawatt-hours (TWh) in 2010 to around 28,000–29,000 TWh by 2021–2022. Moreover, there is potential to accelerate this expansion further: the current solar manufacturing capacity of around 1,100 GW per year could support nearly three times the deployment level seen in 2023 (Pinto et al., 2023).The last decade witnessed a significant shift in the fuel mix used for electricity generation in the US. Between 2014 and 2023, overall electricity generation in the United States remained relatively steady, increasing only marginally from approximately 4,093,564 thousand megawatt-hours (MWh) to 4,183,271 thousand MWh. However, the underlying fuel mix shifted notably. Coal-fired generation declined by 57.33%, from 1,581,710 thousand MWh in 2014 to 675,115 thousand MWh in 2023, primarily due to regulatory pressure and the increasing cost competitiveness of alternative energy sources. In contrast, natural gas generation rose by 60.3% from 1,126,635 thousand MWh to 1,806,063 thousand MWh—due in part to the more widespread availability of low-cost natural gas and its ability to work in conjunction with renewable energy sources. Gas-powered peaker plants provide quick, flexible backup electricity when renewable sources, such as wind and solar, cannot meet demand due to their inherent variability. This allows for integrating higher levels of renewable energy without risking power shortages. Renewable energy expanded considerably, with wind increasing 835.6% from 17,691 thousand MWh to 165,530 thousand MWh, and solar grew 85.4% from 261,522 thousand MWh to 484,708 thousand MWh over the same period. Nuclear output remained relatively stable, fluctuating modestly around the mid- to upper-700,000 MWh range. These trends indicate that, despite an overall plateau in electricity demand in the US, the production landscape has undergone a substantial transformation, favoring cleaner, more flexible, and distributed generation resources driven by market forces, policy incentives, and technological advancements (EIA, 2023). Solar and battery storage to make up to 81% of newly installed U.S. electric-generating capacity in 2024 (EAI, 2024). Utility energy storage in the form of large megawatt-hour batteries charges them when renewable power is abundant and cheap, and discharges them to the grid when the electricity supply is low.

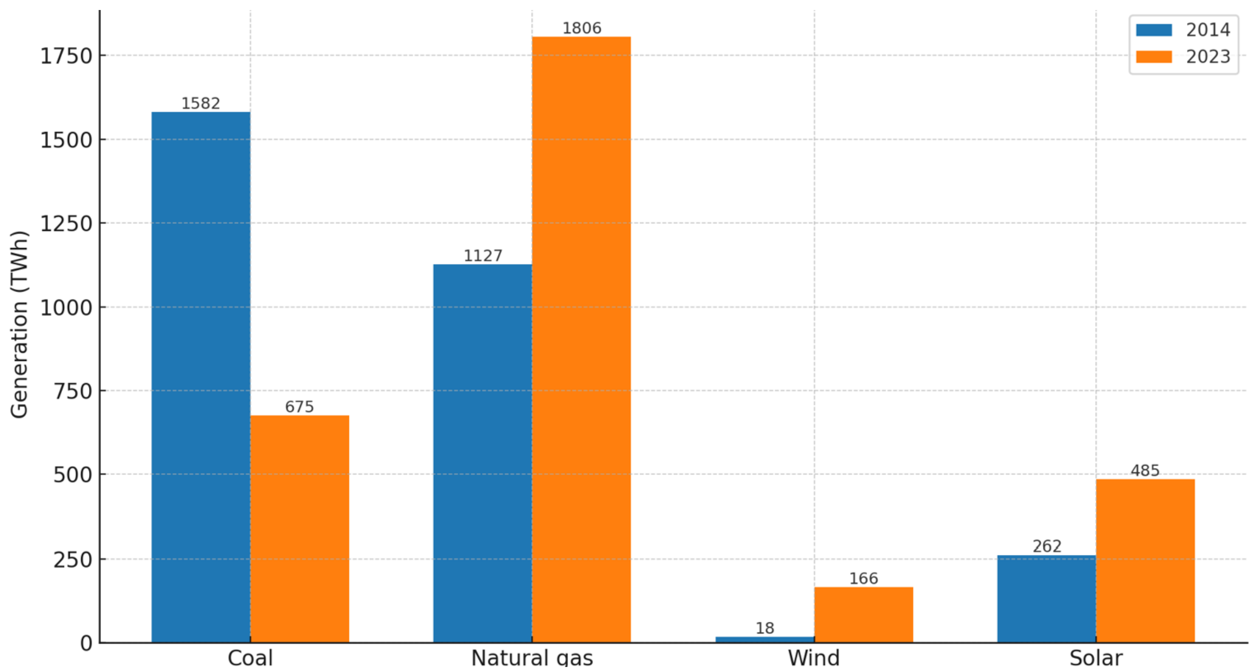


FIGURE 12 ***US ELECTRICITY PRODUCTION FUEL MIX FROM 2014 TO 2023***

Source: (EAI, 2024).

While, in absolute numbers, the electric energy produced by fossil fuels such as coal and gas remains high, based on the provided charts, the U.S. electricity sector underwent a rapid transformation between 2014 and 2023, shifting away from coal-powered electric energy production to natural gas and renewables.

To prevent blackouts when electricity production from wind and solar energy is low, grid operators utilize fast-ramping gas plants—on standby, ready to respond instantly when renewable output falls. This reliance partly explains the recent rise in gas-fired generation. At the same time, the rapid shift in the energy mix underscores the need for smart grids. Smart grids utilize AI and IoT to anticipate weather conditions and renewable energy generation, enabling more effective planning and dispatch. They also support demand response programs: during a supply crunch, the smart grid can signal smart devices in homes and businesses—such as thermostats, batteries, water heaters, or EV chargers—to temporarily reduce consumption, adjusting demand to reductions in supply (Assad et al., 2022). While still a smaller fraction of the overall US electricity generation, rooftop solar, community-scale wind, and microgrids further enhance grid stability and resilience.

The total DER capacity in the U.S. is 300–350+ GW by the end of 2024, depending on which resources are counted and how demand response capacity is measured. Rooftop solar alone could surpass 80–90 GW of cumulative capacity by the mid-2020s, and battery storage 5–10 GW. The ongoing transformation in DERs is driven by rapidly declining costs for hardware and digital technologies. Between 2023 and 2027, approximately 262 gigawatts (GW) of new DER capacity are expected to come online, nearly equaling the 272 GW of utility-scale resources projected to be added to the grid for the same timeframe. Demand flexibility refers to the typical amount of load a demand-based resource can shed under normal conditions, representing an overall capability rather than the specific capacity actively participating in utility or market-driven demand response programs (Hertz-Shargel Ben, 2023). As the United States rapidly expands its renewable energy portfolio, the number of proposed projects seeking to connect to the grid, also called interconnection queues, has increased. The rising adoption of solar photovoltaic, wind, and battery storage systems, along with growth in vehicle-to-grid services, has led to a significant increase in requests for grid connectivity (Baldwin et al., 2025).

According to recent forecasts, global electric energy production is expected to grow over the next 18 years. By 2050, it is expected to undergo a significant transformation, driven by increased renewable energy production. This production is expected to rise from 8,444 to 21,067 Terawatt-hours (TWh) between 2022 and 2050, accounting for roughly half of all electricity generated. Solar-generated electricity is projected to increase sixfold, from 1,421 to 8,521 TWh, while wind-generated electricity is projected to triple, from 1,967 to 5,805 TWh. Coal generation is expected to stagnate at around 9,600 TWh, resulting in a shrinking market share. At the same time, natural gas is projected to grow modestly, while liquid fuels are nearly phased out, resulting in a reduction in generation capacity from 733 to just 56 TWh. Nuclear power is expected to provide a slowly growing and stable source of carbon-free baseload energy, increasing from 2,666 to 3,297 TWh (EIA, 2023a).

TABLE 6 WORLD ELECTRIC ENERGY PRODUCTION FORECAST FROM 2022 TO 2050

Fuel	2022	2025	2030	2035	2040	2045	2050	% Change Per year 2022–2050
Liquid fuels	733	737	378	203	107	69	56	-8.8%
Natural gas	6,699	6,664	6,638	6,726	7,187	7,750	8,266	0.8%

Coal	9,696	9,339	9,165	9,412	9,378	9,475	9,612	0.0%
Nuclear	2,666	2,786	3,020	3,160	3,181	3,216	3,297	0.8%
Renewables	8,444	10,059	12,538	14,690	16,891	19,075	21,067	3.3%
Hydro	4,320	4,715	4,966	5,247	5,331	5,457	5,583	0.9%
Wind	1,967	2,357	3,249	4,012	4,995	5,569	5,805	3.9%
Geothermal	67	110	191	213	238	248	254	4.9%
Solar	1,421	2,241	3,457	4,531	5,639	6,984	8,521	6.6%
Other	669	636	674	687	688	817	903	1.1%
Net generation to grid	28,23	29,58	31,739	34,191	36,744	39,587	42,298	1.5%

Source: (EIA, 2023a).

The biggest challenge is that electricity produced from wind and solar power is intermittent, as they only generate power when the wind is blowing or the sun is shining. A traditional power plant, by contrast, is dispatchable, meaning operators can adjust it better to match fluctuations in consumer demand. On calm, cloudy days, the renewable energy production capacity can drop significantly, as seen in Germany in 2022. In December 2022, Germany experienced calm, cloudy, and extremely wintry conditions for multiple consecutive days (see Figure 13). Wholesale electricity prices in Germany surged above €700 per megawatt-hour (MWh) on December 11th. The normal wholesale electricity price was around €192.81/MWh in 2022 (KIT, 2023; SMARD, 2022).

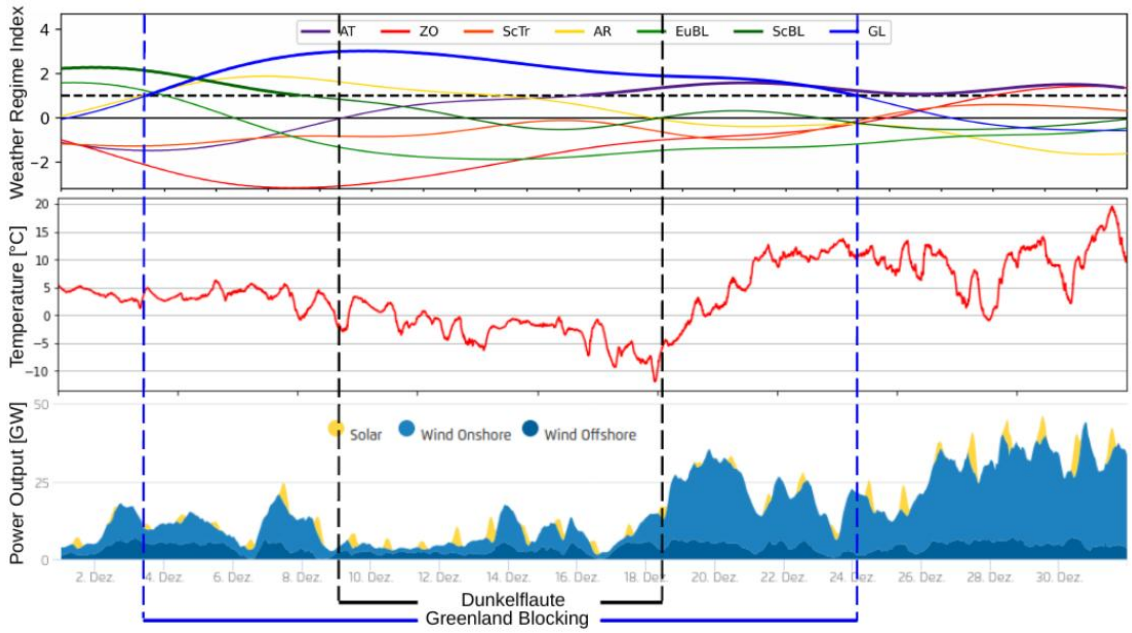


FIGURE 13 LOW WIND AND SOLAR PRODUCTION DECEMBER 2022 GERMANY "DUNKELFLAUTE"

Source: (Grams et al., 2017; KIT, 2023).

Fourth-quarter wholesale day-ahead prices were high on average (≈approximately €193/MWh) but highly volatile, ranging from –€3.78 to €665.01/MWh, with 29 hours of negative pricing, indicating renewable-driven oversupply and scarcity events (Table 7).

TABLE 7: DAY-AHEAD WHOLESALE PRICES, Q4 2022

Measure	**Q4 2022**
Average [€/MWh]	192.81
Minimum [€/MWh]	-3.78
Maximum [€/MWh]	665.01
Number of hours with negative prices	29

Source: (KIT, 2023).

High electricity prices for consumers stem from the costly challenge of balancing cheap but inconsistent renewable energy with expensive gas-fired power plants. A substantial portion of end-customer bills goes toward paying these backup plants as a retainer fee to keep them on standby, ensuring they are ready to run to prevent blackouts, even though they remain idle most of the time. During periods of high demand or low renewable generation, the backup gas plants must run and charge unreasonably high prices to cover their costs. The combined costs of maintaining system readiness and covering occasional price spikes are blended, resulting in higher average electricity bills for all end customers. Volatility underscores the importance of flexible storage technology and demand response for helping to smooth fluctuations. Demand response and energy storage require an intelligent infrastructure. This is a major driver for transforming the traditional centralized grid into a smart grid, utilizing IoT sensorics and AI optimization. The transformation of the conventional power grid into a smart grid is imperative for efficiently integrating variable and distributed energy resources. This is crucial for maintaining grid reliability and providing the technical backbone for new market dynamics, reflecting the shift from monopolistic to competitive structures (Bird et al., 2013).

2.3. The Internet of Things and Artificial Intelligence in the Smart Grid development

The transformation of the traditional, centralized power grid into an intelligent, decentralized grid is necessary to integrate variable renewable energy sources and enable new, competitive electricity markets. This is made possible by the combination of the Internet of Things and Artificial Intelligence. The IoT constitutes a network of physical objects "things"—from home appliances to critical infrastructure—equipped with sensors, software, and connectivity that enable them to collect and exchange data. "Things" primarily refer to physical objects, although they can also have virtual counterparts in augmented or virtual reality environments, such as digital twins. Each IoT device is designed to both sense its surroundings and connect to a network. IoT devices are equipped with sensors that detect and measure physical parameters such as temperature, motion, light, or heart rate. AI then provides the analytical framework to process this data, with machine learning algorithms enabling systems to learn from data, adapt, and make intelligent decisions to optimize states. This subchapter examines the technological architecture of AI and IoT that underpins modern production and smart energy systems. The key layers provide a framework, from the sensors that gather information to the communication gateways that transmit data from the edge to cloud computing platforms, where it is processed. It will also detail how AI-driven analytics create actionable insights that enhance operational efficiency, reduce costs, and facilitate the integration of renewable energy sources. By establishing this technical foundation, this chapter should demonstrate how the fusion of AI and IoT transforms raw data into economic value. The Internet of Things, a subset of information technology, collects large amounts of data from sensors and other sources. Artificial Intelligence runs mathematical optimization over this data in data centers (cloud) and on edge computing devices, and feeds the results back to the system, optimizing how its components interact. IoT facilitates data collection and analysis, driving efficiency through process automation. Given the knowledge of system states, an optimal decision can be made to maximize expected payoff. Information economics is a branch of microeconomic theory that studies how systems influence economic decisions. Intelligent decision-making in information economics suggests that, given knowledge of system states, an optimal decision can be made to maximize the expected payoff. According to Samie et al. (2016), information is used in decision-making to achieve the goal of systems and services to change the knowledge of a decision maker on a particular subject. In the IoT, there is an initial investment in infrastructure, including sensors, connectivity, and data centers. The sensors consume energy and bandwidth to collect and transmit sensing information to edge computing devices or data centers. The difference between value and cost is referred to as information gain, which should be maximized for the designed information system (Lu et al., 2015). “Smart” embedded devices, with their intelligent decision-making capabilities, increase service efficiency across various domains, including the smart electric grid. The smart grid comprises numerous sensors and other data sources that continuously collect high-resolution data. Managing the large volume of data has been identified as a major challenge in IoT. To address this issue, edge computing involves processing data at the edge of the IoT network, close to the embedded devices, nearer where the data is collected (Samie et al., 2016). The rapid development of the IoT is driven by the convergence of ubiquitous computing, cost-effective sensors, increasingly powerful embedded systems, and advances in machine learning (Lin & Xiang, 2023). New AI and IoT-based business applications are emerging in almost every sector of the economy. Devices in an IoT network connect via both wireless and wired infrastructure, enabling seamless data exchange. This connectivity has enabled innovative business applications across diverse sectors—from monitoring goods and livestock in the agricultural industry to facilitating predictive maintenance in transportation systems, such as trains and airplanes (Lynn et al., 2020).Smart thermostats monitor room conditions and fitness trackers record steps and heart rate—to gather data to understand their environment and trigger appropriate responses (Sikder et al., 2018). Network connectivity is maintained via built-in Wi-Fi, Bluetooth, or cellular interfaces, enabling sensors to transmit collected data to other devices, cloud servers, or control systems for centralized management. The AI algorithms on the collected data, treated as discrete information, transform raw sensor readings into actionable insights. Networks, comprising interconnected entities, act as conduits for communication and data transfer, supporting machine-to-machine interactions (Islam et al., 2023). There are numerous conceptualizations of IoT applications (Table 8).

TABLE 8 INFORMATION CONCEPTS FOR IOT-ENABLED SMART SYSTEMS

Information Concept	Description	Source
Optimal decision-making	With a better understanding of system states, choose actions that maximize the expected payoff. Information economics examines how the availability/quality of information influences choices and outcomes.	Samie et al., 2016
Value of information in IoT	This concept weighs the cost of an IoT system (up-front CAPEX and ongoing OPEX) against its benefits. IoT requires upfront CAPEX (sensors, connectivity, and compute) and ongoing OPEX (energy/bandwidth, and data operations). The value of information (VoI) is the improvement in expected payoff from better decisions enabled by data; net benefit ≈ VoI − costs.	Lu et al., 2015
Smart embedded & edge devices	Resource-constrained devices (often AI-enabled) generate massive amounts of high-frequency data. Edge computing processes this data near the source to reduce latency and bandwidth use while improving system responsiveness.	Samie et al., 2016
Internet of Things (IoT)	A cyber-physical system of sensors, connectivity, and software enabling automated monitoring, control, and data exchange across domains (e.g., energy, buildings, industry).	Lin & Xiang, 2023; Lynn et al., 2020
IoT device capabilities	Devices sense physical parameters (e.g., voltage, flow, temperature) and communicate via protocols such as Wi-Fi, BLE/Bluetooth, Zigbee, or 5 G. Data is aggregated through gateways to platforms where analytics drive alerts and actions.	Sikder et al., 2018
IoT networks & protocols	Industrial/app layers (e.g., OPC UA, DDS) and short-range PANs (e.g., Zigbee, Z-Wave, BLE). Wireless backhauls link the edge to cloud platforms where ML/analytics run.	Islam et al., 2023; Al- et al., 2015

Source: author's own, based on sources listed in the table (Ahsan et al., 2023; Al-Fuqaha et al., 2015; Billé et al., 2023; Lin & Xiang, 2023; Lynn et al., 2020; Samie et al., 2016; Sikder et al., 2018*).*

In the IoT ecosystem (Figure 14), communication protocols and specialized procedures facilitate the transmission of information over networks. Domain-specific protocols like OPC UA, DDS, ZigBee, Z-Wave, and Bluetooth Low Energy are providing data transmission from IoT sensor devices to the edge infrastructure and wireless networks such as cellular, Wi-Fi, and LoRa connect to the cloud, where data is analyzed and optimized with machine learning programs (Al-Fuqaha et al., 2015).

This architecture offers tailored solutions for industrial automation, smart homes, and wearable technologies, addressing unique requirements such as real-time control and energy efficiency. Together, these protocols and hardware enable seamless interoperability, supporting the creation, capture, and delivery of value within IoT systems. Processes are critical to the interoperability of entities within the IoT, encompassing both communication and domain-specific processes. They are essential for creating, capturing, and delivering value in the IoT.

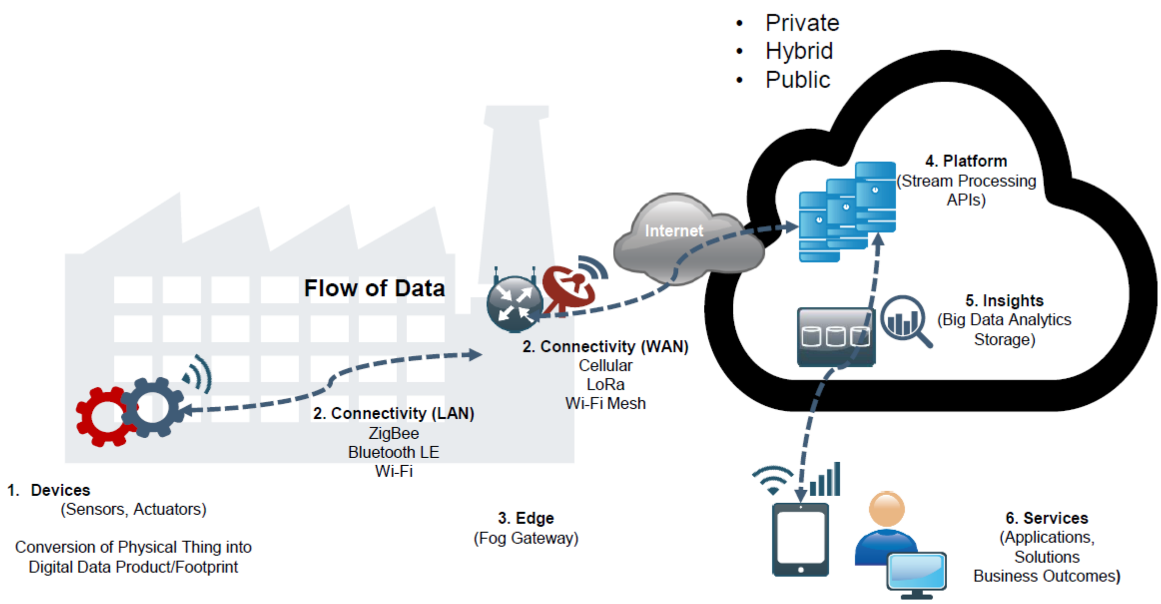


FIGURE 14: IOT ECOSYSTEM DEPICTING DEVICES, CONNECTIVITY, PROCESSING, AND SERVICES

Source: (Kunerth & Ramsey, 2022).

As IoT technology continues to mature, it transforms many aspects of modern life, with connected devices monitoring everything from weather data to logistics to manufacturing. The Industrial Internet of Things plays a pivotal role in measuring processes and optimizing outcomes across sectors such as logistics, manufacturing, and energy production and distribution. Artificial intelligence, in general, and machine learning, as a sub-discipline, play a critical role in enabling systems to learn, adapt, and make intelligent decisions based on the data they collect (Russel & Norwig, 2022). Advanced hardware and software solutions enable companies to monitor industrial processes and machines in real time. IoT sensors enable real-time data collection from machinery and equipment, which AI algorithms analyze to predict maintenance needs, thereby minimizing downtime and maintenance costs (Ucar et al., 2024).This enhances operational efficiency by optimizing machine and equipment runtime and maintenance schedules, resulting in longer equipment lifespans and greater worker safety. In manufacturing settings, vibration and heat sensors monitor machine performance. Vision-based AI systems, running convolutional neural network software on edge computing devices, process visual data for failure monitoring. Data collected by IoT sensors, including temperature, noise, and electrical signals, is transmitted to the cloud, where AI algorithms analyze it to identify anomalies, predict potential failures, and trigger maintenance procedures. This is making manufacturing businesses more competitive through enhanced operational efficiency, optimized resource utilization, and automated decision-making in manufacturing and supply chain management environments (Pradeep, 2023;Ucar et al., 2024). The Siemens Amberg facility in Germany produces approximately 12 million PLCs annually for use in systems such as cruise ships and assembly lines. Microsensors integrated into the production process monitor critical parameters, ensuring real-time data collection and process optimization. This IoT-driven approach combines operational technology (OT) and information technology (IT) to enhance quality control and overall efficiency. Siemens achieves an almost 100% failure-free production rate, demonstrating the transformative impact of IoT on industrial manufacturing (Staufer, 2019). KONUX, a German startup in the transportation sector, deploys machine learning algorithms on IoT sensor data to automate rail operations and maintenance. In collaboration with Deutsche Bahn, KONUX has implemented smart sensor technology that monitors critical infrastructure components, such as rail switches, to detect early signs of degradation and prevent costly failures (Konux, 2021).Their switch analytics case study demonstrates how advanced analytics increases operational reliability and enables a proactive maintenance strategy (Boehm & Weiss, 2017). Forbes notes that unplanned downtime, often due to delayed maintenance, can cost hundreds of thousands of dollars per hour (Sundeep V. Ravande, 2022). Companies reduce costs and downtime but also unlock new revenue streams through optimized digital workflows. This strategic transformation equips organizations with the agility necessary to compete in today's industrial landscape (Behrendt et al., 2021). AI and robotics free up human workers to focus on more intricate and innovative assignments. The reallocation of human talent has the potential Click or tap here to enter text.to boost overall economic efficiency and productivity significantly (Bickley et al., 2022), while AI-powered vision systems ensure higher quality and consistency in product inspections (Gavrilova, 2024).Like the manufacturing sector, the electric energy sector uses IoT sensor data to power AI models. Machine learning models (ML), a subset of AI, are algorithms that analyze large amounts of data, identify patterns, and make predictions or decisions based on those patterns. In supervised learning, models learn input-output relations from labeled training samples. The labels provide the guidance needed for generalization (Liu & Wu, 2012). Common short-term methods include the Autoregressive Integrated Moving Average (ARIMA) model, the Kalman filter, and multiple linear regression (MLR). MLR predicts future numerical values by learning relationships between variables. ARIMA is a statistical model used to analyze and forecast time series data (Andrić et al., 2017; Delua, 2024). The systems learn and adapt as they are exposed to more information. Supervised learning uses labeled examples to predict targets. Accurate demand forecasting is crucial for the control and operation of utility-run smart grids and privately run microgrids. It lets operators optimize production, storage, and distribution. That improves efficiency and reduces costs. Training an AI forecasting model relies on historical consumption trends, weather data, and timestamps (Huang et al., 2022). Weather patterns impact renewable energy production. High-accuracy forecasts use data models that include time of day, past demand, price signals, and meteorological data. In smart grids, supervised learning algorithms forecast grid demand by training on labeled historical usage and weather patterns. In a microgrid, machine learning is used to balance local resources and forecast internal energy demand and generation, thereby minimizing reliance on the main electrical grid (Huang et al., 2022; Liu & Wu, 2012; Wu et al., 2024).

Forecasting and demand response utilize technologies that enable distributed energy resources to participate effectively in energy markets, especially under dynamic, load-driven pricing schemes. Forecasting provides forward-looking estimates of system conditions, including load, prices, and congestion. These estimates inform demand response programs that direct DERs to modify their output or consumption by increasing dispatch or curtailing usage. Forecasting identifies the timing of intervention, and demand response outlines the process through which that intervention occurs. As a result, forecasting and demand response management help integrate larger shares of variable renewable energy into the grid (Morales-España et al., 2022). This is because they can leverage DERs, such as batteries, to stabilize the grid in response to price signals.

Economic models can use data from forecasting, demand response management, and dynamic pricing schemes. Econometrics provides a method for modeling and forecasting electricity prices by linking observed prices to measurable system fundamentals. Multiple linear regression (MLR) is widely cited in standard literature. MLR models quantify the partial contribution of covariates, such as system load, generation availability (including renewable output), fuel costs, weather, and network congestion, to price levels, conditional on the rest. Comparative reviews document the effectiveness of these regression-type models with exogenous input for day-ahead price forecasting across markets (Weron, 2014). Table 9 provides an overview of the basic Smart Grid digitalization strategies.

TABLE 9 DIGITAL INTELLIGENCE FOR SMART GRID OPERATIONS

Step	Core Functions	Examples	Impact
Sensing: IoT sensor devices	Field devices measure states and events	Smart meters, PV inverters, battery BMS, weather stations, feeders, transformers	Provides high-frequency inputs to forecasting models and control
Data Pipeline	Ingest, clean, align, and feature-engineer data	Timestamp alignment, weather joins, lag/rolling features, calendar features	Prepares labeled datasets for supervised learning
Forecasting (ML/Stats)	Predict load/price/renewables using supervised learning.	MLR, ARIMA, Kalman filter; tree/boosting/NN as extensions	Determines when interventions are warranted
Operations & DRM	Translate forecasts into actions	DER dispatch, charge/discharge, curtailment, load shifting; aggregator bids	Specifies how interventions occur to meet reliability and cost goals
Outcomes and Optimization	Key performance metrics and economic outcomes	Lower costs, improved reliability, renewable integration, and emissions avoided	Measurable benefits and continuous optimization

Sources: (Andrić et al., 2017; Delua, 2024; Huang et al., 2017; Morales-España et al., 2022; Weron, 2014).

In large utility-scale solar plants, wind parks, and microgrids, econometric models can use data from Supervisory Control and Data Acquisition (SCADA) systems. SCADA systems collect measurements from field devices such as sensors, meters, and generators, and display them on operator human-machine interfaces, such as monitors and industrial computers, showing trends and alarms, and also provide data for reporting, analytics, and issue-tracking that trigger actions for field workers (El-Shebiny et al., 2007; Sayed & Gabbar, 2017). As electricity generation from renewable energy sources, such as small hydro, biomass, biogas, solar, wind, and geothermal energy, is increasing; the need for distributed grids and prosumer-driven networks is also increasing (IEA, 2023; O'Neil, 2022). Smart grids integrate the actions of generators, consumers, and prosumers to achieve efficient, sustainable, and low-loss operation (Zareen et al., 2012). The smart grid relies on real-time information from utilities and customers to improve reliability and lower costs (O'Neil, 2022; *Smart Grid: The Smart Grid | SmartGrid.Gov*, 2024). Artificial intelligence-based neural network architecture improves forecasting in smart grids. Convolutional networks and fully connected networks capture complex relationships, with accuracy adjusted by tuning filters, neurons, and layers. Timestamps display daily, weekly, and seasonal patterns. (Neumann et al., 2023). Recurrent neural networks (RNNs) are designed to model sequential data and capture temporal dependencies (Kumar et al., 2012). These models allow operators to plan production, storage, and distribution of electric energy with greater accuracy. They also enable quicker responses to changing conditions. (Wazirali et al., 2023) AI models are part of a broader smart grid ecosystem shaped by regulatory frameworks, technology, market players, and assets. Their deployment within this structure enables efficient management of electric energy and ensures power system stability. The functional layer sets out service interactions, while the information layer standardizes data exchanges. The communication layer specifies protocols and transport. The component layer lists physical assets and applications (Ghasempour, 2019; Wazirali et al., 2023).

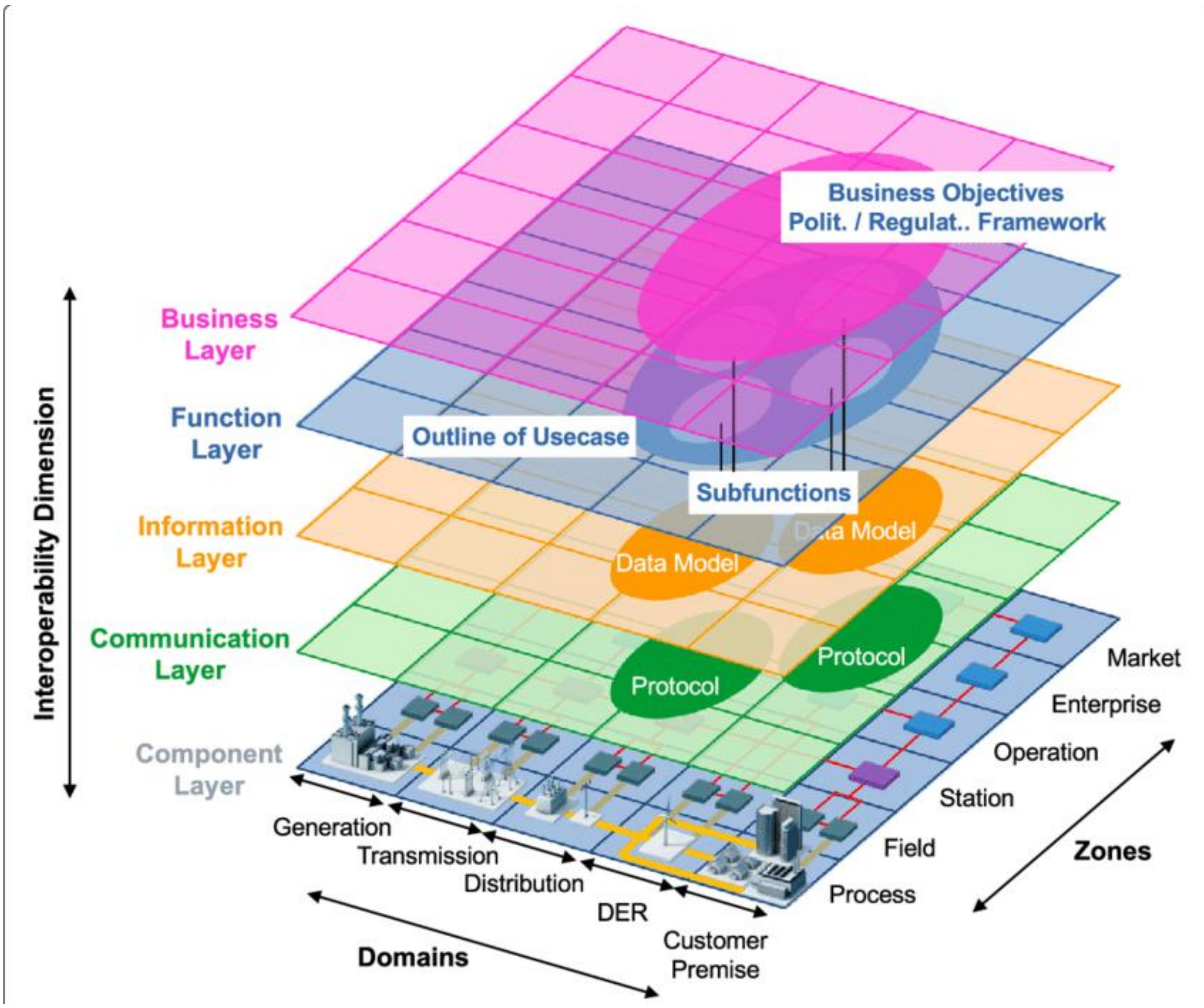


FIGURE 15 SMART GRID ARCHITECTURE MODEL

Source: (Daki et al., 2017); (CCMC, 2014).

Figure 15 presents a multi-layered conceptual framework for analyzing interoperability dimensions and domains within a smart grid. Drawing on the Smart Grid Architecture Model (SGAM), the domains axis reflects the electrical energy supply chain, spanning from large-scale generation and transmission to local distribution and customer premises. The zone's axis indicates the management hierarchy, ranging from physical field hardware to operational control centers, and then to enterprise and market business levels. The vertical interoperability dimension illustrates how components interact through distinct layers, including physical hardware, communication protocols, information models, and business functions. This framework outlines an architecture designed for implementing price-setting mechanisms for distributed energy resources (DERs), prosumers, and consumer optimization approaches, while facilitating competition in energy systems. Each layer of the model, including hardware, protocols, data models, and regulatory frameworks, supports real-time data sharing, dynamic pricing, and market optimization processes.

Dimensions (vertical axis) illustrate how each layer supports system interoperability, aligning components, data, and business goals. Domains (Generation, Transmission, Distribution, DER, Customer Premise) define the physical areas of the energy supply chain, each with distinct functions. Zones (Market, Enterprise, Operation, Station, Field, Process) indicate activity levels within the system, ranging from market operations to field and process tasks.

In terms of functionality, the business layer is based on institutional and regulatory structures that govern the pricing and transaction of electricity across the system. At its center is the market design, defining the mechanisms, such as locational marginal pricing (LMP), used to clear electricity markets. Locational Marginal Pricing represents the marginal cost of delivering electricity to specific locations on the grid, accounting for transmission losses and congestion. Administration of Locational Marginal Pricing (LMP) is conducted by Independent System Operators (ISOs) or Regional Transmission Organizations (RTOs), which are nonprofit entities responsible for overseeing electricity market operations and ensuring system reliability. Retail pricing is determined by tariff catalogs and rate design, which translate wholesale price signals into end-user incentives using instruments such as time-of-use (TOU) rates and real-time pricing (RTP) (Ela et al., 2014; Tesfatsion, 2023). Business-layer policies facilitate incentive schemes for distributed energy resources (DERs) and demand response (DR), providing compensation to prosumers for activities such as load shifting, distributed generation, or ancillary services. These programs aim to increase the elasticity of supply and demand, with the potential to mitigate price spikes and decrease reliance on costly peaking capacity (Asadinejad et al., 2017). Consumer protection policies, including affordability measures and bill caps, help support vulnerable groups while encouraging investment. Performance-based regulation aligns utility actions with policy goals by tying earnings to KPIs such as reliability, DER interconnection times, and cost efficiency (Joskow, 2024b; Pató et al., 2019). Together, these components of the business layer shape how prices are formed, distributed, and governed, ensuring that market outcomes reflect both economic efficiency and broader social objectives.

TABLE 10 BUSINESS LAYER

Policy Business Item	What it is	Purpose	Primary owner(s)	Role in price setting/optimization	Domains affected	KPIs / Outcomes
Market design & rules	The rulebook for how buying/selling electricity works (auctions, products, timing)	Define products (energy, capacity, ancillary), gate times, and clearing methods	Regulators, ISO/RTO, ministries	Sets the mechanism that turns bids and offers into prices	Generation, Transmission, Distribution, DER	Market efficiency, liquidity, price volatility, and reliability metrics
Tariff catalog & rate design	Menu of retail rates (TOU, RTP, demand charges, fixed/basic service)	Align customer incentives with system costs and policy objectives	Regulators, utilities	Determines retail price signals and the pass-through of wholesale costs, enabling RTP/TOU optimization.	Distribution, DER, Customer	Affordability index, cost recovery, participation in optional rates
DER/DR program incentives	Payments and program rules that reward flexible load and DER participation.	Attract prosumers + consumers to provide capacity, energy shifting, and ancillary services	Utilities, aggregators, regulators	Creates elastic demand/supply that stabilizes prices and reduces peak scarcity.	Distribution, DER, Customer	MW enrolled, realized MW, cost per MW, customer satisfaction
Consumer protection & affordability policy	Safeguards such as bill caps, lifeline rates, and disclosure rules	Balance affordability with cost recovery and investment incentives	Regulators, consumer advocates, utilities	Constrain price designs and recovery paths; shape participation and equity.	Customer	Bill burden (% income), arrears rate, disconnection rate
Performance-based regulation (PBR) & KPIs	Link utility earnings to outcomes (reliability, DER integration,	Align utility incentives with societal goals and	Regulators, utilities	Shapes long-run price trajectories via cost efficiency and innovation signals.	Distribution, Customer, DER	SAIDI/SAIFI, interconnection times, cost-to-serve

	service quality)	innovation.				

Source: (Asadinejad et al., 2017; Ela et al., 2014; Joskow, 2024b; Pató et al., 2019; Tesfatsion, 2023).

The function layer (blue) represents the system's functions and subfunctions, emphasizing the processes and operations. It includes the outline of use cases (Chassin et al., 2008). Smart grid communication protocols must strike a balance among trade-offs such as data rate, latency, coverage, energy efficiency, and infrastructure cost to support various use cases. Lora WAN and NB-IoT, with low data capacity (~50–250 kbps) and long-range coverage (up to 15 km), are well-suited for delay-tolerant tasks such as smart metering and asset monitoring due to their low power consumption and minimal infrastructure needs (Che Kamarudin et al., 2024; Ji et al., 2018). In contrast, Zigbee and Wi-SUN offer higher bandwidth (up to 2.4 Mbps) over short to medium distances with mesh topologies, making them ideal for dense environments like home or Neighborhood Area Networks, where reliability and scalability are (Haque et al., 2022; Hirakawa et al., 2022). 5G URLLC, with ultra-low latency (<1 ms) and data rates exceeding 1 Gbps, is essential for time-sensitive applications such as phasor measurement unit (PMU) streaming and real-time DER control in distribution automation, where deterministic performance and sub-second response are mission-critical (Matz et al., 2020).

TABLE 11: *COMPONENT AND COMMUNICATION LAYER*

Technology/ Connectivity	Data capacity	Coverage	Key components	Best-fit grid uses
Lora WAN	Very low (~50 kbps)	5–15 km	Battery sensors/meters; LoRa gateways; network server; backhaul	AMI (meter reads), non-urgent distribution automation, pole/asset monitoring
Zigbee	Low (≤250 kbps)	10–100 m	End devices (sensors/thermostats); coordinators/routers; building gateway	Home Area Networks, smart thermostats, building automation, local controls
Wi-SUN	Medium (≤~2.4 Mbps)	Up to ~5 km (mesh)	Field routers/endpoints; border router; utility management system	Neighborhood Area Networks, smart street lighting, and distribution automation
NB-IoT	Low (~250 kbps)	Up to ~10 km; deep-indoor	Cellular modules (SIM/eSIM); carrier towers/core; device/cloud platform	Smart metering, remote grid monitoring in cellular areas

5G (URLLC)	Very high (>1 Gbps), ultra-low latency	<1 km (dense cells)	5G small cells; 5G core (private/public); edge server/backhaul; 5G devices	PMU streaming, protective relaying, real-time DER control

Source: Che Kamarudin et al., 2024; Haque et al., 2022; Hirakawa et al., 2022; Ji et al., 2018; Matz et al., 2020.

External variables, such as weather conditions (temperature, solar irradiance, and wind speed), affect renewable energy generation and electricity supply. Forecast accuracy for spot price prediction relies on incorporating weather and other exogenous factors. High-resolution load and DER forecasting models predict net consumption profiles (Théate et al., 2023). Smart Meters collect data to support time-based pricing and enable real-time data-driven decisions (Naga Malleswara Rao et al., 2023). Prosumers both produce and consume electricity, adding complexity to the system, altering demand profiles, and influencing system load. Operators utilize optimization models to manage the complex trade-offs in electric power systems, particularly under high penetration of renewable energy, thereby minimizing costs while ensuring reliability. They support decision-making across scheduling, dispatch, and market-clearing processes. The information layer, through its data models, supports the accurate representation of energy prices, demand, and supply, building on algorithms that determine optimal prices based on market conditions and prosumer behavior. By keeping these data consistent, time-stamped, and location-aware, optimization engines and market platforms can compute feasible, cost-optimizing prices and dispatch. The data architecture integrates locational marginal price signals, short-term and day-ahead demand projections, unit-specific generation offers, interval metering telemetry, behind-the-meter flexibility potential, forecasted meteorological variables, and ISO settlement and reconciliation records. Price signals coordinate the more efficient allocation of supply and demand by raising prices when supply is scarce, encouraging either increased production or decreased consumption, and enabling demand response programs. Modern forecasting deploys statistical and machine learning models to predict electricity prices and usage. This is especially critical on short-term horizons, given market volatility. For an economist, this layer provides and translates physical and behavioral data into comparable, auditable numbers, enabling the creation of econometric models. Spot prices in electricity markets are created in auction-based systems. The electricity price is determined through a daily or hourly auction in which the market-clearing price emerges at the intersection of the supply and demand, reflecting available generation and consumption needs: (Pinhão et al., 2022; Rajabpour et al., 2021; Strezoski, 2023; Théate et al., 2023). The day-ahead electricity market operates through a sealed-bid auction, typically structured as a uniform price auction (UPA). In a UPA, all successful bidders are paid the market-clearing price (MCP), which is determined by the intersection of the aggregate supply and demand curves. This mechanism does not discriminate among participants—all winning bidders receive the same price, regardless of their bids. The marginal unit, i.e., the last accepted bid that satisfies demand, sets the MCP, ensuring that the price reflects the cost of the most expensive unit needed to meet total demand (Pinhão et al., 2022). VPPs aggregate distributed energy resources (DERs) into coordinated portfolios that participate in energy markets, offering grid services such as peak shaving, load following, ancillary services, and energy trading—acting like conventional dispatchable plants (Kaiss et al., 2025; Muhr, 2019). DERMS integrate distributed energy resources into the grid and are designed for localized distribution-level optimization, including voltage control, load balancing, and power-flow management (Strezoski, 2023).

TABLE 12 ***INFORMATION LAYER***

Data Item	Description	Function	Users	Tools	Effects
Price Signal	The electricity price for a specific place and time (tariff rate or market price)	Inform customers and devices about power costs so they can adjust their usage or supply energy; this is used for billing/settlement	Operations/optimizers, VPP, TOU aggregators, billing & settlement teams	Databases for time-stamped data and message streams	Direct input to pricing and demand response; must match settlement intervals and locations
Demand Forecast	Expected electricity use in the following hours/days	Plan generation, target demand response, and form price expectations.	Scheduling/operations, DERMS/VPP teams, rate design	Forecasting service and time series store with ML features	Prices up/down can create imbalances
Supply Offer	Bids from generators/ DERs are defined by how much they can produce and at what price	Market clearing and dispatch planning	Market engine and dispatch operations.	APIs and analytical storage (data Lakehouse)	Shapes the clearing price and determines the feasible dispatch
Prosumer Behavior	The flexibility of customers/devic	Design demand response programs and	DERMS/VPP operators and	IoT/edge + cloud platforms	Determines demand response

	es, as well as their reaction to price (elasticity, comfort bounds).	transactive control	pricing/strategy teams	with privacy-preserving aggregation	strength, which is core to elasticity-based pricing.
Meter Read / Load Measurement	Measured electricity used or delivered in regular time intervals	Billing and settlements; create baselines; analyze losses	Billing/finance and analytics teams.	Meter data management system and time series store.	Ground truth for settlements and for evaluating price effects
Settlement & Baseline	Formulas that turn usage and program results into payments/credits	Pay customers, settle markets, and evaluate DR performance	Finance teams, regulators, and customer portals	Rules engine and analytical storage	Closes the loop between prices, behavior, and money flows
Weather & Exogenous Inputs	Outside factors, such as temperature, sun, and wind, affect demand and renewable supply	Improve forecasts and scenario pricing	Forecasting, operations, and risk teams.	Feature Stores and Time Series Data Systems	Explain and predict price swings caused by demand/supply shifts.

Source: (Pinhão et al., 2022; Rajabpour et al., 2021; Strezoski, 2023; Théate et al., 2023).

The function layer, with its subfunctions and use cases, enables the implementation of optimization algorithms that support demand response strategies, load shifting, and energy storage management, thereby enhancing prosumer participation and market efficiency (Hammerstrom, 2007). To understand how data is managed within such a system and how and for what purposes data is used in an intelligent grid system, the following figure is helpful. The layered architecture also supports economic competition by ensuring that all participants, including prosumers, utilities, and third-party aggregators, can interact transparently and efficiently, fostering a competitive energy market. This is particularly relevant in transactive energy systems, as demonstrated by the Retail Automated Transactive Energy System Pilot in Thousand Oaks, CA, and the Olympic Peninsula Demonstration Project, where the architecture enabled the simulation and implementation of competition scenarios, thereby optimizing pricing strategies and market interactions. This framework not only facilitates the integration of various technologies and stakeholders but also supports the economic concepts of competition, which are critical for the development of efficient and resilient energy markets in the context of modern smart grids (Hammerstrom, 2007) (Chassin et al., 2008). Smart grids serve as the crucial backbone for dynamic pricing models, the integration of distributed energy resources, and microgrids, as they provide the necessary ICT infrastructure for real-time communication, data exchange, and automated control. This facilitates dynamic pricing mechanisms and energy trading, thereby optimizing energy use and balancing supply and demand (Chen & Liu, 2017a). By enabling price adjustments in response to fluctuations in supply and demand, smart grids facilitate a more efficient allocation of resources and reflect the true cost of electricity at any given time. This dynamic pricing allows consumers to adjust their usage in response to price signals, thereby promoting demand-side flexibility and energy conservation during peak periods (Eid et al., 2016b). Energy trading between consumers, producers, and prosumers fosters competition, driving down prices and incentivizing innovation and investment in renewable energy sources. This dynamic and responsive pricing environment aligns with economic principles of market efficiency (Misra & Bera, 2018).

CHAPTER 3 CASE STUDIES METHODOLOGY

3.1 Overview of existing studies into energy and IoT

Recent empirical research across several studies (see Table 13) has highlighted the economic and operational impacts of microgrid applications, from rural and community-based systems to industrial and military deployments. A comparison of different studies on microgrids reveals varying outcomes, depending on geography, technology used, and specific applications; however, all studies have shown improvements. Across various contexts, microgrids deliver cost savings of 30–85%. Techniques such as real-time dispatch, internal markets, peak shaving, and deep learning enhance performance and reduce costs. Each setting requires a tailored system design. Market mechanisms work well in communities; resilience is the main driver for commercial, military, and refugee camps. All the case studies in Table 13 use some form of energy management system that incorporates sensors and intelligent microgrid scheduling.

TABLE 13 *RESULTS OF MICROGRID META-STUDIES ON ECONOMIC EFFICIENCY*

Use Case	Specific Improvement	Region/Context	Source & Link
Community Microgrids	84.63% reduction in operational costs; 14.21% reduction in Levelized Cost of Energy (LCOE); 92.3% renewable energy utilization	Rural Australia	(Uddin et al., 2025)
Community Microgrids	54% of cost savings through the internal local energy market	Belgium	(Cornélusse et al., 2019)
Hybrid Renewable Systems	Up to 32% total cost savings; 83% emissions reduction; payback period between 0.9 to 6.2 years	Nyabiheke Camp, Rwanda	(Alonso et al., 2021)
Military Microgrids	Significant reductions in electricity costs; potential for free energy generation in some cases	U.S. Military Bases	(Wood, 2017)
Residential Microgrids	Reduction in electricity bills compared to standard rates	Basalt, Colorado	(Oberhaus, 2020)

Industrial Microgrids	93% round-trip efficiency with lithium-ion batteries	Europe	Mureddu, M., et al. (2022)

Source: Author's own, based on the sources given in the table.

The first example is a project in rural Australia, where community microgrids have achieved an 84.63% reduction in operational costs, a 14.21% reduction in the Levelized Cost of Energy (LCOE), and a 92.3% renewable energy utilization rate. This study underscores the effectiveness of integrated energy management strategies for optimizing operational expenditures and enhancing sustainability at the community level (Uddin et al., 2025). High efficiency gains are observed in a European study. In Belgium, the implementation of community microgrids with local energy markets has resulted in 54% cost savings. This internal market structure enables local generation and consumption balancing, reducing dependency on a centralized grid and creating tangible financial benefits for participants (Cornélusse et al., 2019).

A case study conducted in the Nyabiheke refugee camp in Rwanda found that solar-diesel hybrid mini-grids can deliver up to 32% in total cost savings and an 83% reduction in emissions, with payback periods ranging from 0.9 to 6.2 years. This rapid return on investment, combined with substantial emissions reductions, highlights the economic and environmental viability of hybrid microgrid solutions in challenging, resource-constrained geographies, and where the grid is insufficient or not available (Alonso et al., 2021). Studies across U.S. military base microgrids have revealed reductions in electricity costs through the optimized use of renewable resources and storage technologies. The findings point to the strategic value of microgrids in enhancing both the economic efficiency and energy security for critical infrastructure (Wood, 2017).

AI-powered algorithms enhance microgrid efficiency by optimizing the real-time balance between energy supply and demand, reducing energy waste and unnecessary generation. By leveraging predictive capabilities, AI anticipates peak demand periods and weather patterns and adjusts energy production and distribution accordingly. This enables microgrids to prioritize renewable energy usage and allocate stored power from renewable sources more efficiently, thereby reducing their overall carbon footprint. AI-enabled microgrid systems significantly reduce CO_2 emissions by enabling more efficient energy management and optimizing energy flows in response to real-time conditions. This makes AI a powerful tool in achieving sustainability goals for microgrids (Ukoba et al., 2024).

(Piette et al., 2015) suggests that AI and IoT-powered demand response can reduce peak-related emissions by 10-15%, as they reduce dependence on gas powered peaker plants, which is a power plant that is used to meet peak electricity demand, typically during periods of high usage like hot summer afternoons or cold winter mornings designed to quickly ramp up and provide power for short periods, supplementing baseload power plants This reduces Co2 emissions and support better grid utilization.

Predictive maintenance capabilities are enabled by IoT sensors that monitor the health and performance of key components, such as batteries and inverters. At the same time, AI analyzes data to predict potential failures and proactively address issues before they lead to malfunctions. By ensuring equipment operates at optimal efficiency, energy production losses from faulty or degraded components are prevented, preventing shutdowns. Predictive maintenance capabilities also extend the lifespan of the assets, reducing the frequency of repairs or replacements, which are also emissions-intensive. AI- and IoT-enabled predictive maintenance can reduce emissions by 5-10% by avoiding inefficient energy use and supporting prolonged, effective operation of microgrid assets (Wu et al., 2024). During installation and planning, AI-driven automation can streamline project management and execution processes, reducing costs and time-to-completion. Generating power close to the point of use also reduces transmission and distribution losses associated with centralized power systems. (ESENOGHO et al., 2021) states that a localized approach to electric energy production is particularly beneficial in remote or rural areas, as shown by the Madagascar cell phone tower project. This fosters a more resilient and sustainable energy infrastructure, particularly in regions with limited access to centralized power.

(Valentine, 2023) states that Microgrids can optimize energy flows for EV charging based on real-time demand, grid conditions, and renewable energy availability. AI algorithms can predict peak charging times and adjust loads to off-peak hours, reducing strain on the main grid and minimizing reliance on carbon-intensive power sources, as demonstrated in studies on smart charging. Vehicle-to-grid (V2G) systems enable EVs to function as mobile energy storage units that can supply energy to the grid during peak demand. Vehicle-to-Grid (V2G)-enabled electric vehicles (EVs) can serve as valuable resources for providing reactive power support, regulating active power, balancing load, and filtering current harmonics.

3.2. Methodology for case study design

To analyze the economic effects of the transition from the traditional to IoT and AI-enhanced energy production and distribution, several case studies have been selected. A multi-case study design process has been utilized. A multi-case study design is a qualitative research method that involves the detailed examination of multiple instances—referred to as "cases" of a phenomenon to explore similarities and differences, test hypotheses, and build or refine theory (Eisenhardt, 1989); (Yin & K. Yin, 2013). This approach enables researchers to systematically compare diverse contexts, thereby providing a rich and holistic understanding of complex issues. This research employs a case study selection methodology to ensure findings yield meaningful economic insights from AI and IoT implementations within microgrids and smart grids. The following criteria were established to guide the selection process, balancing economic analytical depth with practical policy relevance: system configuration and energy framework. The analysis focuses on two primary system configurations: microgrids and smart grids. Microgrids are hybrid electricity-generation plus storage systems that combine PV or wind, batteries, gas or diesel generators, and bidirectional inverters, balancing intermittent renewables with diesel or gas while optimizing battery cycling. In microgrids, AI-driven weather and load forecasting, combined with IoT-enabled state-of-charge monitoring, optimizes energy dispatch, minimizes fuel consumption, lowers the Levelized Cost of Energy (LCOE), and enhances Internal Rate of Return (IRR) by efficiently managing distributed resources and load shifting. Smart Grids enable demand-side flexibility programs that leverage AMI smart meters, controllable loads such as HVAC or EV chargers, and price-signal platforms to shift or shed demand. AI engines provide real-time pricing with autonomous load adjustments, thereby flattening peak demand, enhancing grid reliability, reducing consumer costs, and increasing economic welfare.

These two energy frameworks demonstrate how digital intelligence and sensorics can unlock both supply-side efficiency and demand-side responsiveness, yielding economic gains by optimizing solar production, better managing battery cycling, and reducing fuel consumption in microgrids. Additionally, they utilize demand response schemes in smart grids to improve grid reliability and create welfare gains.

The selected case studies must incorporate a substantive, measurable layer of artificial intelligence (AI), such as machine learning (ML) applications and Internet of Things (IoT) control and sensor systems. This ensures that causal links between the technological implementation of those technologies and economic outcomes can be analyzed. Cases that feature only rudimentary automation without machine-learning-based algorithmic decision-making are not useful. Data richness requires that each case study has sufficient public or permission-based access to comprehensive datasets tailored to specific analytical frameworks for conducting economic research. This data includes (1) productivity analysis data (capital and labor inputs, ICT investment records, cost savings documentation) essential for Total Factor Productivity (TFP) calculations following Solow-residual methodology as demonstrated in the Blue Lake Rancheria case; (2) investment efficiency metrics (financial records allowing to calculate LCOE, IRR, and NPV) which aligns with neoclassical investment theory as utilized in the Airtel Madagascar analysis; (3) transactive energy data (dynamic pricing signals, energy conservation metrics) supporting demand elasticity to pricing exemplified by the Olympic Peninsula project; and (4) market transformation data (smart meter/AMI records, demand changes to pricing, peak/off-peak consumption patterns) critical for evaluating structural shifts through econometric modeling as seen in California's TOU pricing pilots. The cases were chosen to maintain methodological integrity and to ensure hypothesis testing regarding efficiency gains, investment returns, and market adjustments.

Conditions require that each selected case study provide precise pre-implementation economic data, established both before and after AI/IoT integration, for microgrids and for demand changes due to smart grid pricing. These baselines enable the calculation of Total Factor Productivity (TFP), Levelized Cost of Energy (LCOE), Internal Rate of Return (IRR) for microgrids, demand elasticity, and other economic indicators for smart grid case studies. Without such benchmarks, it would not be possible to attribute economic performance to AI/IoT, and the causal effect of AI/IoT cannot be established.

Diverse economic and physical contexts ensure the research incorporates case studies from both developed and developing economies, along with varied market structures and ownership models (commercial, community, and hybrid models). This diversity allows testing of how different economic conditions can influence outcomes. The case study design criteria for exploring the economic impacts of AI and IoT in energy systems outline operational requirements alongside economic or methodological rationales to ensure meaningful causal inference and the broad applicability of findings (Table 14).

TABLE 14 CASE STUDY SELECTION CRITERIA

#	Criterion	Requirement	Economic / Methodological Rationale
1	**AI / IoT Integration Depth**	The case must deploy a measurable layer of AI, ML, or IoT-driven decision-making.	Isolates causal links between digital intelligence and productivity and financial metrics, enabling tests of Hypothesis 1 (↑ efficiency, ↓ costs, financials↑) through TFP, LCOE, and IRR.
2	**Data Richness & Transparency**	Public or permission-based access to complete economic datasets: • Capital/Labor/ICT data inputs for TFP • Financial ledgers for LCOE-IRR • Dynamic-pricing logs and• Smart-meter records for demand elasticity studies.	Ensures that each analytical framework (Solow residuals, CAPM-style investment appraisal, auction/consumer-choice theory) can be populated, allowing for robust causal identification across complementary methods.
3	**Documented Baseline and Post-Implementation Conditions**	Clear *pre-implementation and after-implementation of (AI/IoT) benchmarks or pre-pricing and comparable post-implementation* demand data for TOU pricing.	This approach enables the estimation of differences in TFP, LCOE, IRR, elasticity, and other metrics, allowing improvements to be explicitly attributed to the digital intervention rather than external shocks.
4	**Economic Diversity**	The portfolio spans developed and developing economies, mixing commercial, community, and hybrid ownership models.	Tests the generalizability of digital-efficiency gains across varied market structures, cost of capital, and policy regimes—vital for drawing policy-relevant conclusions.

Source: author's own.

The case study design compares two major distributed energy system configurations—microgrids and smart grids—based on their typical hardware stacks, operational challenges, and the specific ways in which AI and IoT technologies improve performance, economic efficiency, and system reliability (Table 15).

TABLE 15 CONCEPTUALIZATION OF GRID ANALYSIS

Configuration Type	Typical Hardware Stack	Operational Challenge	How AI / IoT Adds Value
Microgrids: Hybrid Generation + Storage Systems (renewables + diesel/gas gen + battery)	Solar PV or wind, battery-energy storage, gas or diesel gensets, bidirectional inverters	Balancing variable renewables with reliable—but costly—diesel and gas gensets while optimizing battery cycling and fuel consumption and creating stable micro grid conditions. Sell excess energy at a high price to the grid when possible	• AI forecasting refined dispatch schedules • IoT sensors track state-of-charge & genset, and solar health • EMS minimizes fuel burn and curtailment, boosting LCOE and IRR.
Smart Grids: Demand-Side Flexibility Programs (dynamic-pricing/demand-response)	AMI smart meters, controllable loads, price-signal platform	Shifting or shedding demand to flatten peaks and integrate higher shares of renewables	• AI engines generate price or control signals for time-of-use pricing • IoT devices execute load adjustments autonomously • Results in lower peak demand charges and improved grid reliability, supporting welfare gains

Source: author's own.

In the context of this thesis, which examines the impact of AI and IoT technologies on the productivity of electricity generation, economic efficiency, investment performance, and demand elasticity in response to pricing changes, a multi-case study design is employed for several reasons. It permits systematic comparisons across different settings (e.g., various types of microgrids, geographies, smart grids, and dynamic pricing pilots), enabling them to identify contextual variations. These comparisons are crucial for testing whether AI and IoT integrations yield similar benefits across varying environments (Stake, 1995). Second, by triangulating data from multiple cases and including meta-studies at the end of each section, the robustness and validity of the findings are enhanced, thereby reducing the likelihood that the idiosyncrasies of any single case drive conclusions. This design uses multiple data sources, methods, or theoretical perspectives to study a phenomenon. This design provides a detailed account of each instance and supports the development and refinement of mid-range theories on the transformative role of AI and IoT in the electric energy sector. These theories offer more focused explanations of how specific aspects of AI and IoT technologies lead to outcomes within segments of the energy sector (Hedström & Udehn, 2011); (Kathleen M Eisenhardt, 1989). The concept of mid-range theories aligns with the research of Eisenhardt (1989b), which moves from cases to conceptual ideas, and Hedström & Udehn (2011), whose work focuses on mechanism-based explanations. Mechanism-based explanations focus on mechanisms that produce outcomes. In our case, they examine how and why AI and IoT have specific effects in the energy sector by revealing the causal steps and interactions within each process. The case studies address the three hypotheses outlined in the introduction: first, the integration of AI and IoT technologies into electricity generation in microgrids leads to a significant increase in operational efficiency, economics, and a measurable improvement in financial metrics compared to traditional, non-smart methods—primarily through data from real-time data monitoring, predictive maintenance, and other optimization techniques. Second, the widespread deployment of distributed renewable energy resources such as solar and wind electricity generation, enabled through AI and IoT-enhanced smart grid technology drives a structural shift from historically monopolistic base load dominated market structures toward more competitive and decentralized markets that necessitate new pricing mechanisms such as time of use pricing as proposed in the theoretical concepts analysis (chapter 2) to match better changing supply and demand ecosystems. The adoption of AI and IoT in microgrids and other distributed energy resources is positively associated with greater investment efficiency, as evidenced by lower capital risk, shorter payback periods, and improved financial returns. To test these hypotheses, this study employs an inductive, multiple-case study design, as outlined by Eisenhardt (1989). The selected cases serve distinct yet complementary roles: the Blue Lake Rancheria microgrid in California and Airtel Madagascar's cell tower microgrids provide data to assess economic operational efficiencies, supporting Hypothesis 1, and furthermore, these cases offer insights into investment performance by capturing data on capital and operational expenditures to calculate payback periods and returns on investment, thereby testing Hypothesis 3. The Olympic Peninsula Demonstration Project and the California Statewide Opt-in Time-of-Use Pricing Pilots shed light on market transformation through dynamic pricing, demand elasticity, and decentralization, addressing Hypothesis 2. This approach, grounded in systematic cross-case comparisons, interviews, archival records, and quantitative metrics, is well positioned to validate or refute the proposed hypotheses, thereby ensuring that the study's conclusions are broadly applicable. while the chosen multi-case study design supports the exploration of the economic impacts of AI and IoT technologies in energy production and distribution, several methodological limitations of the case study design are acknowledged. Given the limited number of selected cases—Blue Lake Rancheria Microgrid, Airtel Madagascar Microgrids, Olympic Peninsula Demonstration Project, and California Statewide TOU Pricing Pilots—the ability to generalize findings across diverse geographic locations, regulatory environments, and technological frameworks is challenging (Flyvbjerg, 2013). While the standard physics and methodology remain the same, the geography, weather patterns, economic and legal frameworks, and technology stacks of each location are unique and influence the overall economic outcome of each case. Despite the limitations of the approach, some general conclusions can be drawn from the selection of typical microgrid technical designs and economic calculations. Second, there is a risk of selection bias due to the purposive selection criteria, which emphasized case studies with documented successes and available quantitative data, potentially excluding cases with less favorable outcomes or incomplete documentation, thus skewing results toward positive evaluations of AI and IoT impacts (Eisenhardt, 1989).This has been avoided by selecting mid-range projects rather than the most publicized success stories. Third, the analyzed case studies usually rely heavily on archival and secondary quantitative data, which vary in quality, granularity, and measurement standards across cases, limiting robust statistical validation and meaningful comparisons (Elman et al., 2007).

Despite employing quantitative indicators such as TFP, IRR, LCOE, and dynamic demand elasticity, clearly establishing causality between the implementation of AI and IoT technologies and the magnitude of economic outcomes has some limitations due to the potential influence of confounding variables like broader economic, climate, geographic conditions, and different technology stacks (George & Bennett, 2004).The above limitations have been addressed by conducting a comparative analysis of multiple meta-studies on microgrids. This analysis follows the microgrid case studies and the TOU pricing case studies, concluding with a comparative assessment of various TOU-related meta-studies. Given the evolving nature of technological innovation and component pricing, the findings may have limited temporal relevance, underscoring the need for ongoing data collection and longitudinal analyses to ensure sustained validity (Yin & K. Yin, 2013). While acknowledging the methodological limitations, steps were taken to mitigate these issues and enhance the validity of the study's findings. Careful case selection was employed to ensure meaningful analytical generalization, aligning closely with the methodological principles articulated by Yin (2014) and Hollweck (2015), who emphasize the importance of choosing representative cases. In this context, the selected cases represent distinct AI and IoT application scenarios within the electric energy sector. The Blue Lake Rancheria Microgrid was purposefully chosen for its rich, verifiable operational data, sourced from tribal energy reports and California Energy Commission records (Carter, Saucedo, et al., 2019), which enabled the calculation of Total Factor Productivity (TFP) metrics. Airtel Madagascar's microgrids similarly provide extensive documented financial information from internal company equipment pricing and reports from (Braun, 2016) - to calculate Levelized Cost of Energy (LCOE), Internal Rate of Return (IRR), and Net Present Value (NPV)— allowing for precise economic analysis aligned with industry-standard financial evaluation frameworks (IEA, 2024; Ray & Douglas, 2021). The Olympic Peninsula Demonstration Project and the California statewide Time-of-Use (TOU) pricing pilots were specifically selected because they provide comprehensive and granular smart-meter data from advanced metering infrastructure (AMI), reflecting methodological best practices outlined in contemporary studies on dynamic pricing and demand elasticity (George & Bell, 2018). This robust dataset enabled measurement of shifts in consumption in response to dynamic pricing.

To mitigate potential selection bias, the chosen studies explicitly represent cases with scientifically documented outcomes, consistent with Eisenhardt (1989a), who recommends minimizing positive-outcome bias. Variability in data quality and measurement was mitigated by relying on rigorously updated archival and secondary data sources, cross-verified against independent reporting and official institutional documents, to ensure consistency, accuracy, and enhanced reliability (Angrist et al., 1999). Establishing causality is approached through careful comparative analysis across cases, explicitly selecting cases in which AI and IoT were demonstrably integral to the technical design and in which observed economic impacts could be isolated. This methodological alignment with structured, focused comparison frameworks, as advocated by George & Bennett (2004), helped isolate the hypothesized relationships from confounding external variables, such as varying fuel prices, technology compositions, or regulatory frameworks.

Innovation and rapidly declining costs of components like solar photovoltaic modules, computer chips, and battery storage will have an impact (Ritchie, 2024). However, this does not undermine the relevance and need for AI- and IoT-enabled digital optimization. Modern grids and microgrids cannot function effectively without smart technologies, as renewable energy sources cannot be economically integrated and technologically managed without them (Benbouzid et al., 2024). Automation is a prerequisite for managing smart grids and microgrids.

3.3 Case study selection

The research examines four case studies. Two case studies illustrate the application of economic frameworks to evaluate microgrids, particularly the efficiency of investments and the productivity gains achieved through the integration of smart technologies. Two case studies examine the impact of AI and IoT on smart grids, highlighting how they facilitate time-of-use pricing (TOU) and the economic consequences that follow. The goal is to examine how Artificial Intelligence (AI) and the Internet of Things (IoT) influence economic metrics in those two settings. Microgrids, through advanced controls and automation, can integrate diverse energy sources (such as solar, diesel, or gas generators and batteries) and thereby optimize energy flow and reduce waste. This capability improves input efficiency in the energy system, resulting in cost savings and productivity gains.

Case Study 1: Blue Lake Rancheria Microgrid (California)

The case study aims to address quantifying the economic benefits of microgrids. This case study examines whether AI and IoT contribute to productivity gains by enabling the optimization of microgrid operations. Improvements in energy production, enhanced decision-making processes, and reduced operational costs are examined to determine their impact on productivity metrics. The challenge lies in translating these cost savings into measurable economic benefits, particularly in the context of productivity improvements and incorporation into a theoretical economic framework. Productivity improvements are examined through the economic framework of Total Factor Productivity Analysis (TFP). Cost optimization involves reducing production costs without compromising output, which can be achieved through technological innovation, process improvements, and more effective resource allocation. Cost minimization implies that firms improve their productivity by reducing the amount of inputs required to produce a given output (Emerson, 2019). The focus is on how these technologies enhance the efficiency of energy production and distribution, improve decision-making processes, and reduce operational costs, thereby enabling demand response and supporting the theoretical framework of productivity improvements. This problem definition will guide the case study in assessing how microgrids, empowered by IoT and AI, deliver quantifiable economic benefits through cost savings and enhanced productivity, grounded in the principles of economic theories of production theory and how those benefits translate into additional benefits such as increased reliability, reduced Co2 emissions and electrification for off grid sites for economic development and resiliency – including saving lives during a significant power shut off.

Case Study 2: Airtel Madagascar Microgrids for Cell Phone Towers

The second case study analyzes Airtel Madagascar's deployment of intelligent, AI- and IoT-enabled microgrids to power a network of cell phone towers. This project provides insight into the examination of investment efficiency across several hundred geographically decentralized microgrids in remote, mostly off-grid locations. The economic framework examines the influence of automation (AI and IoT) on key metrics, including Levelized Cost of Energy (LCOE), Internal Rate of Return (IRR), and Net Present Value (NPV). AI and IoT can reduce downtime and extend asset life, enabling intelligent load management that boosts utilization efficiency and, in turn, reduces the cost per kilowatt-hour generated. The Internal Rate of Return (IRR) is a key financial metric defined as the discount rate at which the net present value of future cash inflows exactly equals the initial investment outlay, resulting in a net present value of zero. From a financial decision-making perspective, an investment is considered economically attractive if its IRR exceeds the investor's required rate of return or the cost of capital. This study examines how strategic investment in AI and IoT can contribute to a higher IRR. AI and IoT can thus improve investment returns by enhancing a project's cash flow and economic returns over its lifecycle. The study also examines how predictive maintenance and intelligent energy management, along with labor, machinery, and capital, can enhance Total Factor Productivity (TFP).

Case study 3: Smart Grid/ Time-of-Use Pricing Pilots/ Transactive Energy case studies

The Olympic Peninsula Demonstration Project—conducted by Pacific Northwest National Laboratory as part of the GridWise Smart Grid program focused on deploying transactive-based real-time/TOU pricing signals across residential, commercial, and municipal loads. These electricity consumer groups are encouraged to adjust their electricity usage patterns when provided with real-time price signals, and behavioral changes are observed. It is observed that pricing signals can influence the price elasticity of demand and whether industrial and private customers shift some of their electricity consumption in response to them, thereby better utilizing existing infrastructure. One goal of the project was to adjust price signals to encourage energy consumption when renewable energy output was high. This system aimed to better and more economically integrate renewable energy sources into the grid. The Olympic Peninsula Demonstration Project's findings underscore the transformative potential of integrating dynamic pricing mechanisms within smart grid frameworks. By aligning economic incentives with energy consumption behaviors, the grid can potentially become more resilient, efficient, and sustainable.

Case study 4: California Statewide Opt-in Time-of-Use Pricing Pilots and Time-of-Use Pricing Effects.

This case study investigates how time-of-use (TOU) pricing can influence consumer electricity consumption behavior, focusing on demand elasticity and the roles of artificial intelligence (AI) and the Internet of Things (IoT). The analysis highlights the economic and environmental outcomes of implementing dynamic pricing in utilities, covering millions of customers, examining changes in electricity usage patterns during designated peak and off-peak periods. Within this economic framework, it is observed whether dynamic pricing through TOU rates promotes shifting consumer demand away from times of peak demand, potentially decreasing the need for infrastructure upgrades and additional electric generation capacity. Smart meters, sensors, AI, and IoT-enabled devices are essential for enabling, capturing, and analyzing the economic impacts of TOU pricing. They collect real-time consumption data, helping utilities to analyze usage patterns and manage electricity loads more accurately. Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E) implemented large-scale statewide TOU pricing pilots to understand and quantify these behavioral shifts and their associated economic effects.

Table 16 provides an overview of the selected case studies in the thesis, organizing them by economic framework, research objective, data sources and methods, hypotheses addressed, and key analytical variables. It enables a structured comparison across cases to evaluate the role of AI and IoT in different energy system contexts.

TABLE 16 RESEARCH FRAMEWORK FOR CASE STUDY ANALYSIS

	Economic Theory Framework	Research Focus/ Objective	Data Sources/ Methods	Hypotheses Addressed	Key Variables/ Indicators
Blue Lake Rancheria Microgrid (California)	Total Factor Productivity (TFP) Analysis	Evaluate productivity gains and operating cost reductions from AI and IoT integration in a microgrid	Archival data, cost records, and interviews.	H1: Integration of AI/IoT leads to increased operational efficiency and cost reduction	TFP, Capital (K), Labor (L), ICT (I), Pre/post implementation cost savings
Airtel Madagascar Microgrids (Cell Tower Towers)	Investment Efficiency & Productivity Analysis	Assess cost-effectiveness and financial profitability improvements through AI and IoT integration in various cell tower microgrids.	Financial records, surveys, interviews, and data from companies and institutions	H1: Efficiency improvements; H3: Enhanced investment efficiency through improved financial metrics	LCOE, IRR, NPV, TFP
Olympic Peninsula Demonstration Project (PNNL)	Dynamic pricing analysis/ Price elasticity of demand	Dynamic pricing and demand impacts	Dynamic pricing trial data and archival data	H2: Structural market shifts and demand elasticity effects from TOU pricing	Dynamic pricing signals, energy conservation metrics
California Statewide Opt-in TOU Pricing Pilots	Dynamic pricing analysis/ Price elasticity of demand	Investigate the impact of Time-of-Use (TOU) pricing on consumer behavior, demand elasticity, and market decentralization	Smart meter data, Advanced Metering Infrastructure (AMI) records, consumer surveys, pricing experiments, archival data	H2: Structural market shifts and demand elasticity effects from TOU pricing	TOU rates, elasticity of demand, off-peak vs. peak consumption, cost savings

Source: author's own.

CHAPTER 4 CASE STUDIES ANALYSIS

4.1. Microgrid Case Study: Blue Lake Rancheria

Background

Blue Lake Rancheria microgrid is a community microgrid at Blue Lake Rancheria, a federally recognized tribal government and Native American community near Blue Lake in Humboldt County, California, approximately 300 miles north of San Francisco. The microgrid, situated at the intersection of three tectonic plates, is vulnerable to natural disasters, such as heavy rainstorms and forest fires, which frequently cause power outages. The microgrid supports the tribal government offices, an EV charging station, a convenience store, a hotel, a casino, and critical energy and water system infrastructure. It also supplies electricity to an American Red Cross evacuation center and a six-building campus, aiming to enhance the energy resiliency of the Blue Lake Rancheria Tribe in the surrounding area. The microgrid includes 420 kilowatts of solar photovoltaics and a 500 kW/950 kilowatt-hour battery energy storage system. (Carter et al., 2019). It is grid-connected to the Pacific Gas and Electric (PG&E) distribution grid at 12.5 kilovolts through a computer-controlled circuit breaker and is also designed to run autonomously when needed. (Blue Lake Rancheria Microgrid – Schatz Energy Research Center, 2019).

FIGURE 16 THE BLUE RANCHERIA MICROGRID PICTURE PROJECT OVERVIEW

Source: adapted from Blue Lake Rancheria Microgrid – Schatz Energy Research Center (2019).

The Blue Lake Rancheria project is an example of how microgrids reshape economic efficiency and cost structures. Microgrids, such as those at Blue Lake Rancheria, have emerged in the energy sector, particularly as demand for sustainable, resilient, and efficient energy systems continues to rise. The Blue Lake Rancheria project operates connected to the primary grid or as an independent islanded system, providing enhanced energy security and reliability for the tribe and its casino. The significance of this microgrid lies in its ability to optimize and integrate renewable and fossil fuel energy sources, which are crucial for achieving economic efficiency. One way the Blue Lake Rancheria microgrid contributes to cost savings is by reducing demand charges by switching to island mode when grid electricity costs are high. The local grid provider levies demand charges based on the highest electricity consumption rate over a billing period. The Blue Lake Rancheria microgrid mitigates these charges by utilizing energy storage systems and generating power on-site. This shift in energy production and use translates into cost savings for the tribe and its casino, enhancing the economic viability of the microgrid (Lund et al., 2012). It mitigates demand charges primarily through load management strategies enabled by the integration of the Internet of Things (IoT) and machine learning (ML). IoT equips the Blue Lake Rancheria microgrid with sensor technology and ML to monitor and optimize electricity generation across multiple devices and systems. Real-time monitoring and optimization enable effective responding to demand charges and pricing signals. Its IoT-enabled sensors and devices track energy usage patterns, predict peak demand periods, and automatically shift loads to avoid costly demand charges from the utility (Li et al., 2020). Load shifting occurs when non-essential loads are moved to off-peak hours, and demand response occurs when energy consumption is adjusted in response to grid signals or economic incentives. The Blue Lake Rancheria Microgrid supports the local grid operator in managing the fluctuating nature of renewable energy sources (RES) through advanced metering technologies. Microgrids help grid operators manage the intermittency of renewable energy sources and contribute to long-term generation planning reserves (P. et al., 2023). The Blue Lake Rancheria Microgrid demonstrates that microgrids reduce reliance on the main grid, resulting in lower overall energy costs. Energy storage systems within the microgrid enable the storage of excess renewable energy, which can be used during periods of high grid prices, thereby further reducing energy costs (Parhizi et al., 2015). The microgrid also contributes to cost efficiency by reducing ancillary charges, including service fees from electric utilities for grid infrastructure services, frequency regulation, voltage support, and spinning reserves, which ensure the stable operation of the main grid. By reducing electricity demand from the utility, Blue Lake Rancheria microgrid also contributes to the broader goal of achieving a more sustainable and resilient energy infrastructure (Marqusee et al., 2021).

The central research problem in this case study is the broader economic impacts of IoT and AI on electricity production. Analyzing this case should shed light on how ICT automation not only increases efficiency but also frees up economic resources for businesses and consumers, thereby reducing CO2 emissions and contributing to climate change mitigation. It should be recalled that, according to the hypotheses, AIoT (Artificial Intelligence of Things) is expected to enable microgrids to enhance efficiency and responsiveness by utilizing real-time data analysis and predictive analytics. This case study demonstrates that the integration enables the Blue Lake Rancheria Microgrid to manage demand forecasting more effectively, respond to dynamic pricing, and perform proactive maintenance, collectively improving operational efficiency and providing stabilizing effects for the grid (Alaba et al., 2024). Additionally, smart meters (IoT devices) at Blue Lake Rancheria provide the local utility, Pacific Gas and Electric (PG&E), with microgrid data, including energy usage and grid performance, which is crucial for managing supply and demand more effectively (S. Kumar et al., 2023). This case study also illustrates the adoption of Time-of-Use plans. By incentivizing off-peak usage, as in Blue Lake Rancheria's case, PG&E's ToU plans help balance demand, reduce costs, and promote environmental sustainability. This transition demonstrates the potential for economic principles to drive positive changes in electricity consumption and utility operations (PG&E, 2024).

Assessment

Using Siemens microgrid management software, Blue Lake Rancheria microgrid predicts the reservation's power load needs and dynamically manages its distributed electric power generation through integrated weather and load forecasting. The availability of power-usage data enables the reservation to maintain a stable and high-quality electricity supply for residential and commercial consumers. These insights support load management, reduce vulnerability to external grid disturbances, and ensure service continuity without unplanned outages or interruptions (Walton, 2015). The Microgrid Management System (MGMS) developed by Siemens was installed onsite to manage the Blue Lake Rancheria Microgrid (BLRMG). It was tested at the Idaho National Laboratory, a U.S. Department of Energy (DOE) national laboratory (INL), to ensure that its functionalities meet the required standards of INL and provide the BLRMG operators with training. The design and conformance of the MGMS's technical functionalities are crucial to achieving the overall project objectives outlined earlier (Mohanpurkar et al., 2017). The Siemens Microgrid Management System (MGMS) is an industrial Supervisory Control and Data Acquisition (SCADA) platform built on the Siemens Spectrum 7 software suite. This advanced system offers both operator-controlled and autonomous microgrid operations and is optimized for a forecasted planning horizon. Key features of the MGMS include protection mechanisms such as generation monitoring, interlocks, export and import limit controls, and photovoltaic curtailment. In terms of control, the MGMS enables optimal generation dispatch, frequency, and voltage regulation in island mode, load sharing when the Battery Energy Management System (BESS) is in parallel with Genset 1 (Gen1), as well as manual operator control, load shedding capabilities, and the development of event sequences. The IoT-enabled system records and analyzes current and historical data on weather, energy generation, loads, and actor states, creating near-term load and solar photovoltaic generation forecasting (Siemens Microgrid Brochure, 2021). This data enables the system's controller hardware to adjust, such as optimal generation dispatch, frequency, voltage regulation, and load sharing. AI machine learning algorithms analyze the data to optimize operations, predict potential issues, and forecast near-term loads and PV, improving the efficiency and resilience of the microgrid (Siemens AG, 2021). Controller-Hardware-In-the-Loop (CHIL) testing is a vital method for evaluating controllers in power and energy systems. In this approach, controllers interface with a Dynamic Real-Time Simulator (DRTS) through analog or digital signals, enabling performance assessment under realistic, simulated conditions. In this project, the Microgrid Management System (MGMS) and an SEL 700GT+ relay were integrated as controller-hardware-in-the-loop (CHIL) nodes on the DRTS platform. Comprehensive functional tests were executed on the MGMS, while a spectrum of operating scenarios was applied to the 700GT+ relay. In close collaboration with the SERC team, relay parameters were iteratively refined to achieve optimal protection performance and seamless coordination with the MGMS. (Mohanpurkar et al., 2017). The effort is centered on validating the MGMS under real-time conditions. Controller-hardware-in-the-loop (CHIL) testing is crucial for AI- and IoT-enabled power systems, as it safely recreates complex, rapidly changing grid conditions in a controlled laboratory environment. By exercising smart controllers and IoT devices under those conditions, engineers can verify performance, tune algorithms, and uncover hidden failure modes before any hardware is deployed.

Combining CHIL with tightly coordinated, command-driven device control substantially reduces the risk of new technology rollouts and paves the way for more resilient, efficient energy systems. In this intelligent architecture, each field device behaves as a “controlled actor,” acting only when instructed by a supervisory controller. An SEL-2505 Remote I/O module brokers all command and status signals among the SEL-700GT relay, ATC-900 controller, ATS-1 switch, and Gen-1 generator, ensuring that all components stay in sync. (SEL-2505 Remote I/O Module | Schweitzer Engineering Laboratories, 2024).

The California Energy Commission (CEC) report, entitled “Demonstrating a Secure, Reliable, Low-Carbon Community Microgrid at the Blue Lake Rancheria”, constitutes the primary data source for analyzing the financial and operational impacts of the microgrid. It quantifies cost reductions from demand, energy, and ancillary charges, providing critical insights into the economic and operational performance of the microgrid system. The reports from Blue Lake Rancheria Microgrid,(Carter, Chapman, et al., 2019;)(Blue Lake Rancheria Microgrid – Schatz Energy Research Center, 2024;) and (Mohanpurkar et al., 2017) serve as foundational resources for extracting detailed quantitative information about the microgrid, including project-specific data such as site load, microgrid monetary savings, CO2 reduction, and energy production data from solar, batteries, and gensets (EnergyMix, 2019). The Blue Lake Rancheria Microgrid comprises a 420 kW photovoltaic array and — following a 2019 upgrade — a battery energy storage system rated at 1,150 kW/1,950 kWh, along with a microgrid controller, protective relays, and a legacy 1 MW backup generator for full-site resilience. These resources enable energy storage for use during grid outages or periods of peak grid demand. A Microgrid Management System (MGMS) coordinates energy generation, storage, and distribution. The PCC protective relay guarantees safety and reliability during grid disconnections and reconnections. Resilience is enhanced by a 1 MW backup diesel generator, designed to provide power during prolonged grid outages. The project's initial total capital investment was $6,300,000, with $500,000 allocated explicitly to the energy management system, including sensors, software, and controllers. Economic benefits were evident, with electricity cost savings totalling $160,000 in 2017, representing a 25% reduction. Projected savings of $190,000 in 2018 were due to anticipated efficiency improvements. The system achieved an emissions reduction of 158 metric tons of CO2 equivalent (CO2e) in 2017, with an expected reduction of 170 metric tons of CO2 in 2018. The microgrid's resilience was demonstrated during a grid outage, when it successfully islanded, preventing a blackout and ensuring an uninterrupted energy supply, which ultimately saved four lives (EnergyMix, 2019).

The energy costs prior to the implementation of the microgrid were \$ 677,778. Given that the annual savings of \$61,000 represent 9 percent of the original energy expenditures (Carter et al., 2019, p.37), the initial energy costs can be calculated (see equation) as approximately \$677,778 per year. The savings achieved through a voltage rate switch, from secondary to primary voltage rates, account for these \$61,000 annually. Additionally, microgrid-related efficiency improvements contribute to an additional \$97,000 in annual savings, which vary with seasonal fluctuations in energy demand.

$$\text{Original Energy Costs} = \frac{\text{Savings}}{\text{Percentage Reduction}} = \frac{61{,}000}{0.09} \approx 677{,}778 \quad (17)$$

The project illustrates the efficiency through load reduction. Data for 2017 demonstrated notable improvements in energy efficiency and operational cost savings for the Microgrid. The annual energy consumption data reveal a significant reduction. The gross site load was recorded at 3,810 MWh before the microgrid's complete optimization, decreasing to a net site load of 3,240 MWh. This reduction is equivalent to 570 MWh, representing a 15% decrease in annual energy use. From an economic perspective, this 15% reduction results in direct cost savings from reduced procurement costs and lower operational expenditures. The reduction also alleviates strain on existing energy generation resources, thereby improving the overall efficiency of the energy system. Efficiently managing loads in the microgrid minimizes energy waste by cycling equipment based on real-time demand, thereby lowering costs, extending equipment life, and reducing CO_2 emissions. (Kumar Nunna & Doolla, 2013). Examining the average demand figures, the gross site load averaged 435 kW, which was reduced to 370 kW for the net site load, resulting in a microgrid saving of 65 kW, or a 15% decrease. The microgrid generates its own electricity with solar panels during the day and saves any excess power in a large battery. An intelligent control system then uses this stored battery energy to power the facility during peak hours, when grid electricity is most expensive. By strategically deploying its own solar and battery storage, the microgrid reduces the energy it purchases, thereby lowering its average demand on the utility grid.

Peak demand was reduced. The gross site load reached 754 kW. In comparison, the net site load peaked at 625 kW, resulting in microgrid savings of 129 kW, a 17% decrease. This was achieved by utilizing the battery storage system (500 kW/950 kWh) and Siemens MGMS to discharge stored energy during high-demand periods, thereby shaving peak loads and reducing demand charges from PG&E. The load factor, a key indicator of utilization efficiency, improved—the ratio of actual kWh delivered to the possible kWh that could be delivered over a specific period. The gross site load had a load factor of 0.58, which marginally increased to 0.59 for the net site load. A higher load factor implies that the energy infrastructure is utilized more efficiently, resulting in a lower average cost per unit of energy produced. This minimizes waste and maximizes value (Dakota Energy Association, 2025). The microgrid helped smooth energy consumption, making the average usage closer to peak usage. The collective impact of these changes highlights the economic benefits of smart microgrid deployment and energy management, encompassing direct cost reductions, improved resource management, and deferred capital investments**.** Table 17 summarizes key load characteristics at the Blue Lake Rancheria site in 2017, comparing gross and net values to quantify the energy savings and efficiency gains achieved through microgrid implementation.

TABLE 17: KEY LOAD CHARACTERISTICS OF BLUE LAKE RANCHERIA MICROGRID

Load Characteristic	2017 Gross Site Load	2017 Net Site Load	Microgrid Savings	% Due to Microgrid
Annual energy use (MWh)	3810	3240	570	15% decrease
Average demand (kW)	435	370	65	15% decrease
Peak demand (kW)	754	625	129	17% decrease
Load factor	0.58	0.59		1.72% increase

Source: *Blue Lake Rancheria Microgrid – Schatz Energy Research Center (2019).*

Microcontrollers execute real-time control of power hardware, ensuring efficient energy conversion and rapid system response. At the same time, IoT sensors collect detailed operational data on energy flows and equipment status throughout the microgrid. Local and cloud IT systems then process this extensive sensor data with the aid of artificial intelligence and advanced control algorithms to facilitate accurate load and generation forecasting, optimized dispatch of electric energy-producing sources, and adaptive adjustments to system operations. This data-driven, intelligent control reduces energy use by minimizing operational losses and waste, lowering average demand through optimized load scheduling and equipment management, and curtailing peak demand using predictive algorithms and timely energy storage deployment. This results in a notable decrease in both total energy consumption and operational costs (Aldin et al., 2024; Mariyaraj & Thankappan, 2024). IT systems provide the necessary infrastructure for data collection, processing, and communication, while AI algorithms optimize load management and energy distribution, preventing demand spikes and improving load balancing (Barja-Martinez et al., 2021). AI and IoT work together to enhance the microgrid's productive efficiency by reducing energy waste, lowering the average cost of energy production, and deferring the need for costly infrastructure investments (Hirsch et al., 2018). As a result, the microgrid operates more economically and sustainably, contributing to overall system reliability and energy security. While the macroeconomic TFP framework discussed in Chapter 2 often uses GDP or industry-level value-added as output, the TFP analysis can also be applied at a more granular project level. In such cases, the definition of "output" must be tailored to the project's specific objectives. In this case study, the output (Y) for the Total Factor Productivity (TFP) analysis is defined as the tangible economic value created by the implemented system, specifically the $160,000 in verified annual cost savings in 2017 and $190,000 in 2019 due to the microgrid. This is grounded in the economic principle that efficiency gains, manifested as cost reductions, represent real resources freed for alternative productive uses, thereby enhancing overall economic welfare. Such an approach aligns with the economic thought, which emphasizes that optimal resource allocation—a cornerstone of economic efficiency is achieved when resources are directed to their most valuable applications, a process directly evidenced by the realization of these savings (Fowlie & Meeks, 2021). For the Blue Lake Rancheria the data from (Carter, Saucedo, et al., 2019) is as follows: The project involves a capital investment of $6,300,000; an ICT investment of $500,000; projected annual savings from energy management, which constitute the output, of $160,000 in savings in 2017 and $190,000 in 2018; and annual labor costs for system upkeep estimated at $200,000 per year. The adjusted Cobb-Douglas Production Function is therefore:

$$Y = A \times K^{\alpha} \times L^{\beta} \times I^{\gamma} \quad (18)$$

For the analyzed project, the inputs are as follows: the adjusted total capital for hardware equipment is $4,300,000 (derived from an initial total capital of $5,800,000 minus $1,500,000 attributed to initial labor costs), resulting in an annualized capital input (K) of $215,000; the total ICT investment is $500,000 over 20 years, yielding an annualized ICT input (I) of $25,000; and the total annual labor input (L) is $125,000, which includes $50,000 per year for ongoing maintenance plus the annualized portion of a \$1,500,000 initial labor cost (\$75,000 per year). The output elasticities used are $\alpha = 0.5$ for capital, $\beta = 0.3$ for labor, and $\gamma = 0.2$ for ICT.

Final TFP calculation is therefore as follows:

$$A = \frac{Y}{K^{\alpha} \times L^{\beta} \times I^{\gamma}} \quad (19)$$

$$A = \frac{160{,}000}{215{,}000^{0.5} \times 125{,}000^{0.3} \times 25{,}000^{0.2}} \approx 1.37 \quad (20)$$

For the year 2018, the savings were 190,0000, and the calculation is as follows

$$A = \frac{190{,}000}{215{,}000^{0.5} \times 125{,}000^{0.3} \times 25{,}000^{0.2}} \approx 1.60 \quad (21)$$

Conclusions

With the output defined as \$160,000 in 2017 annual cost savings, a TFP of 1.37 is a positive indicator. It suggests that the project or system is efficiently converting its capital, labor, and ICT investments into valuable cost reductions, generating \$1.37 in savings for every \$1 of input cost. With the output defined as \$190,000 in 2018 annual cost savings, a TFP of 1.60 is a positive indicator, suggesting that the project or system is efficiently converting its capital, labor, and ICT investments into valuable cost reductions, generating \$1.60 in savings for every \$1 of input cost. This confirms hypothesis 1.

4.2 Airtel Madagascar Cell Phone Tower Microgrids

Background

Airtel is a leading GSM mobile operator in Madagascar, with over 2.5 million mobile phone users and a market share of more than 40%. Airtel Madagascar faced challenges with difficult site accessibility, high diesel operational expenses (OPEX), and high diesel delivery costs due to the limited reach of grid power infrastructure before investing in microgrids. This case study examines the impact of microgrid investment on economic efficiency. The telecommunications and information sectors face significant challenges due to rapid network expansion, increasing energy consumption, and environmental impacts. Globally, millions of cellular towers offer substantial opportunities for enhancing energy efficiency through advanced software and hardware solutions, optimizing energy provisioning, and reducing operational costs (Valverde, 2020). Mobile Network Operators (MNOs) and Tower Companies (Towercos) incur substantial expenses to power their towers in the telecom market. Many of these towers are located in areas with limited or no access to grid power, leading to reliance on inefficient diesel generators. The cost of diesel fuel and generator maintenance can constitute up to 60% of operating expenses in such cases (H. Zhang et al., 2010a). To reduce operational expenses, MNOs and Towercos deploy technologies to improve energy use management and supply chain operations. The adoption of information and communication technologies (ICT) enables more efficient energy production and lowers transaction and coordination costs. Digitalized systems also improve asset utilization and extend equipment lifespans by optimizing operations and enabling predictive maintenance (Eltamaly et al., 2021). Towercos and MNOs are increasingly adopting hybrid energy solutions combining renewable energy generation, energy storage, and an Energy Management System (EMS) to reduce costs. This is crucial to the smooth, efficient operation of Base Transmitter Stations (BTS) and to keeping operational and fuel costs down. Systems range from simple diesel generator and battery setups to more complex hybrid systems incorporating renewable energy sources. An ICT-enabled energy manager is a key component of these hybrid energy solutions, responsible for monitoring and managing energy-generating solutions of varying complexity. In many cases, the energy manager is an open-platform controller equipped with sensors and adaptable software, ensuring efficient operation. Implementing the smart technology solution will offer numerous advantages, including reduced energy consumption, lower fuel costs, and a smaller environmental footprint (Zhang et al., 2010b). Optimizing the performance of gensets, batteries, and inverters in energy systems involves several key strategies to enhance efficiency, reduce operational expenses, and increase system longevity. An unreliable power supply can be a significant challenge for cell phone towers, which require a stable, consistent power supply to operate. Cell phone towers use electrical power to operate equipment, such as radio transmitters, base stations, and other electronic components, essential to providing cellular service to their customers. Suppose the power supply at cell phone tower sites is unreliable, the cell phone operator may experience service disruptions, causing significant inconvenience to customers and impacting emergency services and public safety. To mitigate this risk, many cell phone tower operators use backup power systems, including batteries, diesel generators, and solar power. When off grid, they rely entirely on these energy sources. The backup systems can provide power to the tower during grid power outages, ensuring the tower remains operational and minimizing service disruptions. The quantitative analysis will focus on reduced energy costs, energy savings, and CO2 reductions resulting from the implementation of an energy management system. The Energy Management System (EMS) and Energy Manager (EM) form the basis of the solution. The site's whole energy infrastructure is under the authority of the Energy Manager, who runs control algorithms. The energy manager monitors the battery charge level and starts the generator when the charge level is low. Additionally, the performance of the solar array and the charge controllers is continuously monitored. In addition to the on-site remote management system already in place, the energy manager provides a data interface.

EMS is an IoT- and AI-enabled system that optimizes energy use based on real-time data and predictive analytics. The system enables the efficient integration of diverse energy sources, including solar, diesel, and battery storage, to ensure a reliable, sustainable power supply for off-grid sites. By utilizing real-time data on power demand, weather conditions, and energy availability, the EMS can automatically switch between energy sources to minimize fuel consumption and reduce carbon emissions. The use of AI algorithms also enables predictive maintenance, reducing downtime and maintenance costs. The cost savings with the EMS Automated Hybrid option result from implementing an Energy Management System (EMS) that optimizes the use of both solar and diesel power sources. The EMS system enables automatic switching between solar and diesel power. This results in reduced diesel consumption, lower diesel OPEX, and fewer carbon emissions.

Assessment

A comprehensive green power feasibility analysis was conducted using GSMA's Green Power for Mobile methodology, which involved detailed data collection. The study identified 258 off-grid sites for Green Power feasibility analysis, and generic recommendations have been proposed for energy efficiency and OPEX reduction. The 258 off-grid sites in the network relying on a diesel generator as the primary power source are implemented with DG-battery hybrid power systems. The average daily run of diesel generators is ~10 hours.

After a thorough analysis of the network data, GPM has concluded that the on-grid sites may not be suitable for a Green Power design, as grid power availability is, on average, more than 17 hours per day. It was decided to implement an EMS Energy Management System (EMS) enhanced by IoT and AI capabilities across the 258 off-grid sites. (GSMA: Green Power for Mobile, 2013). Table 18 categorizes telecom site types by load size, quantity, and model examples, distinguishing between indoor and outdoor installations.

TABLE 18 TELECOM INVESTMENT SITE TYPES

Load	Total Sites	Example Models	Description (Indoor/Outdoor)
550 W	123	OD1_S, OD1_SW_I, _II	Outdoor, low-load, basic connectivity
900 W	58	OD2_S, OD2_SW_I, _II	Outdoor, medium load, more equipment
1.2 kW	13	IN1_S, IN1_SW	Indoor, moderate-load, controlled env.
1.4 kW	8	OD3_S	Outdoor, high-load, specialized setup
1.8 kW	14	IN2_S, IN2_SW	Indoor, high load, more capacity/features

Source: (*GSMA: Green Power for Mobile*, 2013)

Table 18 presents the telecom infrastructure, comprising various site types with distinct operational characteristics. These include 550 W outdoor, low-load sites (OD1 models) for basic connectivity; 900 W outdoor, medium-load sites (OD2 models) balancing weather resistance with moderate equipment; 1.2 kW indoor, moderate-load sites (IN1 models) for controlled environments; 1.4 kW outdoor, high-load sites (OD3 models) for specialized, capacity-intensive outdoor setups; and 1.8 kW indoor, high-load sites (IN2 models) designed for maximum equipment capacity and features in controlled settings.

The subsequent financial and productivity analysis, including the levelized cost of energy, total factor productivity, and the internal rate of return, focuses exclusively on the 550-watt sites because complete data is available for both the pre-implementation and post-implementation periods. This enables a more precise isolation of the impact of the energy management system on performance outcomes. Analyzing the energy system's performance before and after the implementation of the artificial intelligence- and Internet of Things–driven energy management system provides the data needed to calculate total factor productivity (TFP), the levelized cost of energy (LCOE), and the internal rate of return (IRR). The metrics allow for an assessment of the economic and financial impact of the technologies used. Pre- and post-EMS calculations quantify the impact of AI and IoT on overall systemic efficiency. LCOE comparisons before and after show the degree to which these technologies increase lifecycle cost-effectiveness per unit of energy generated. Optimized operations and more efficient maintenance routines, achieved with AI, curtail long-term expenditures and extend the lifetime of the equipment. Internal rate of Investment (IRR) calculations for the EMS investment evaluate the financial viability and specific return generated by the AI and IoT integration. This is done by weighing the initial capital outlay against the subsequent net economic benefits, such as sustained operational cost savings or enhanced productivity, relative to the pre-EMS baseline.

Table 19 explains key performance metrics—TFP, LCOE, and IRR—used to evaluate the economic and operational impact of EMS, AI, and IoT, highlighting their roles in measuring efficiency gains, cost-effectiveness, and investment returns.

TABLE 19 PERFORMANCE METRICS

Metric	Logic for Use
TFP	Quantifies improvements in systemic efficiency by measuring how effectively capital, labor, and fuel are converted into energy output, highlighting the operational optimizations enabled by EMS, AI, and IoT.
LCOE	Demonstrates lifecycle cost-effectiveness by comparing the cost per unit of energy produced before and after EMS implementation, reflecting the impact of EMS (AI and IoT) on operational and maintenance savings over time.
IRR	Assesses the financial viability and return on investment in EMS by comparing the initial capital outlay with the resulting net economic benefits, such as cost savings and productivity gains, relative to the pre-EMS baseline.

Source: author's own.

This multi-metric approach provides a robust, empirical basis for quantifying the economic contributions and performance improvements attributable to AI and IoT within the energy systems of the case studies.

Table 20 compares the performance of a 550 W telecom site under two configurations: "As Is Manual Hybrid" and "With EMS Automated." In both cases, the constant site load remains 550 watts. With the manual hybrid system, the site draws 190 kWh from the grid annually, consumes 4,523 liters of fuel annually, and operates the generator for 4,380 hours annually. When EMS automation is implemented, grid energy demand drops to zero (a 100% reduction), generator fuel consumption decreases to 2,346 liters per year (a reduction of approximately 48%), and generator runtime is reduced to 1,203 hours per year (a reduction of approximately 73%).

TABLE 20 CONFIGURATION, GENSET RUN TIME, AND FUEL SAVINGS BEFORE AND AFTER EMS

Configuration / Simulation Results	As Is Manual Hybrid	With EMS Automated
Load: Constant site load DC (W)	550	550
Grid energy AC demand per year (kWh/y)	190	0
Genset total fuel consumption incl. equalization per year (l/y)	4,523	2,346
Genset total runtime incl. equalization per year (h/y)	4,380	1,203

Source: Braun (2016).

Table 21 lists the main cost components for installing the EMS system at a telecom site, along with their associated costs. The table shows that the Energy Manager hardware costs $1,589, and the Energy Manager application license is $690. Sensors for monitoring the environment, load, and batteries cost $770. Power distribution and conversion equipment cost $93, and cooling equipment costs $61. The total cost for all these items is $3,203.

TABLE 21: COST OF ENERGY MANAGEMENT SYSTEM COMPONENTS PER CELL TOWER

Item	**USD**
Energy Manager Hardware	1,589
Energy Manager Application License	690
Sensors (environment, load, batteries)	770
Power distribution and conversion	93
Cooling	61
Total	**3,203**

Source: *Braun (2016).*

Figure 17 illustrates the Energy Management System (EMS) that intelligently manages power inputs from solar panels, diesel generators, and batteries to efficiently power a telecommunications site.

The diagram shows the energy management system implemented at each telecommunications base transceiver station (BTS) site. The inputs include data from fuel tanks, photovoltaic (PV) panels, wind turbines, conventional generators, and battery storage systems. The EMS manages infrastructure and operational support elements, including cooling systems, security, service components, sensors, and other site-specific equipment. The Heliocentris EMS orchestrates these inputs, optimizes energy production and consumption, and ensures a continuous, reliable electricity supply. The electricity, symbolized by the electron icon (“e^-”), is then delivered to the BTS site, where it powers telecommunications operations.

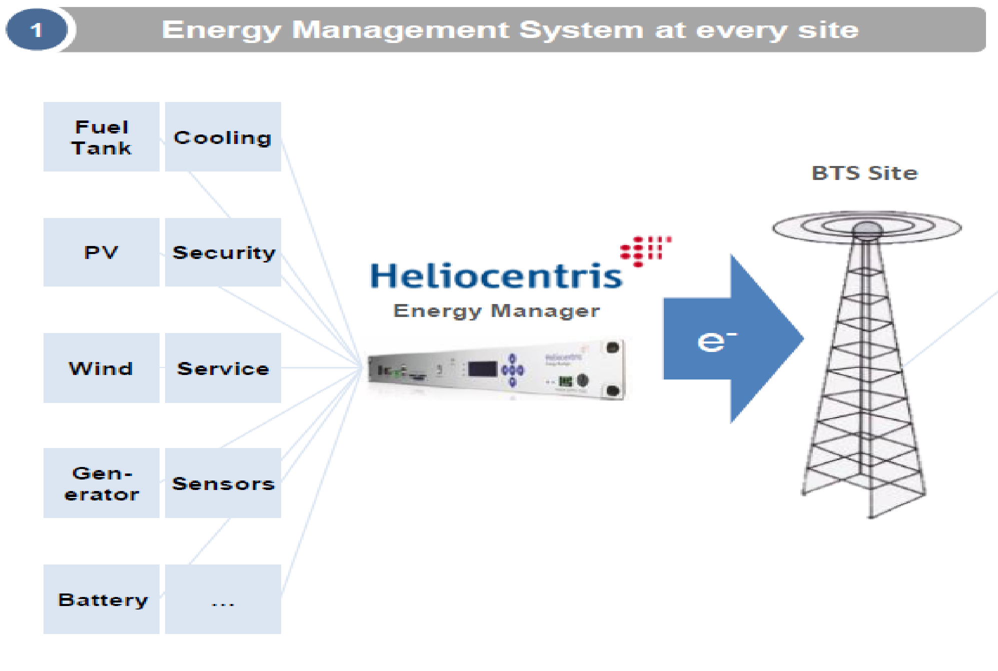


FIGURE 17 ENERGY MANAGEMENT SYSTEM WITH VARIOUS COMPONENTS

Source: adapted from Heliocentris (2016).

Figure 18 illustrates data from a 550W telecom site, showing improvements before and after implementing an Energy Management System (EMS), resulting in operational enhancements.

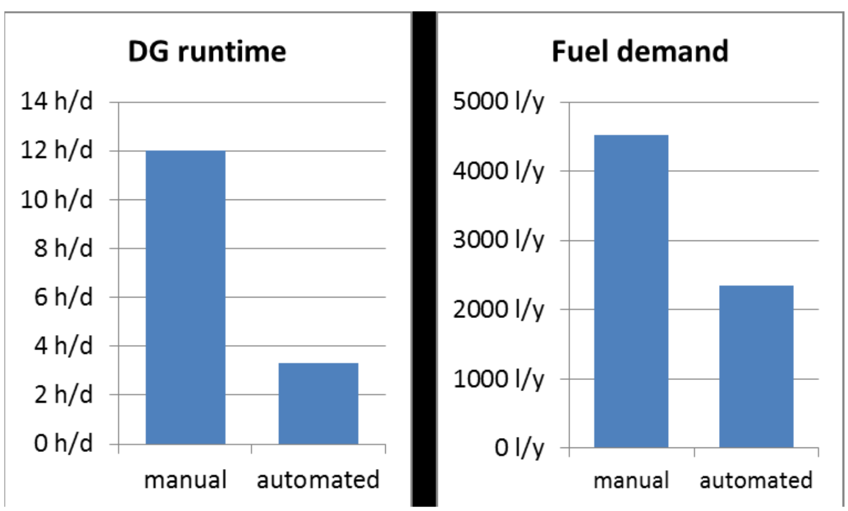


FIGURE 18 RUN TIME REDUCTION AND FUEL REDUCTION DUE TO EMS

Source: Adapted from Heliocentris (2016).

The diesel generator (DG) runtime is reduced from approximately 12 hours per day in manual operation mode to about 3.3 hours per day in automated mode, utilizing the EMS. Annual fuel demand declines from 4523 liters at manually managed sites to approximately 2346 liters at automated sites (Heliocentris, 2016). The process begins with system inputs, including energy sources and supporting infrastructure, specifically a diesel generator, necessary cooling, and services. The site is designed to operate at a constant load of 550 watts, representing a typical low-load telecom application. Next, an Energy Management System (EMS) is introduced. In this case, the EMS is the Heliocentris system, which utilizes AI and IoT-based automation. The EMS is responsible for optimizing the use and management of energy at the site. As the EMS is implemented, operational outcomes change. Compared to the baseline scenario without EMS, the diesel generator's daily runtime is reduced from 12 hours to about 3.3 hours. Annual fuel consumption drops from 4,500 liters to 2,350 liters. Operational efficiency improves due to better scheduling and control of energy sources, and operating expenditures (OPEX) decrease due to reduced fuel use and fewer generator operating hours. Operational improvements translate into enhanced financial metrics. The logic flows from the initial system setup, through the introduction of advanced energy management, to measurable operational and financial benefits.

The impact of deploying a Heliocentris EMS at 550W low-load telecom sites, including generator runtime, fuel consumption, operational efficiency, expenditures, and financial performance metrics compared to baseline conditions, is provided in Figure 19.

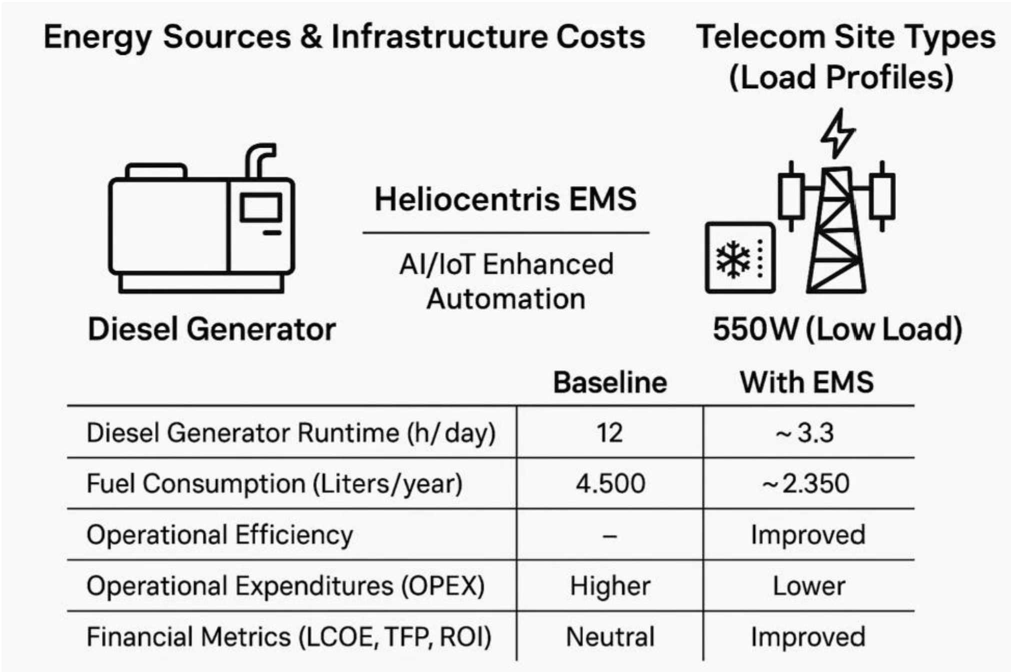


FIGURE 19 EFFECTS OF EMS APPLICATION

Source: adapted from Heliocentris (2016).

In 2013, the grid-connected electricity cost in Madagascar was estimated at between $0.20 and $0.26 per kWh, and in rural areas, at between $0.50 and $0.70 per kWh. This high cost is attributed to the reliance on diesel and heavy fuel oil for electricity generation, which made energy prices in the country more expensive compared to other regions. Additionally, the energy infrastructure faced challenges with inefficiencies and limited reach, leading to elevated costs, especially outside major urban areas (Climatescope 2023 | Madagascar, 2023).

The cost structure of the EMS-type investment is presented in Table 20.

TABLE 20 COST STRUCTURE WITHOUT EMS FOR 550 W SITES OVER 5 YEARS AS A MANUAL HYBRID

	Year 0	*Year 1*	*Year 2*	*Year 3*	*Year 4*	*Year 5*
As is Manual Hybrid						
Cost of solutions						
Genset fuel consumption		5,880	5,880	5,880	5,880	5,880
Fuel delivery		548	548	548	548	548
O&M (QTE)		164	164	164	164	164

Genset:						
- Useful life	2.5					
- Cost	7,726					
- Replacement exp.		3,090	3,090	3,090	3,090	3,090
Battery:						
- Useful life	8.4					
- Cost	8,903					
- Replacement exp.		1,060	1,060	1,060	1,060	1,060
Total costs		10,742	10,742	10,742	10,742	10,742
Cash outflow (undiscounted)	53,711					

Source: (A. Chen 2016).

Table 20 presents the costs for a 550 W telecom site operating with a manual hybrid system, excluding EMS, over a period exceeding five years. The annual fuel consumption is 5,880 liters, and costs are incurred for fuel delivery, operation, and maintenance. The generator is replaced every 2.5 years, and the battery every 8.4 years. The annual cost is $10,742, and the total five-year cash outflow is $53,711.

Table 21 presents the same site after an EMS automated hybrid system is installed. This system requires an initial investment of $3,203. With EMS, fuel consumption is reduced to 3,050 liters per year. Yearly costs for fuel delivery and maintenance are also reduced. The generator's useful life improves to 9.1 years, and the battery's useful life changes to 4.9 years. The annual cost after the initial investment is $6,045, and the five-year cash outflow is $33,538.Table 5 represents the cost structure for 550 W sites over 5 years as a manual hybrid with integrated EMS.

TABLE 21 COST STRUCTURE WITH EMS FOR 550 W SITES OVER 5 YEARS AS MANUAL HYBRID

	Year 0	*Year 1*	*Year 2*	*Year 3*	*Year 4*	*Year 5*
With EMS Automated Hybrid						
Cost of EMS solutions	3,203					
Genset fuel consumption		3,050	3,050	3,050	3,050	3,050
Fuel delivery		284	284	284	284	284
O&M (QTE)		45	45	45	45	45
Freight & insurance per container	10					
Freight & insurance from port to sites	100					

Genset:						
- Useful life	9.1					
- Cost	7,726					
- Replacement exp.		849	849	849	849	849
Battery:						
- Useful life	4.9					
- Cost	8,903					
- Replacement exp.		1,817	1,817	1,817	1,817	1,817
Total costs	3,313	6,045	6,045	6,045	6,045	6,045
Cash outflow (undiscounted)	33,538					

Source:(Chen & Kunerth, 2016).

Overall, installing the EMS system reduces fuel use, maintenance, and replacement costs. The annual and total five-year costs are both lower than with the manual hybrid system. The EMS delivers operational improvements that yield long-term cost savings. For the financial evaluation of Airtel's off-grid systems, incorporating these electricity rates helps estimate the potential savings or revenue that would be realized if these sites were grid-connected.

To provide a thorough financial and productivity analysis, the Levelized Cost of Energy (LCOE), Return on Investment (ROI), Total Factor Productivity (TFP), and Internal Rate of Return (IRR) can be calculated.

In particular, LCOE enables comparison of the cost efficiency of each power solution by measuring the cost per unit of energy generated. This is particularly useful for understanding which system produces energy at the lowest cost, making it ideal for evaluating the long-term operational affordability of hybrid power systems (Matsuo, 2022). LCOE is particularly relevant when evaluating renewable energy. It enables direct comparison across different technologies by capturing all relevant costs throughout the system's operational lifespan. This is why LCOE is widely used in both academic and industry studies to assess the cost-effectiveness of energy solutions (KOST et al., 2021). For the analyzed case, the calculation is based on the given cost components and annual energy output of 4,752 kWh. Before the implementation of EMS, IoT, and ML, the components of the total annual cost include genset fuel consumption at $5,880, fuel delivery at $548, operations and maintenance (O&M) at $164, genset replacement expense at

$3,090, and battery replacement expense at $1,060. Total Annual Costs, based on the above data, amount to $ 10,742. Therefore:

$$\text{LCOE} = \frac{10{,}742}{4{,}752} \approx 2.26\text{USD per kWh} \quad (22)$$

The Levelized Cost of Energy (LCOE) for the manual hybrid system is approximately $2.26 per kWh, significantly higher than the typical range of $0.25 to $0.50 per kWh for optimized diesel gensets. This is mainly due to the high fuel, maintenance, and replacement costs associated with non-optimized diesel generator setups. This value could now be compared to the post-EMS system investment. Assuming the initial investment of $3,203 and an average lifetime of the EMS of 7 years, the annualized Cost of AI and IoT Automation Investment is calculated as:

$$\frac{\text{Initial Investment}}{\text{Average Useful Life}} = \frac{3,203}{7} \approx 457.57 \text{ USD per year} \quad (23)$$

With EMS, the total annual costs include genset fuel consumption at $3,050, fuel delivery at $284, operations and maintenance at $45, freight and insurance per container at $10, freight and insurance from port to sites at $100, genset replacement expense at $849, battery replacement expense at $1,817, and annualized AI and IoT automation investment at $457.57. The total annual costs amount to $6,612.57. This, in turn, enables the calculation of the Levelized Cost of Energy. The numbers for the analyzed project are:

$$\text{LCOE} = \frac{6{,}612.57}{4{,}752} = 1.39\text{USD per kWh} \quad (24)$$

The reduction in the Levelized Cost of Energy (LCOE) from $2.26 per kWh to $1.39 per kWh highlights the significant cost reduction in electricity production per kWh achieved through the integration of EMS enhanced by ML and IoT in energy systems. The reduction is driven by optimizing fuel and resource management, enabling predictive maintenance, and enhancing operational efficiency. IoT and ML-enabled predictive maintenance minimizes downtime and repair costs by aligning maintenance schedules with real-time data, as predicted by theory (Khakurel et al., 2018). AI algorithms also enhance resource allocation by enabling intelligent switching between energy sources based on demand and cost efficiency (Zhao et al., 2019). AI-enabled diesel generators can achieve cost reductions by improving operational responsiveness and resource allocation, as evidenced in a study by Kiray et al. (2021). These combined improvements result in an almost 40% reduction in LCOE in the case study, underscoring the financial and operational value of AI and IoT in developing sustainable, cost-effective energy solutions.

A similar assessment could be performed using Total Factor Productivity (TFP). High TFP values suggest that a system utilizes its inputs effectively to produce more output per dollar spent. This is valuable for comparing systems' overall operational efficiency and is essential for determining which system maximizes energy production relative to its costs (Z. Zhang & Ma, 2023).

The implementation of AI and IoT increases TFP by ensuring that resources are used more effectively. The technology reduces waste, lowers operational costs, and increases energy output, thereby raising the amount of energy generated per dollar spent. This improvement in TFP reflects a more productive and resource-efficient system, aligning with enhanced economic sustainability (Haider et al., 2021). Calculations for TFP at 550W sites before the implementation of EMS could be used as the starting point. The annual genset fuel consumption is 5,880 units each year over the analysis period. Fuel delivery costs amount to $548 per year, while operations and maintenance (O&M) expenses total $164 annually. The genset has a useful life of 2.5 years and an initial cost of $7,726. Its replacement expense is $3,090 per year. For the battery, the useful life is 8.4 years, with an initial cost of $8,903 and an annual replacement expense of $1,060. Since we do not have the proper elasticities of labor and capital available, as we do not know the number of hours of labor allocated at a given time for construction and maintenance, we exclude those elasticities. Summing up all these costs, the total annual cost amounts to $10,742 per year for each of the years analyzed. Based on this, TFP could be estimated as follows:

$$\mathrm{TFP} = \frac{\text{Annual Output}}{\text{Total Annual Input Cost}} = \frac{4{,}818\mathrm{kWh}}{\$10{,}742} \approx 0.4485\mathrm{kWh}/\$ \quad (25)$$

Calculations for 550W sites after the implementation of EMS could be performed for comparison. The annual output is 4,818 kWh, with a total annual input cost of $6,045, which includes genset fuel consumption ($3,050), fuel delivery ($284), operations and maintenance ($45), annualized genset replacement expense ($849), and annualized battery replacement expense ($1,817). Initial one-time setup costs are excluded, as the $6,045 figure represents recurring operating costs for typical years. This produces:

$$\text{TFP} = \frac{4,818\ \text{kWh}}{\$6,045} \approx 0.7970\ \text{kWh/\$} \quad (26)$$

The implementation of the Energy Management System (EMS) has led to substantial improvements in both operational efficiency and cost-effectiveness at the 550W sites. Total Factor Productivity (TFP) increased significantly from approximately 0.4485 kWh per dollar of input cost to 0.7970 kWh per dollar, representing a 77.70% improvement and indicating that the system is now considerably more effective at converting inputs into energy output. Significant cost reductions accompany this: the total annual input cost to generate the same output of 4,818 kWh has decreased from $10,742 to $6,045, representing a reduction of approximately 43.73% in recurring operational expenses. The enhanced performance is due to Machine Learning (ML) optimizing fuel and power through predictive analytics and intelligent decision-making, and to the Internet of Things (IoT), which includes sensors that capture fuel levels and runtime and transmit collected data to cloud infrastructure where machine learning takes place. This ecosystem enables real-time, data-driven monitoring and adjustments that reduce runtime and enable proactive maintenance.

The last step in the investment efficiency assessment could be based on the Incremental Internal Rate of Return (IRR)((Fiduciary Organization - Incremental IRR, 2025)); (M. Liu, 2024). The incremental nature of IRR, which accounts for the excess required rate of return (or cost of capital), is beneficial for justifying upgrades, add-ons, or new technologies (e.g., investing in an AI/IoT-driven EMS versus maintaining the old system).

The incremental cash flows are determined by subtracting the cash flows of the "before EMS" scenario from those of the "after EMS" scenario. For the "before EMS" (Manual Hybrid) case, the initial investment in Year 0 is -$16,629, and the annual operating costs for Years 1 through 5 are -$10,742 per year. For the "after EMS" (EMS Automated Hybrid) case, the initial investment in Year 0 is -$19,942, and the annual operating costs for Years 1 through 5 are -$6,045 per year. The incremental initial investment in Year 0 is (-$19,942) minus (-$16,629), which equals -$3,313, representing the additional upfront cost to implement the EMS. The incremental annual cash flow for Years 1 through 5 is ($6,045) minus ($10,742), resulting in a net benefit of $4,697 per year, which reflects the annual cost savings from adopting the EMS. Therefore, the incremental cash flow stream for the AI/IoT-enabled EMS is as follows: Year 0, -\$3,313; Years 1-5, +\$4,697 each year. This leads to the estimate of IRR:

$$0 = -3313 + \frac{4697}{(1+r)^1} + \frac{4697}{(1+r)^2} + \frac{4697}{(1+r)^3} + \frac{4697}{(1+r)^4} + \frac{4697}{(1+r)^5} \quad (27)$$

which in turn produces r = 1.40 meaning IRR is 140%.

Conclusions

The implementation of AI and IoT-enabled Energy Management Systems (EMS) in Airtel Madagascar’s off-grid telecom sites shows an improvement in both economic efficiency and financial performance. Predictive analytics, intelligent automation, and real-time monitoring optimized diesel generators into optimized hybrid energy units, yielding measurable productivity gains. Results show significant reductions in operational expenses, stemming from reduced fuel consumption and fuel delivery costs, resulting from less generator runtime, which led to a 48% decrease in fuel and a 73% decrease in generator operating hours. As a result, the Levelized Cost of Energy declines from \$2.26/kWh to \$1.39/kWh, while Total Factor Productivity rises by nearly 78%, underscoring the automated hybrid system's increased efficiency. The incremental Internal Rate of Return (IRR) of 140% provides financial evidence to support the adoption of AI/IoT-driven EMS technologies. This IRR of 140%, derived directly from the positive net cash flows after accounting for its incremental costs, quantifies the scale of these net economic benefits. Beyond cost savings, the system enhances sustainability. The Airtel Madagascar case confirms Hypothesis 1—that the integration of AI and IoT improves operational efficiency and reduces costs.

4.3 California state-wide time of use pricing (TOU) enabled by AI and IoT

Background

In 2016, California's three largest investor-owned utilities—Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E)—conducted large-scale time-of-use (TOU) pricing pilots, with over 50,000 customers participating. These pilots tested eight TOU rate structures, with participants randomly assigned to different rate options or kept on their existing plans as controls. The primary goal was to examine how dynamic pricing affects customer electricity consumption behavior and whether shifting usage from peak to off-peak periods can optimize grid efficiency. Due to legal restrictions that prevented customers from being automatically switched to time-of-use (TOU) rates before January 2018, participation in these early pilots was voluntary and opt-in. A second set of pilots, involving default enrollment, began in early 2018 and is still ongoing. The first results from these pilots were available in early 2019 (S. S. George & Bell, 2018). This case study contributes insights into the elasticity of demand for electricity under various dynamic pricing conditions. Consumers demonstrated varying levels of responsiveness to price signals, with those using smart technologies such as automated thermostats and smart meters exhibiting the highest elasticity. Lowering peak demand reduces strain on the grid and reliance on high-cost, carbon-intensive sources of generation, such as gas peaker plants, during peak demand periods (Zummo et al., 2017). By encouraging off-peak usage, TOU pricing models aim to reduce overall system costs and support California's goals for integrating more distributed renewable energy sources into the grid. Aligning electricity consumption with periods of higher solar and wind availability also reduces greenhouse gas emissions and promotes cleaner energy production. The pilots examined the broader potential of dynamic pricing to enhance grid stability and reliability, potentially reducing the need for additional infrastructure investments by improving the utilization of existing infrastructure. This is important as the grid needs to evolve to accommodate growing renewable and distributed energy resources (Zummo et al., 2017). In this case study, it is explored how dynamic pricing, through TOU rates, may affect consumer electricity consumption behavior and the potential economic and environmental gains from TOU pricing. Additionally, the analysis examines how consumer response to price fluctuations is associated with the economic concept of the elasticity of demand and its broader implications for future energy market designs.

Renewable energy production is volatile and dependent on seasons and weather patterns. For example, solar plants produce excess energy at noon during the summer months and low to no energy in winter evenings. This does not always align with consumers' demand behavior, which tends to peak in the mornings and evenings. Electricity cannot be stored economically on a large scale for long periods, and most of it must be consumed immediately after production. This characteristic, combined with the highly variable duration curve, poses significant challenges for electricity markets with a high share of renewable energy sources. A central issue is the mismatch between supply and demand during peak periods, when demand is high, and production can be low, and during off-peak periods, when demand is lower, and generation often outpaces demand. Traditional average-cost pricing does not accurately reflect the actual marginal costs of producing electricity from renewable energy. At times, extreme challenges arise when no wind or solar power is available. but electric energy must meet consumer demand (Borenstein & Holland 2005). During those periods, electricity must be imported from other regions or countries or produced with fossil fuels. This is why traditional average-cost pricing can lead to market distortions, as it does not accurately reflect the volatility of renewable energy production and demand patterns. Under average-cost pricing, consumers, insulated from the actual cost of electricity production at a given time, may be incentivized to consume more during periods of low production, when scarcity should signal higher prices. This can result in enhanced consumption during peak demand periods and low production periods, where demand tends to be inelastic (i.e., less responsive to price changes), and underconsumption during peak production periods, where demand could be more responsive to lower prices (Joskow et al., 2004).

Off-peak demand prices should be more reflective of the marginal cost of energy, which is typically lower during reduced demand and high production. Such pricing adjustments could align consumer behavior with the true costs of electricity generation, smoothing the load curve and reducing the need for expensive, inefficient peak plant generation from gas plant capacity during peak demand and low renewable energy production in the mornings and evenings, or for electricity imports from other regions. This would increase consumer surplus by lowering the average price consumers pay for electricity and by better utilizing the existing generation assets (Caves et al., 1984). Following the model proposed by (Borenstein & Holland, 2005) it is assumed that consumers are equipped with real-time metering devices, thereby eliminating the need for traditional load profiling. Despite having access to real-time prices, consumers exhibit imperfect reactions to these prices, which are determined by Load Serving Entities (LSEs) and can deviate from wholesale prices. Borenstein and Holland posit two key assumptions in this context: (a) consumers respond primarily to the average expected price rather than to the more granular, state-contingent real-time prices and consumer demand,

Often, consumers fail to fully internalize the correlation between the state of nature (e.g., a heatwave) and the real-time prices. In an ideal scenario, a rational consumer would recognize that their energy demand—such as increased air-conditioning use during a heatwave—coincides with higher real-time prices and adjust consumption accordingly to minimize costs. However, the reliance on average prices suggests cognitive simplification, in which consumers are unable or unwilling to react dynamically to fluctuating prices in response to real-time market conditions. The implications of this model are significant in the context of energy market efficiency. While time-of-use pricing is theoretically optimal for demand-side management, the practical limitations of consumer behavior, as illustrated by Borenstein & Holland (2005), hinder the full realization of its benefits. Without precise, real-time responses to price signals, consumers contribute to inefficiencies in energy consumption, leading to peak-demand challenges and increased costs.

Integrating AI and IoT technologies offers potential to address the challenges of bounded rationality in electricity markets by enabling consumers to automate adjustments to energy usage in response to real-time price signals. Tracking and responding to complex, time-varying prices is a cognitive burden to consumers and often leads to suboptimal decision-making or avoidance of responding. AI and IoT technologies mitigate this by enabling automated, optimized responses to electricity pricing at specific price points. IoT-enabled smart devices—such as thermostats, appliances, and electric vehicle (EV) chargers—can make real-time adjustments to energy consumption based on live data and specific pricing points. For example, smart thermostats, such as the latest Nest and Ecobee models, can regulate heating and cooling according to real-time prices and weather conditions, optimizing electricity use while maintaining comfort. Smart appliances can be programmed to operate during off-peak hours when electricity is cheaper, aligning household demand with pricing and supply conditions (Ahmad et al., 2022). IoT devices are integral to this market transformation, with innovations such as smart meters, sensors, and building management systems facilitating real-time energy monitoring and automation. These technologies enable automatic adjustments to energy consumption based on real-time data feeds. For example, automating energy usage based on real-time pricing signals, improving demand-side management, and reducing consumer energy costs (Abir et al., 2021).

The use of AI and IoT technologies also enables advanced capabilities, such as energy storage management, local microgrid market optimization, and the integration of solar, wind, geothermal, and gas sources into the grid. AI algorithms, combined with IoT infrastructure, can forecast energy prices and predict generation availability, enabling better utilization of renewable energy assets and improving the overall efficiency of grid operations. This extends to more complex tasks, such as analyzing physical faults within the grid, performing power line inspections using drones, and detecting energy theft (Khan et al., 2024). AI and IoT technology can mitigate the inefficiencies identified by (Borenstein & Holland, 2005), aligning consumer behavior more closely with the ideal rational response to dynamic pricing structures that utilize IoT devices and ML.

Assessment

This case study examines the impact of Time-of-Use (TOU) pricing on consumer behavior, with a focus on demand elasticity and the role of smart technologies in enhancing responsiveness to dynamic electricity pricing. By analyzing shifts in electricity consumption during peak and off-peak periods, the study will examine the economic and environmental benefits of TOU pricing, particularly in optimizing grid efficiency, reducing costs, and promoting the adoption of renewable energy and electric vehicles. In the context of price elasticity of demand, TOU (Time-of-Use) pricing plays a critical role in shaping how consumers respond to fluctuating electricity prices by leveraging the principles of elasticity to manage consumption behavior. The elasticity of demand refers to the sensitivity of consumers to price changes, specifically whether a price increase results in a significant demand reduction (elastic) or a minimal change in behavior (inelastic). TOU pricing can impact both inelastic and elastic behaviors, depending on the time of day and the availability of smart technologies.

To collect the necessary data for analyzing the economic effects of Time-of-Use (TOU) pricing and the elasticity of demand in electricity markets, a comprehensive AI, IoT, sensor, and data infrastructure is required. Smart meters, as part of the Advanced Metering Infrastructure (AMI), provide real-time consumption data from consumers, enabling utilities to analyze patterns and respond dynamically to changes in load (S. S. George & Bell, 2018; Y. Wang et al., 2019).

Figure 20 illustrates various analytical techniques to optimize the performance and functionality of smart meter systems in energy management.

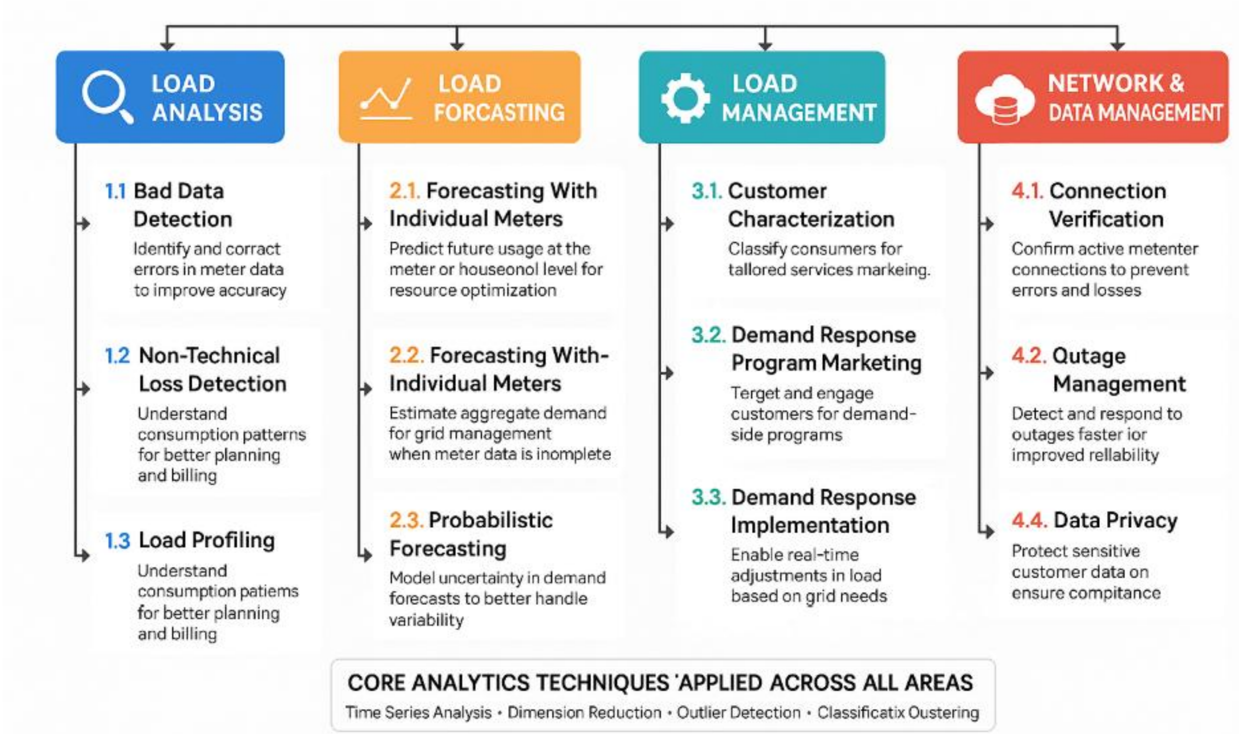


FIGURE 20 SMART METER ANALYTICAL MODELS

Source*: adapted from Wang et al. (2019).*

Smart Meter Data analytics is one of the technologies that enable a modern smart grid. This smart grid spans the entire energy system—generation, transmission, distribution, and end users across residential, commercial, and industrial sectors. It transforms large amounts of detailed data collected from smart meters and IoT (sensors and connectivity) into actionable insights for both daily operations and long-term planning. Actionable insights are derived by AI analyzing large datasets collected from IoT devices such as smart meters. AI techniques include time series analysis, deep learning, classification, and clustering. By leveraging these analytic methods, utilities improve efficiency, reliability, security, and customer service throughout the grid. Each application in this framework fulfills an operational need. Load Analysis is fundamental for understanding when and how energy is consumed, using methods such as bad data detection to ensure data accuracy, non-technical loss detection to uncover issues such as energy theft, and load profiling to reveal consumption patterns among different customers. These insights support better grid planning, resource allocation, and the design of tailored energy programs. Load forecasting enables utilities to predict future electricity consumption at the level of individual meters or across entire regions. Probabilistic forecasting and aggregate analysis enable better alignment of energy supply with demand, more effective integration of renewable resources, and more informed investment planning. Building on this, load management applications help utilities shape consumption patterns to make the grid more flexible. Customer characterization enables the segmentation of end users, supporting targeted communication and the effective marketing of demand response programs. Through these programs, utilities can encourage customers to shift energy use away from peak periods, thus enhancing grid resilience and reducing overall system costs. Figure 21 below illustrates how these things interact with each other.

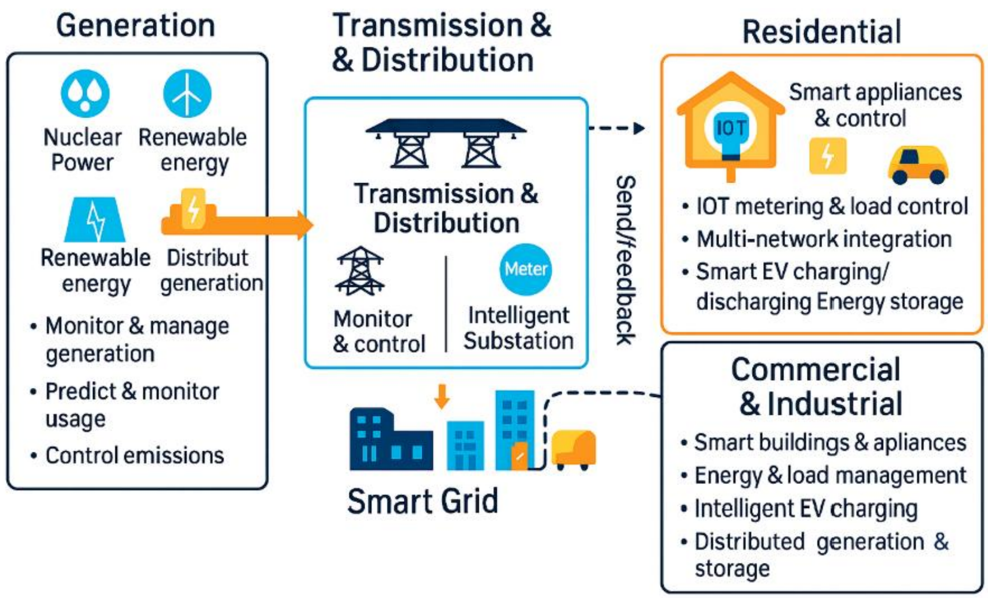


FIGURE 21 INTEGRATED SMART GRID ECOSYSTEM: FROM GENERATION TO INTELLIGENT CONSUMPTION

Source*: adapted from Kumar et al.(2020) and author's own.*

Beyond energy consumption, smart meter analytics also addresses network and data management. Connection verification ensures customer data aligns with the physical grid, supporting accurate billing and a faster response to outages. Advanced outage management leverages real-time meter data to detect and resolve disruptions promptly, further boosting reliability. Given the volume of data produced by smart grids, tools like data compression are essential for efficient storage and transmission, while strong data privacy protections are vital for maintaining customer trust and complying with regulations. All these analytics applications are crucial for implementing advanced rate structures, such as time-of-use (TOU) pricing. Smart meters supply the interval data necessary for TOU, which charges different rates depending on when energy is used. Load profiling and customer characterization analytics help utilities design optimal pricing periods and target customers who stand to benefit the most from shifting their usage patterns. Analytics also help measure the impact and effectiveness of these programs, while reliable data and robust privacy practices ensure fair billing and secure operations.

Table 22 below shows which technologies are utilized for specific applications and the economic realities they influence.

Table 22 Smart Meter Data Analytics detailing IoT sources, AI layers, outcomes, and relevance for TOU pricing

Application Use Case	**Analytical Techniques (AI)**	**Hardware / Data Source (IoT)**	**Main Purpose / Outcome**	**Relevance TOU Pricing – (Economics)**
Load Analysis	Time Series Analysis, ML	Smart Meters, Grid Sensors	Understand patterns, ensure system integrity	Defines peak/off-peak periods for TOU rates
Bad Data Detection	Outlier Detection, Classification	Smart Meters, Networks	Ensure accuracy of all data	Critical for reliable TOU billing
Non-Technical Loss Detection	Classification, Anomaly Detection	Smart Meters, Sensors	Detect theft/errors, ensure fair cost distribution	Prevents loss that could distort TOU outcomes
Load Profiling	Clustering, Dimension Reduction	Smart Meters	Create customer usage profiles	Identifies usage types for custom TOU periods
Load Forecasting	Time Series Forecasting, Deep Learning	Smart Meters, SCADA	Predict short/long-term demand	Predicts demand for TOU pricing adjustments
Load Management	Optimization, Predictive Analytics	Smart Meters, Switches	Shape and shift demand	Enables demand shifting in response to TOU rates
Customer Characterization	Segmentation, Clustering	Smart Meters, Customer Data	Classify customers by behavior	Targets groups for TOU incentives/communications
Connection Verification	Data Matching, Validation	Smart Meters, GIS, AMI	Match physical connections with data	Ensures correct meter-customer TOU application
Outage Management	Event Detection, Real-Time Analysis	Smart Meters, Sensors	Detect and resolve outages quickly	Prevents mis-billing due to outages in TOU periods
Application Use Case	**Analytical Techniques (AI)**	**Hardware / Data Source (IoT)**	**Main Purpose / Outcome**	**Relevance TOU Pricing – (Economics)**

Data Privacy	Encryption, Access Control	Smart Meters, Servers	Protects sensitive customer information	Required for regulatory-compliant TOU programs
Demand Response	Predictive Analytics, Segmentation	Smart Meters, Control Systems	Shift load to optimize grid performance	Leverages TOU to motivate customer participation

Source: *author's own.*

PG&E refers to Pacific Gas and Electric Company, which serves Northern California by providing both natural gas and electricity services. SCE stands for Southern California Edison, one of the largest electric utilities in California, serving much of the region, including Los Angeles, and surrounding areas. SDG&E represents San Diego Gas & Electric, the company that provides energy services to San Diego County and southern Orange County. These utilities serve approximately 33.3 million people, which accounts for most of California's population. Peak period hours refer to the specific times when peak rates apply, during which electricity costs are higher due to increased demand and reduced production. The % impact indicates the percentage change in electricity usage during peak-period hours under each rate plan relative to a baseline or normal rate. Absolute Impact (kW) measures the absolute difference in kilowatts during peak-period hours under each rate plan, compared to the baseline per customer. Each row represents a different utility company and illustrates how various rate plans affect electricity usage during designated peak hours across different seasons. The data helps analyze how changes in rate plans can influence consumer behavior regarding energy consumption during high-demand periods. In this case, a comparison of price elasticities of demand of the three utilities, PG&E, SCE, and SDG&E, for summer, winter, and spring, utilizing pilot rate 1, is made.

The basic data for this procedure is provided in Table 23 below, which shows percentage and absolute reductions in peak-period load for each rate and service area are detailed by season. During the pilot program's first summer, Southern California Edison's (SCE) Rate 3 had the lowest impact, with an average load reduction of 2.7% and a peak reduction of 0.03 kW. In contrast, the highest reduction was observed with Pacific Gas and Electric Company's (PG&E) Rate 2, averaging 6.1% and 0.06 kW. In the winter, SCE's Rate 1 showed the lowest impact with reductions of 1.4% and 0.01 kW. The highest reductions were seen in PG&E's Rate 1 and Rate 2, each with an average reduction of 3.6% and 0.03 kW. In the following summer, the lowest impacts were 3.6% and 0.04 kW for SCE's Rate 1, and the highest were 5.6% and 0.06 kW for PG&E's Rate 3. On average, the peak period reduction across all rates over the two summers was 4.6%. With time-of-use (TOU) price signals (Tier 2 peak-to-off-peak price ratios) ranging from approximately 1.3 to 2.0, these load reductions are statistically significant. They could substantially decrease the need for peaking capacity. The default enrollment of all residential customers might enhance this effect. It is essential to acknowledge that, particularly in regions with hot climates, there is inherent seasonal variability in bills due to changes in usage and the tiered rate structure, even under the ordinary accounting tariff (OAT). To manage bill volatility across seasons, utilities offer tools like balanced payment plans. These plans enable customers to pay a consistent monthly bill based on their historical usage and current rates, with periodic adjustments made to account for any discrepancies. The impact of such plans on mitigating the effects of time-of-use (TOU) price signals remains a topic of discussion. It is being explored through ongoing default pilot programs at each investor-owned utility (IOU) (S. George & Bell, 2018).

TABLE 23 TOU OUTCOMES BY CALIFORNIA UTILITY AND TIME PERIODS BY RATE STRUCTURE

Utility	Metric	Rate	Summer 2016	Winter 2016/2017	Summer 2017	Peak Period Hours
PG&E	% Impact	1	5.8%	3.6%	5.3%	4 PM – 9 PM
PG&E	Absolute Impact (kW)	1	0.06 kW	0.03 kW	0.06 kW	
PG&E	% Impact	2	6.1%	3.6%	3.8%	6 PM – 9 PM
PG&E	Absolute Impact (kW)	2	0.06 kW	0.03 kW	0.04 kW	
PG&E	% Impact	3	5.5%	3.5%	5.6%	4 PM – 9 PM
PG&E	Absolute Impact (kW)	3	0.06 kW	0.03 kW	0.06 kW	
SCE	% Impact	1	4.4%	1.4%	3.6%	2 PM – 8 PM
SCE	Absolute Impact (kW)	1	0.06 kW	0.01 kW	0.06 kW	
SCE	% Impact	2	4.2%	2.0%	4.1%	5 PM – 8 PM
SCE	Absolute Impact (kW)	2	0.06 kW	0.02 kW	0.06 kW	
SCE	% Impact	3	2.7%	3.2%	4.0%	4 PM – 9 PM
SCE	Absolute Impact (kW)	3	0.03 kW	0.03 kW	0.05 kW	
SDG&E	% Impact	1	5.4%	2.3%	4.6%	4 PM – 9 PM
SDG&E	Absolute Impact (kW)	1	0.04 kW	0.02 kW	0.03 kW	
SDG&E	% Impact	2	4.6%	1.7%	4.1%	4 PM – 9 PM

SDG&E	Absolute Impact (kW)	2	0.04 kW	0.01 kW	0.03 kW	
SDG&E	% Impact	3	N/A	N/A	N/A	
SDG&E	Absolute Impact (kW)	3	N/A	N/A	N/A	

Source: George & Bell (2018) and author's own.

Table 24 shows the time-of-use electricity rates for PG&E customers on weekdays during the summer of 2017, distinguishing between peak and off-peak hours. Electricity costs 41.0¢ per kWh during peak hours (5:00 pm to 8:59 pm) and 30.7¢ per kWh during all other off-peak hours.

TABLE 24 ***TIME OF USE PRICING SCHEDULE ACCORDING TO TIME AND ASSOCIATED RATE STRUCTURE***

Period	Time	Rate (¢/kWh)
Off-Peak	1:00 am – 4:59 pm	30.7¢
Peak	5:00 pm – 8:59 pm	41.0¢
Off-Peak	9:00 pm – 12:00 am	30.7¢

Source: George & Bell (2018) and author's own.

To calculate the elasticity of demand for PG&E during peak-period hours in summer 2017, one needs to know how quantity demanded changes in response to a change in price. The formula for elasticity (ε) is a ratio of the percentage change in demand quantity to the percentage change in price. It could be estimated based on the data from Table 26 the percentage change in price is given as:

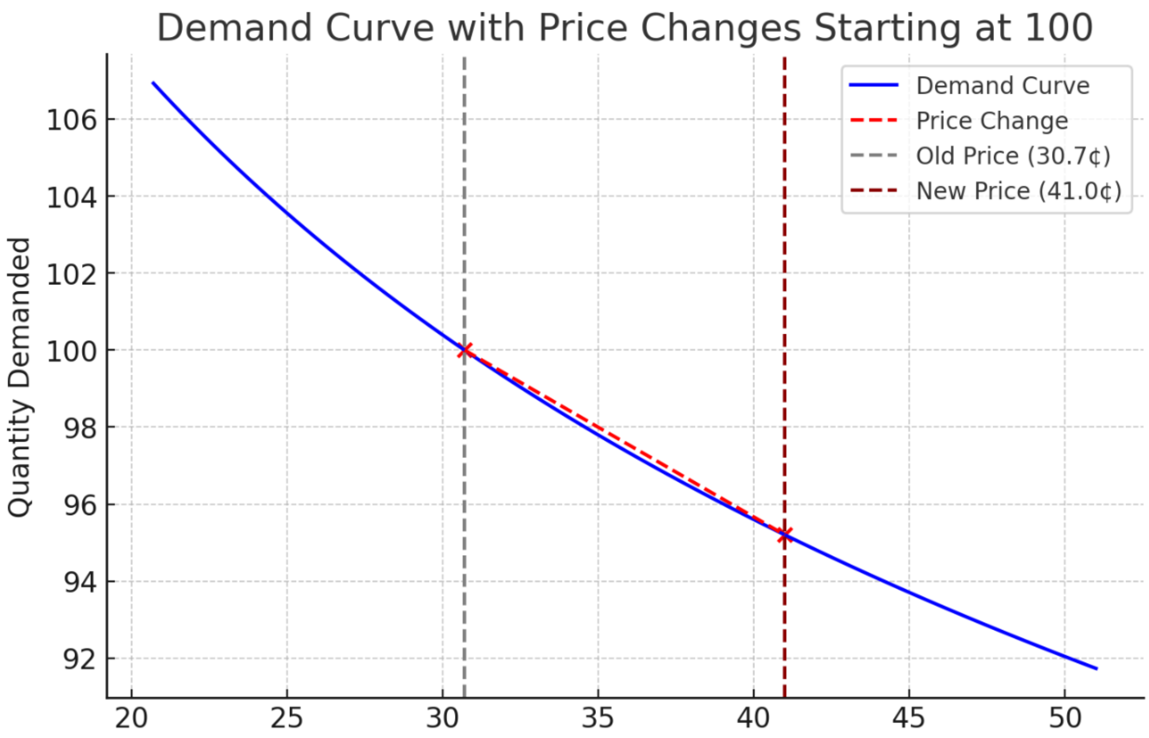
$$\left(\frac{\text{New Price} - \text{Old Price}}{\text{Old Price}}\right) \times 100 = \left(\frac{41.0-30.7}{30.7}\right) \times 100 = 33.55\% \quad (28)$$

Substituting the above value into the elasticity formula, the percentage change in price for PG&E during the peak period in summer 2017 is approximately 33.55%. The elasticity of demand for this period is approximately -0.17. The elasticity of demand for PG&E during peak periods in summer 2017, calculated at -0.17, indicates relatively inelastic demand. This suggests that while percentage changes in price lead to smaller percentage changes in quantity demanded, the impact can still be substantial when considering PG&E's large customer base. Although the electricity demand is relatively insensitive to price, minor price adjustments can affect overall revenue. For consumers, inelastic demand means that price increases could disproportionately impact their budgets, as reducing consumption may not be sufficiently feasible to offset the higher costs. From an economic standpoint, increased utility costs can ripple through the economy, affecting the prices of goods and services, particularly in energy-intensive sectors. This has the potential to contribute to inflationary pressures, as the energy market will behave according to typical macroeconomic rules (Blinder & Rudd, 2008).

Price adjustments during peak periods also serve as a demand management tool. By raising prices, utilities like PG&E can encourage consumers to shift their energy use to off-peak times, thereby aiding load management and reducing the need for costly peak-time energy production (see Figure 20). This is based on findings from the Federal Energy Regulatory Commission, which supports the use of time-variant pricing to manage load and enhance grid efficiency (Datchanamoorthy et al., 2011). Regulatory bodies play a crucial role in balancing the utility's need to cover operational and infrastructural costs against consumer affordability. Regulatory oversight ensures that price increments are justified and that consumers are shielded from excessive increases, as discussed in energy economics literature (Joskow, 2024).

Conclusions

With electricity lacking close substitutes, slight price increases can yield significant revenue gains for the utility, translating into substantial producer surplus. However, these price increases disproportionately reduce consumer surplus, as households and businesses face higher expenditures without equivalent increases in utility. Economically, adjusting prices during peak demand periods can lead to consumer efficiency gains by shifting consumption to less costly off-peak times, thereby optimizing resource allocation and potentially enhancing overall social welfare. Nevertheless, certain consumer groups, such as retirement homes, healthcare facilities, refrigerated storage facilities, and manufacturing plants, may have a limited ability to shift their demand. These groups are particularly vulnerable during periods of extreme heat or cold, potentially facing serious health risks and economic hardships. Policymakers and regulators must therefore carefully assess the broader economic impacts, balancing the utility’s financial requirements and infrastructure investments with the broader societal goal of minimizing the economic burden on vulnerable consumers and maintaining equitable access to essential services.



Price in cents per kWh

FIGURE 22: DEMAND ELASTICITY TIME OF USE PRICING SCHEDULE ACCORDING TO TIME AND ASSOCIATED RATE STRUCTURE

Source: *author's own.*

In essence, while the demand elasticity for PG&E suggests a market with low sensitivity to price changes, the large number of affected consumers means that even small price changes can have broad economic and social impacts. This underscores the importance of meticulous rate setting, regulatory review, and the strategic use of demand-side management to shape consumption patterns responsibly.

The California case study could be compared with other meta-studies on utility TOU (Table 25). The study "Evaluating Residential Real-Time Pricing" by Elevate Energy examines the impact of Illinois' residential real-time pricing (RTP) programs, such as ComEd's Hourly Pricing, which were implemented following a 2006 legislative mandate. The analysis reveals that participants exhibited price elasticities ranging from -0.08 to -0.09, indicating a modest reduction in electricity consumption in response to hourly price fluctuations. These relatively low elasticity values are attributed to factors such as limited consumer awareness, the absence of enabling technologies, and the inherent challenges that residential customers face in adjusting their usage patterns in real time (Star et al., 2006).

Carvallo & Schwartz (2023) The Lawrence Berkeley National Laboratory report shows that price-based demand response programs, such as Portland General Electric's Smart Grid Test Bed, reduced average summer demand by 10–15%, with similar significant peak reductions observed in Southern California Edison's and San Diego Gas & Electric's programs. Labandeira et al. (2017) reported a mean short-run price elasticity of electricity demand of around -0.1 and a mean long-run elasticity of -0.4 from studies around the world. (Bernstein & Griffin, (2005) reviews pilot programs and experiments on TOU and RTP reported residential electricity demand as often being in the range of -0.1 to -0.3 and long-run elasticities.

TABLE 25 ELASTICITIES OF DEMAND AND DEMAND REDUCTION DUE TO PRICING SCHEMES ACROSS SEVERAL STUDIES

Study	Program/Location	Reported Elasticity or Reduction	Effect	Explanation/Notes	Reference
Evaluating Residential Real-Time Pricing (Illinois)	ComEd Hourly Pricing	-0.08 to -0.09 (PED)	Modest reduction in consumption	Low elasticity is due to limited consumer awareness, a lack of enabling technology, and challenges in real-time adjustment.	(Star et al., 2006).
Determinants of Price Elasticity	General	Varies	Elasticity depends on several factors	Price differentials, consumer info/awareness, smart tech, and demographics all influence elasticity.	Synthesis of studies
LBNL Price-Based DR Resource Report	PGE, SCE, SDG&E (US utilities)	10–15% reduction (PGE Smart Grid Test Bed)	Significant peak demand reductions and load shifting	DR program design, customer engagement, and enabling tech are key drivers.	(Carvallo & Schwartz, 2023b)
World Review of Elasticity	Various countries (global)	-0.1 (short-run), -0.4 (long-run)	Global average PED values	Summarizes short- and long-run elasticity globally.	(Labandeira et al., 2017)
Review of TOU and RTP Programs	Residential (various studies)	-0.1 to -0.3 (short-run), -0.4	Range of elasticities from pilot programs	Long-run elasticities are two to three times larger than the short-run.	(Bernstein & Griffin, 2005)

		to -0.7 (long-run)			

Source: author's own, based on sources indicated in the table.

The magnitude of electricity price elasticities is influenced by the size of price differentials, consumer information and awareness, the availability of enabling technologies like smart devices, and demographic and housing characteristics. The specifics of how much demand changes and how this is measured differ widely based on the study's focus, methodology, the type of pricing scheme, the consumer group, and the available technology. However, the overarching theme remains consistent: dynamic pricing and price signals are effective tools for prompting consumers to reduce or shift their electricity consumption, resulting in significant impacts on demand.

4.4 Case Study Smart Grid Pricing Efficiency: Transactive Energy Pilot in the U.S. Pacific Northwest

Background

Smart grids create significant opportunities to enhance efficiency through demand response (DR), in which consumers adjust electricity use in response to real-time price signals. Traditional marginal cost pricing often fails to reflect demand fluctuations, potentially leading to inefficiencies. More advanced models, such as Time-of-Use (TOU)and Dynamic Pricing, adjust prices based on peak demand (Chen & Liu, 2017a). The Pacific Northwest Smart Grid Demonstration was a $179 million transactive energy pilot project that commenced in 2010 and lasted for five years. The initiative divided the Pacific Northwest power grid into 27 subregions, each capable of exchanging information with neighboring regions. Each sub-region operated under a local balancing authority responsible for estimating the cost of electricity delivered to adjacent sub-regions. This cost was calculated based on an estimate of the quantity of power to be exported, allowing for efficient energy flow management across the grid. Directed by the Battelle Memorial Institute (Battelle), Pacific Northwest Division in Richland, Wash., the project involves more than 60,000 metered customers. BPA is contributing $10 million to the five-year project, which was matched with an additional $10 million from DOE (Battelle Memorial Institute, 2015a). The Pacific Northwest Smart Grid Demonstration categorized its tests into three functional areas to evaluate smart grid capabilities. First**,** conservation and efficiency focused on systems that conserve energy or enhance efficiency, targeting either operational improvements or reductions in energy consumption. (Battelle Memorial Institute, 2015a)**.** The Pacific Northwest Smart Grid Demonstration categorized its tests into three functional areas to evaluate smart grid capabilities. First, conservation and efficiency focused on systems that conserve energy or enhance efficiency, targeting either operational improvements or reductions in energy consumption. Second, demand-responsive (transactive) systems were deployed to respond to real-time demand-response signals from the project's transactive system, enabling dynamic adjustments in energy usage based on grid conditions and price signals. The project also demonstrated how dynamic pricing can mitigate the intermittency of renewable energy sources by sending price signals that encourage energy consumption when renewable output is high. These results provided a scalable model for integrating dynamic pricing with smart grid technologies to enhance grid reliability and operational efficiency on a larger scale. The reliability category involved installing systems designed to improve the consistency and dependability of power delivery to customers, thereby enhancing the grid's ability to maintain stable service even during fluctuating demand. Our case study will mostly focus on the first two functional areas, efficiency increase and dynamic pricing, and the economic theories around it. The concept of dynamic pricing involves adjusting electricity prices in real-time based on supply and demand conditions. This relates to marginal cost pricing, where prices reflect the cost of producing the next unit of electricity, encouraging efficient energy use. Additionally, the theory of price elasticity of demand plays a role, as consumers adjust their energy usage in response to price fluctuations. This interaction between supply, demand, and pricing is also a key feature of market-clearing theory, where the equilibrium price is determined through the interaction of these factors. In the context of smart grids, productive efficiency can be achieved by optimizing electricity flows, minimizing losses, and ensuring that energy inputs (generation and transmission) are utilized to their fullest potential without waste (Hsieh & Chiu, 2016). According to the Battelle Memorial Institute, the managed load resources deployed in the Pacific Northwest Smart Grid Demonstration worked in tandem with the non-wire resources assembled by BPA to address transmission constraints on the Olympic Peninsula. The project utilized various controllable assets that responded to energy price signals, including five 40-horsepower water pumps distributed between two municipal pumping stations, with a combined capacity of approximately 150 kW. These pumps were incrementally bid into the energy market when water reservoir levels exceeded a designated height. Two distributed diesel generators (175 kW and 600 kW) were activated when the supply was inadequate to serve the facility's electrical load. These generators shifted approximately 170 kW of building electric load off the grid by converting it to their own power. Additionally, a small 30-kW microturbine was used to respond to the two-way market, operating in parallel with the grid. Market prices for these units were based on actual fixed and variable operating costs. A residential demand-response system was implemented across 112 homes for electric water and space heating, utilizing gateways with two-way communication capabilities. This system enabled residents to see current market prices and preprogram their demand-response preferences. Participants were divided into three utility price contract types (fixed, time-of-use, and real-time) and a control group. Although all homes were metered, only the price-responsive appliances (~75 kW) were controlled by the project (Hammerstrom et al., 2007).

In the context of smart grid systems, dynamic pricing mechanisms aim to optimize energy consumption by encouraging consumers to adjust their electricity use in response to price signals. However, accurately measuring the price elasticity of demand—the degree to which energy consumption responds to price changes proposes challenges due to data inconsistencies, such as zero or constant prices, incomplete data points, and periods without significant price variation.

As price-responsive electricity markets gain traction in the United States, especially with time-of-use (TOU) rates and critical peak pricing models, AI and IoT technologies are playing a transformative role in managing and optimizing these dynamic pricing systems. These technologies not only provide the necessary infrastructure for monitoring electricity usage but also enable a smarter, more responsive energy grid. Administering Time of Use Rates requires advanced utility interval meters capable of monitoring and differentiating between customers' peak and off-peak electricity usage. Although programs with advanced notifications and longer time intervals do not require automation, the adoption of TOU rates has been somewhat accelerated by the availability of interval meters and energy-management systems that can automate customer responses (Hammerstrom et al., 2007). The backbone of TOU pricing systems is the advanced metering infrastructure (AMI), which integrates smart meters and IoT devices to track real-time energy consumption. IoT-enabled interval meters collect granular data on customers' electricity usage during peak and off-peak periods. This data is communicated to utility companies through IoT networks, allowing for accurate billing and rate adjustments based on the time of consumption.

The deployment of AMI has been crucial in advancing the adoption of TOU pricing by automating the collection and transmission of usage data.

(Faruqui & Sergici, (2010),state that AMI-enabled dynamic pricing programs, such as time-of-use, critical-peak pricing, and real-time pricing, are expected to yield significant demand reductions during peak hours. These IoT networks facilitate seamless communication between smart meters, home energy management systems, and utility companies. AI algorithms play a crucial role in predicting electricity demand patterns, optimizing energy distribution, and setting dynamic pricing. Machine learning models can analyze historical usage data, weather conditions, and real-time grid performance to predict demand spikes and adjust prices accordingly. By utilizing predictive analytics, AI helps utilities implement more efficient TOU pricing, reducing the risk of blackouts during peak demand and optimizing grid performance. A study by Antonopoulos highlights that "AI-based forecasting algorithms are pivotal in predicting demand with high accuracy, allowing utility providers to establish more precise dynamic pricing strategies and ensure grid reliability" (Antonopoulos et al., 2020). Huang et al. (2017) suggest that price-based demand response (PBDR) offers electricity consumers an opportunity to adjust their energy use in response to fluctuating electricity prices, helping to reduce grid strain during peak demand periods. IoT-based home energy management systems (EMS) enable automation of consumer responses to TOU pricing. These systems can communicate with smart thermostats, appliances, and other IoT-enabled devices to shift electricity usage to off-peak times. AI algorithms in EMS optimize energy consumption based on real-time price signals and user preferences, creating cost-saving opportunities for consumers. Research from Cheng and Lee (2019) notes that AI-driven EMS can autonomously adjust heating, ventilation, and air conditioning (HVAC) systems and other high-energy devices in response to price signals, ensuring both energy savings and grid stability. He further asserted that in commercial buildings, sensor-enabled Case-Based Reasoning (CBR) and Knowledge-Based Systems (KBS) work in conjunction with Artificial Neural Networks (ANN) and fuzzy logic tools to manage energy systems effectively. These tools not only perform model-based control and forecast factors such as weather, occupancy, and energy consumption, but also engage with demand response programs and time-of-use (TOU) pricing. These systems engage with demand response and time-of-use (TOU) pricing using smart meters and IoT-enabled devices. Smart meters are essential for providing real-time consumption data and supporting dynamic pricing. According to Darby, smart meters provide a real-time feedback loop, enabling both users and utilities to respond more effectively to energy demand and pricing signals (Darby, 2010). Energy management systems, integrated with smart meters and AI tools, optimize energy consumption based on pricing and demand signals. Capozzoli et al. (2017) state that EMS, combined with real-time data from smart meters, enables dynamic energy optimization by adjusting control setpoints in response to external signals such as TOU pricing.

Assessment

This study focuses on data from the University of Washington (UW) Seattle campus, which served as a subproject within the Pacific Northwest Smart Grid Demonstration (PNWSGD). The University of Washington (UW) monitors and manages over 15 million square feet of space that serves more than 40,000 students daily. A key expectation for the university was to achieve annual energy cost savings of more than $350,000. To facilitate this, several asset systems were demonstrated at the UW site. These included enabling assets, such as one steam turbine, two diesel standby generators, and two small-scale solar photovoltaic (PV) facilities; building heating, ventilation, and air-conditioning (HVAC) controls and lighting controls; student residence and university facilities pilot sub-metering; and a facility energy management system (FEMS). These systems were utilized to conduct six experiments, the details of which form the focus of the Technology Performance Report (Battelle Memorial Institute, 2015b). To achieve these objectives, several asset systems were demonstrated, including essential data collection infrastructure, power generation assets (a steam turbine, two diesel standby generators, and two small-scale solar photovoltaic facilities), building HVAC and lighting controls, pilot sub-metering in student residences and university facilities, and a facility energy management system (FEMS). These integrated systems facilitated six distinct experiments, the specifics of which are detailed in the Technology Performance Report (Hammerstrom et al. 2007).

The empirical basis for the current analysis is the University of Washington Facilities Services Site Tests dataset, obtained from the eGRID data repository (Kuchar, 2015). Thereport was deemed suitable for several reasons: it characterizes a microgrid operating within a larger smart grid framework; it contains data pertinent to the study of pricing elasticities in a supply and demand system; it reflects the deployment of an Energy Management System (EMS) and sub-metering technologies; and it encompasses a variety of power sources, from renewable solar to diesel generators. Central to the price elasticity analysis are several key variables. These include KW_01, representing energy demand in kilowatts; COST_PK_ENERGY_MDC, signifying the energy price during peak periods under the Medium Demand Charge category; Pct_Change_Demand, indicating the percentage change in demand between consecutive observations; and Pct_Change_Price, denoting the corresponding percentage change in price.

The dataset was cleaned and refined by me to address issues such as zero or constant price entries. This was done to calculate meaningful price elasticity values that accurately reflect consumer behavioral responses to price variations. Additionally, insights were derived regarding the efficacy of dynamic pricing strategies in shifting energy consumption, thereby contributing to both cost minimization and enhanced grid efficiency.

The data analysis presented in Table 26 below focuses on the relationship between energy demand (KW_01) and the price of energy (COST_PK_ENERGY_MDC). The dataset underwent a filtering and refinement process to eliminate extreme values and ensure the accuracy of elasticity calculations. The columns selected for this analysis encompassed KW_01 (energy demand), COST_PK_ENERGY_MDC (peak-time energy price), the derived Pct_Change_Demand and Pct_Change_Price, and the resultant elasticity, calculated as the ratio of the percentage change in demand to the percentage change in price. The data cleaning protocol involved removing rows with missing values for demand and price. Instances where demand dropped by 100%, likely indicating operational shutdowns or anomalies rather than typical market responses, were excluded. To foster a more balanced analysis, extreme elasticity values (beyond a ±10 range) were also omitted. The initial dataset, containing 3000 rows, was systematically reduced through these cleaning procedures, ultimately yielding a focused dataset of 17 key data points that captured the demand-price relationship devoid of extreme fluctuations. To illustrate the characteristics of this refined dataset, a conceptual representation of a sample table is provided (Table). This illustrative table presents specific observations from the filtered dataset.

For example, representative data from such a sample would include an observation (e.g., original row identifier 579) with a demand (KW_01) of 2288 kW, a price (COST_PK_ENERGY_MDC) of $0.0606, a percentage change in demand of -12.9182%, a percentage change in price of 6.502636%, and a resultant elasticity of -1.9866. Another illustrative entry (e.g., original row identifier 591) shows a demand of 2895.833 kW and a price of $0.0569, with a demand change of

+26.56614%, a price change of -6.10561%, and an elasticity of -4.3511. These entries, representative of the 17 refined data points, demonstrate varied consumer responses to price alterations, with the calculated elasticity values quantifying this sensitivity. Table 28 serves as a representative sample dataset, while the actual percentage change and elasticity computations were performed on the full chronological dataset. This is consistent with standard practice in empirical energy-economics research when working with large time-series datasets.

TABLE 26 SAMPLE DATASET

ROW	KW_01	COST_PK_ENERGY_MDC	Pct_Change_Demand	Pct_Change_Price	Elasticity
579	2288	0.0606	-12.9182	6.502636	-1.9866
591	2895.833	0.0569	26.56614	-6.10561	-4.3511
1498	1280	0.0606	-55.7986	6.502636	-8.58091
1543	1592	0.0606	-39.4081	6.502636	-6.06032
1555	2352	0.0606	12	7.067138	1.698
1673	1368	0.0606	-53.6946	6.502636	-8.25736
2277	1484	0.0606	-43.5186	6.502636	-6.69245
2429	1784	0.0606	11.5	7.067138	1.62725
2654	1280	0.0606	-55.7986	6.502636	-8.58091
2700	2407.923	0.0606	-18.4943	6.502636	-2.84413
2882	2627.413	0.0569	30.84727	-6.10561	-5.05228

Source:(Kuchar, 2015) and author's own .

The percentage change in demand expresses the difference between current and previous demand levels as a fraction of the previous demand. This fraction is then converted into a percentage to indicate the relative change. The percentage change in demand (KW_01) between consecutive rows could be calculated using the formula:

$$\text{Percentage\_Change in \_Demand} = \left(\frac{\text{KW\_01}_t - \text{KW\_01}_{t-1}}{\text{KW\_01}_{t-1}}\right) \times 100,$$

where KW_01_t the demand at the current time and KW_01_{t-1} is the demand at the previous time period.

Calculating the percentage change in demand between consecutive rows allows to quantify the relative magnitude of demand fluctuations over time, which is essential for understanding responsiveness to factors like price change– which is a fundamental aspect of DSM strategies like dynamic pricing; this quantified change is then used to determine price elasticity, which in turn informs how effectively these strategies can shift load and optimize grid profiles, as envisioned by the hypothesis. The next step is the calculation of the percentage change in price (COST_PK_ENERGY_MDC) between consecutive rows, given by the formula:

$$\text{Pct\_Change \_Price} = \left(\frac{\text{COST\_PK\_}ENERGY\text{\_MDC}_t - \text{COST\_PK\_ENERGY\_MDC}_{t-1}}{\text{COST\_PKEENERGY\_MDC}_{t-1}}\right) \times 100 \ (29),$$

where $\text{COST\_PK\_}ENERGY\text{\_MDC}_t$ is the price at the current time and $\text{COST\_PK\_ENERGY\_MDC}_{t-1}$ is the price at the previous time.

Calculating the percentage change in price between consecutive rows enables the quantification of the relative magnitude of price fluctuations over time. This, when compared with the percentage change in demand, facilitates the calculation of the price elasticity of demand. This elasticity measure is crucial for understanding how sensitive demand is to price changes, a key factor in assessing the effectiveness of dynamic pricing strategies. This single numerical value provides a standardized measure of how much demand is expected to change in response to a given price change, which is fundamental for evaluating the effectiveness of price-based demand-side management strategies. The final average elasticity was -4.51, indicating that demand tends to decrease as price increases, suggesting that the systems in the dataset are very sensitive to price changes.

Price elasticity is interpreted based on its value: if $E>1$, demand is elastic, meaning consumers are highly responsive to price changes; if $E<1$, demand is inelastic, indicating consumers are less responsive; $E=1$ signifies unit elastic demand, showing a proportional response in quantity demanded to price changes; $E=0$ means demand is perfectly inelastic, with no change in quantity despite price changes; and $E=\infty$ indicates perfectly elastic demand, where any change in price causes an infinite change in quantity. In terms of economic impact, a correlation coefficient of -0.695 was found between price and demand, indicating a strong inverse relationship, supporting the idea that higher prices lead to lower demand. This negative relationship was further demonstrated through visualizations, such as a scatter plot (Figure 23).

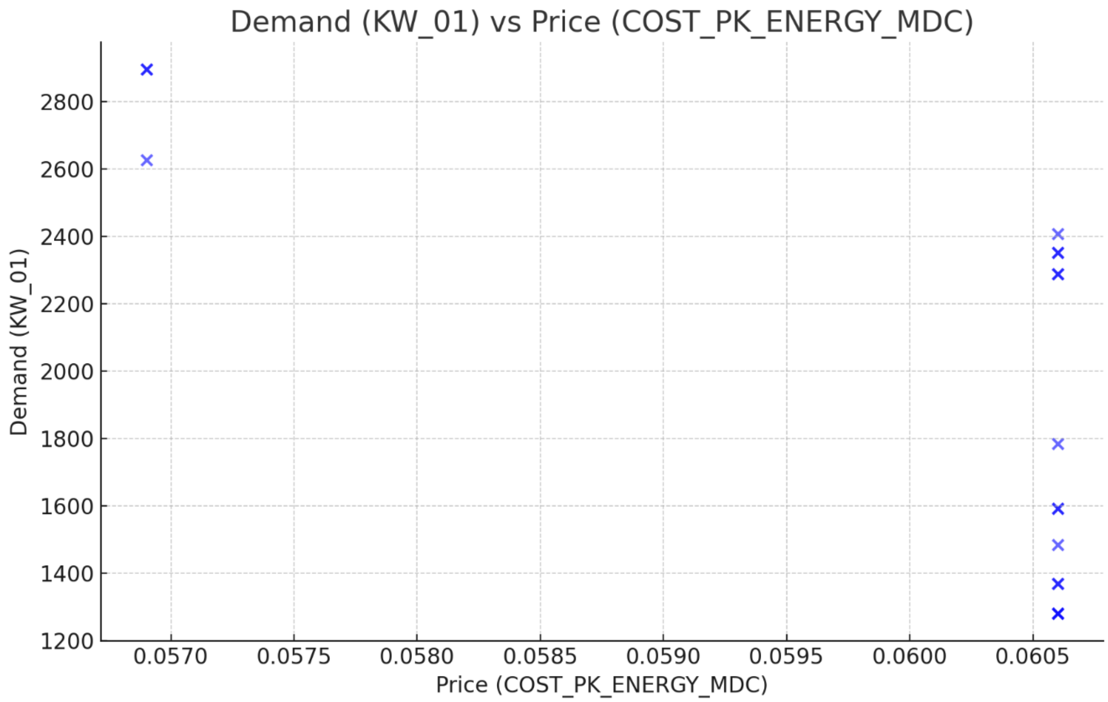


FIGURE 23 ***SCATTER PLOT DESCRIBING THE RELATIONSHIP BETWEEN ENERGY PRICE AND DEMAND***

Source: author's own.

The scatter plot above shows the relationship between energy price and demand, with the x-axis representing the energy price (COST_PK_ENERGY_MDC) and the y-axis representing energy demand in kilowatts (KW_01). Each blue 'x' marks a specific instance in which a particular price level corresponded to a particular level of energy demand, allowing for an examination of how price changes might influence consumption. The scatter plot shows an inverse relationship between price and demand, even though price varies only across two discrete tariff levels (≈0.0570 and ≈0.0606). At the lower tariff, demand consistently remains high (approximately 2600–2900 kW), whereas at the higher tariff, demand drops significantly (approximately 1300–2400 kW). This pattern indicates an adverse price effect: as energy prices increase, demand decreases. The wide spread of values across price levels suggest that additional operational or environmental factors also influence consumption, but the shift between the two price clusters demonstrates meaningful price responsiveness. This behavior aligns with economic theory and is consistent with a price-responsive load or an active Energy Management System adjusting consumption in response to tariff changes.

Conclusions

The analysis of the University of Washington dataset provides several key insights into the relationship between energy price and demand within the microgrid. The University of Washington dataset exhibits a stable, economically consistent inverse relationship between price and demand. Demand exhibits dynamic behavior, fluctuating in response to price variations over time. The consistently negative correlation observed underscores a stable inverse relationship between price and demand, aligning with fundamental economic principles. Based on this analysis, the calculated average price elasticity of -4.51 indicates a high price elasticity of demand. This value suggests that energy demand within the UW system tends to decrease significantly as prices increase, indicating a discernible degree of price sensitivity among consumers or within the operational protocols of the university's facilities. This finding is further substantiated by a strong inverse relationship between price and demand, evidenced by a correlation coefficient of -0.695. This robust negative correlation reinforces the economic principle that, as prices escalate, demand tends to contract. It is important to note the impact of extreme values on the initial dataset. The presence of several extreme elasticity figures, especially in instances where demand plummeted by 100% (likely to represent operational shutdowns or anomalies rather than typical market responses), had the potential to skew the overall elasticity calculation. The removal of these outliers was a crucial step in achieving more accurate and representative results. The removal of extreme values is necessary because elasticity is intended to measure marginal responsiveness, and periods in which demand collapses to zero represent discontinuous system states that produce values incompatible with the conceptual framework of elasticity and would otherwise compromise the metric’s interpretability and validity.

While a detailed visualization of daily demand patterns was not the primary focus of this specific extract, the data generally suggests that demand fluctuates throughout the day. These fluctuations often correspond with peak and off-peak pricing periods, with demand typically rising during standard operational or business hours and declining during nighttime or off-peak hours. This pattern is consistent with typical energy consumption behaviors and is a key consideration for demand-side management strategies.

The data points towards operational sensitivity, indicating that certain periods or conditions exhibit heightened demand sensitivity to price changes. In some observed cases, relatively small price adjustments led to significant shifts in demand. This suggests that external factors, such as specific operational decisions, prevailing market conditions, or the nature of the university's energy-consuming activities, can heavily influence energy use and its responsiveness to price signals.

These conclusions have direct implications for understanding the potential of demand-side management (DSM) strategies, as posited in related hypotheses (such as H3, which suggests AI and IoT technologies enable effective DSM for optimized grid load profiles). The observed price sensitivity and the inverse relationship between price and demand confirm that there is a basis for dynamic pricing to influence consumption. The moderate elasticity suggests that while price signals can induce changes, the magnitude of these changes may be influenced by operational constraints and the inherent needs of a large institution. Identifying and removing anomalies, along with understanding daily patterns and operational sensitivities, are critical data processing and analytical steps that serve as essential inputs for any AI-driven DSM system aiming to optimize load profiles. The findings support the idea that, with accurate data, responsiveness to that data (facilitated by IoT and sub-metering, as used in the UW project), and careful analysis (a precursor to AI-driven optimization), dynamic pricing can indeed be a tool to shift energy consumption. This, in turn, contributes to cost minimization and grid efficiency, as hypothesized.

4.4. Summary of case studies

Findings from the Blue Lake Rancheria Microgrid and Airtel Madagascar case studies support hypothesis 1, demonstrating that AI and IoT integration can enhance operational efficiency and lead to measurable reductions in operating costs and improved financial outcomes. Findings from the Blue Lake Rancheria Microgrid and Airtel Madagascar case studies robustly support Hypothesis 1, demonstrating operational efficiencies and measurable reductions in operating costs resulting from the integration of AI and IoT. Specifically, the Blue Lake Rancheria Microgrid case exhibited a Total Factor Productivity (TFP) of, indicating highly efficient utilization of capital, labor, and ICT (AI and IoT) inputs to yield considerable output gains over a 20-year period. Airtel Madagascar Microgrids showed a substantial decrease in Levelized Cost of Energy (LCOE), from \$2.26 per kWh for manual hybrid systems to \$1.39 per kWh for automated hybrid systems integrated with AI and IoT technologies. This nearly 40% reduction highlights the impact of technology-enabled predictive maintenance, optimized fuel management, and efficient resource allocation, all of which directly translate into lower operational expenditures.

The Olympic Peninsula Demonstration Project and the California Statewide TOU Pricing Pilots provided evidence supporting hypothesis 2. These cases illustrated dynamic pricing and decentralized energy resources, enabled by smart grid capabilities utilizing AI and IoT, shift consumer demand behaviors and lead to structural market transformations. Dynamic pricing strategies like TOU enhance grid efficiency by encouraging consumers to shift their electricity usage from peak to off-peak periods, reducing peak load stress.

Data from Airtel Madagascar Microgrids support Hypothesis 3 by demonstrating that the adoption of AI and IoT has substantially improved investment efficiency. Through lower capital risks, shorter payback periods, and higher returns, the use of AI and IoT has been shown to influence financial outcomes positively.

The Blue Lake Rancheria Microgrid (California) demonstrates how AI and IoT contribute to productivity gains through optimization, leading to improved energy production, enhanced decision-making, and reduced operational costs. IoT-enabled sensors and AI predict peak demand periods, allowing for the shifting of loads to avoid charges. The Airtel Madagascar Microgrids for Cell Phone Towers case analyzes the deployment of intelligent AI and IoT in microgrids, examining the influence of AI and IoT-enabled automation on levelized cost of energy (LCOE), internal rate of return (IRR), and total factor productivity (TFP). The implementation of an Energy Management System (EMS) along with AI and IoT technologies reduced generator fuel consumption by approximately 48% and runtime by approximately 73%. The LCOE decreased from approximately \$2.26 per kWh to \$1.39 per kWh after EMS implementation. The Olympic Peninsula Demonstration Project is part of the GridWise Smart Grid program. This project focused on deploying transactive-based real-time/TOU pricing signals to influence electricity usage patterns among various consumer groups. It explored how pricing signals affect the price elasticity of demand and aimed to integrate renewable energy sources into the grid better. California Statewide Opt-in Time-of-Use Pricing Pilots investigated how TOU pricing influences consumer electricity consumption behavior, focusing on demand elasticity and the role of AI and IoT in optimizing grid efficiency and reducing costs. Smart meters, sensors, AI, and IoT devices were essential for enabling, capturing, and analyzing the economic impacts of TOU pricing. The pilots observed statistically significant reductions in peak period load across various rate plans.

Despite the compelling findings, the analysis conducted acknowledges several methodological limitations inherent to the multi-case study design. These include the limited generalizability due to the selected number of cases, potential selection biases favoring documented successes (although selection was based on a designed methodological framework), variability in data quality, and the inherent challenge in establishing unequivocal causality, given the complex nature of energy systems, as geography, weather patterns, and local energy prices influence them. This underscores the necessity for ongoing data collection and longitudinal studies. In conclusion, the evidence across all four case studies confirms that integrating AI and IoT technologies delivers economic benefits, advancing energy productivity, enhancing market efficiency, and improving investment performance. The study's findings suggest that continued investment and research in these technologies will yield substantial long-term benefits in terms of economics, the environment, and society. Future research should aim to extend these findings through broader geographical coverage, diverse technological contexts, and longer temporal frameworks to further validate and refine these critical insights.

CONCLUSIONS

The results in Chapter 4 build on the findings and theoretical work of Chapters 1 to 3. The historical context of the four industrial revolutions, as provided in Chapter 1, revealed a pattern of how technological progress, from simple mechanization to digitization through artificial intelligence and the internet of things, has driven productivity and efficiency improvements in economies over the last 250 years, as described in key economic theories relevant to energy markets, including neoclassical production theory and total productivity. Total factor productivity is introduced in the context of efficiency and productivity in converting inputs (labor, capital, technology, ICT, energy) into output, drawing on classical and neoclassical production theory. Chapter 1 is foundational, as it establishes the conceptual and analytical economic framework that underpins the case studies in Chapter 4. It outlines the methods for measuring productivity, assessing investments, and interpreting market behavior within the broader context of digital automation enabled by AI and IoT technologies. Chapter 2 provides an overview of the energy sector from a broad economic perspective. It discusses the fundamental role of energy as an input factor in modern economies, its historical evolution, and its correlation with GDP. It also delves explicitly into the electric energy markets. Chapter 3 explains the architecture and functionality of AI and IoT in general and how its architecture shapes and influences the modern electric energy sector. Chapter 4 presents empirical evidence to support the hypotheses formulated in the introduction, building upon the theories presented in Chapter 1 and the context established in Chapters 2 and 3. It provides concrete examples of case studies illustrating the economic impacts of AI and IoT on electric smart grids and microgrids. Chapter 4 consolidates the research findings derived from the analysis and explicitly outlines the results in relation to the hypothesis. It sheds light on the broader implications of the findings for public welfare, macroeconomic dynamics, and the formulation of effective policy interventions within the electric energy sector. The dissertation’s analysis of four distinct case studies – the Blue Lake Rancheria Microgrid, Airtel Madagascar's remote power systems, the Olympic Peninsula Demonstration Project, and the California Statewide Time-of-Use (TOU) Pricing Pilots – provides validation for all three of the hypotheses brought forward in this research, offering practical insights into the real-world economic impacts observed across diverse deployments. In addition, research across several meta-studies further highlights and consolidates economic and operational impacts, ranging from rural and community-based systems to industrial and military deployments, as well as smart grid-enabled time-of-use utility case studies. The case studies examined in Chapter 4 verify the hypotheses. The summary of the case study findings and the research hypotheses is provided in Table 27.

TABLE 27 RESULTS OF HYPOTHESIS TESTING

Hypothesis Number	Hypothesis Statement	Core Claim	Supporting Case Studies	Verification Status
H1	AI/IoT integration enhances operational efficiency and reduces costs.	AI/IoT enables optimization, automation, and predictive monitoring leading to resource savings (fuel, maintenance, OPEX), reduced LCOE, increased IRR., and TFP improvements.	Blue Lake Rancheria (BLK), Airtel Madagascar	**H1 Supported by:** **BLK Microgrid:** TFP: 1.60 ↑ Ops Cost: - 28.0% Load: -15% ↓ **Airtel Microgrids:** Fuel costs: - 48.1% LCOE: - 38.5% ↓ Ops Costs: - 43.73% TFP:77.7% or 1.77 ↑ IRR: 140% **Meta studies:** Ops costs: - 32 % - -84.63% ↓ LCOE: -14.21%
H2	AI and IoT technologies are pivotal for integrating variable renewable energy and fostering a shift toward competitive market structures.	AI/IoT enables the management of renewable dispersed energy resources, supports grid stability, and resilience services.	Blue Lake Rancheria, Olympic Peninsula California Statewide TOU	**H2 supported by:** - Enablement of TOU and dynamic pricing through Smart Meters (IoT) and smart grid, leading to more competitive market structures and adjustments of demand and supply

				- Microgrid optimization through sensors, controllers, and ML, and integration of DERs
H3	AI and IoT technologies enable effective demand-side management (DSM) strategies, such as demand response (DR) and dynamic pricing, leading to optimized grid load profiles.	IoT (smart meters) provides data/channel for DSM; AI/analytics optimizes programs and analyzes responses, enabling load shifting.	Olympic Peninsula UW California Statewide TOU Different TOU studies	**H3 supported by:** Price elasticity of -4.51 Peak demand reduction -1.4% - (-6.1%) Case study: - 5.3% Elasticity of demand: -0.17 Elasticity of demand: - 0,1 – -0,4 (Short run) - 0,4- - 0.7 (Long run)

Source: author's own.

Hypothesis 1 (H1) posits that the integration of AI and IoT enhances operational efficiency and reduces costs. The core claim is that AI and IoT enable optimization, automation, and predictive monitoring, leading to resource savings (fuel, maintenance, OPEX), reduced Levelized Cost of Energy (LCOE), increased Internal Rate of Return (IRR), and improvements in Total Factor Productivity (TFP). This is supported by the Blue Lake Rancheria (BLK) and Airtel Madagascar case studies. The hypothesis is supported by the BLK Microgrid data, which shows a TFP of 1.37 in 2017 and 1.60 in 2018, an operational cost reduction of 25% in 2017 and 28% in 2018, a 15% reduction in annual energy use and average demand, and a 17% reduction in peak demand. For Airtel Microgrids, there was a 48.1% reduction in fuel consumption, a 38.5% reduction in LCOE, a 43.73% reduction in operational expenditures, a TFP improvement of 77.70% (1.77), and an incremental IRR of 140%. Meta-studies further support the findings of the two case studies, reporting operational cost reductions of 30-85% and LCOE reductions of 14.21%.

Hypothesis 2 (H2) posits that AI and IoT technologies are crucial for integrating variable renewable energy sources and promoting a shift toward more competitive market structures. The core claim is that AI and IoT enable the management of renewable, dispersed energy resources, supporting grid stability and resilience services. This is supported by the Blue Lake Rancheria, Olympic Peninsula, and California Statewide Time-of-Use (TOU) case studies. Verification is demonstrated through the enablement of TOU and dynamic pricing via Smart Meters (IoT) and smart grids, leading to more competitive market structures and adjustments of demand and supply. Additionally, optimization through sensors, controllers, and machine learning facilitates the integration of distributed energy resources (DERs) within microgrids and larger smart grids.

Hypothesis 3 (H3) proposes that AI and IoT technologies enable effective demand-side management (DSM) strategies, such as demand response (DR) and more dynamic pricing, leading to optimized grid load profiles. The core claim is that IoT (smart meters) provides data and communication channels for DSM, while AI and analytics optimize programs and analyze responses, enabling load shifting. This is supported by the Olympic Peninsula and California Statewide TOU case studies, as well as various other studies. The hypothesis is supported by observed peak demand reductions ranging from 1.4% to 6.1% in the California Statewide TOU case studies. The selected PG&E California case study showed a 5.6% impact on peak demand in Summer 2017, with an elasticity of -0.17. Other studies report short-run elasticities of -0.08 to -0.09, indicating a 10-15% reduction in average summer demand, and global average short-run elasticities of -0.1 to -0.3, with long-run elasticities ranging from -0.4 to -0.7. The significantly high average price elasticity of -4.51 in the University of Washington (UW) system is an outlier compared to typical electricity demand elasticities, which generally range from -0.1 to -0.4 in other studies.

The calculated average price elasticity of -4.51 in the Olympic Peninsula University of Washington Campus signifies a high price elasticity of demand, significantly higher than in the TOU studies. This value suggests that energy demand within the UW system tends to decrease significantly as prices increase, indicating a discernible degree of price sensitivity among consumers or within the operational protocols of the university's facilities. The correlation coefficient of -0.695 further reinforces this strong inverse relationship between price and demand in the observed data. This unusual sensitivity to price changes likely stems from the institutional nature of the UW campus, where energy management systems and operational protocols enable automated, substantial load adjustments in response to dynamic pricing signals. Unlike residential consumers, who may face cognitive burden in responding to real-time prices, the UW system's ability to control specific, flexible loads with automated responses, such as HVAC and lighting, and to utilize assets like water pumps and diesel generators can result in a more pronounced demand response.

The results, which validate three key hypotheses —H1 on efficiency and cost reductions, H2 on renewable integration and market competitiveness, and H3 on demand-side management—offer insights for various stakeholders. Enhanced case studies demonstrate significant improvements across key financial indicators. The Airtel Madagascar project delivered an Internal Rate of Return (IRR) of 140% through its AI/IoT-based Energy Management System (EMS), achieved a Levelized Cost of Energy (LCOE) reduction of 38.5% (from $2.26/kWh to $1.39/kWh), and reduced operational costs by 43.73%. Supporting meta-studies further indicate potential LCOE reductions up to 14.21% and operational cost savings ranging from 30% to 85%. These improvements translate into shorter payback periods and lower capital risk. Increases in Total Factor Productivity (TFP)—such as a 1.778 increase in the Airtel project and a 1.60 increase at Blue Lake Rancheria—highlight how AI/IoT-driven automation enhances overall output relative to inputs. These findings closely align with the economic theories introduced in Chapter 1, underscoring the viability of investments in smart grids and microgrids. Such investments facilitate the integration of variable renewable resources (Hypothesis 2), reducing volatility and improving long-term financial returns. The transition to competitive market structures, driven by dynamic pricing and demand response (Hypothesis 3), enabled by smart grid technology, opens significant opportunities for AI and IoT companies and their investors. LCOE (Levelized Cost of Energy) and TFP (Total Factor Productivity) evaluate efficiency and performance in energy production, and economic productivity captures the combined efficiency with which all inputs are utilized in the production process. TFP is an indicator of technological progress and innovation. Automation supported by AI and IoT can be directly linked to the TFP growth drivers. This research has shown that both LCOE and TFP are significantly affected by AI and IoT-empowered automation. As shown in the case studies and meta-studies, LCOE decreases with technological improvements, and TFP increases with technological advancements and improved resource utilization, driving economic growth. AI and IoT enhance investment efficiency and increase financial returns, which is associated with reduced capital risks, shorter payback periods, and significantly improved financial outcomes for microgrid projects. For example, the Airtel Madagascar case study provides a compelling illustration of this principle, showing an Internal Rate of Return (IRR) of approximately 140% for the AI/IoT-driven Energy Management System (EMS), thus making it a highly sound economic proposition. Meta-studies on diverse deployments (rural, industrial, military) showed broad applicability.

Based on the results, some practical recommendations could be suggested. Examining the overall growth potential of the smart grid and microgrid market, findings from the case studies can be of significant importance to investors, technology companies, utilities, and policymakers. Aligning with the results of this research on the viability of AI and IoT in microgrids and smart grids, the market for these two segments is predicted to grow significantly over the next few years, both worldwide and in the US. The global microgrid market is projected to reach USD 236.18 billion by 2034, up from USD 51.40 billion in 2025, at a compound annual growth rate (CAGR) of approximately 16-18%, driven by the need for energy resilience and the increasing integration of renewable energy sources. The U.S. microgrid market was valued at USD 12.47 billion in 2024 and is expected to reach approximately USD 71.10 billion by 2034, expanding at a CAGR of 19.01% from 2025 to 2034. Based on connectivity, the grid-connected segment is expected to hold the largest market share in the coming years (Shivarkar, 2025). The smart grid market is expected to grow from USD 66.1 billion in 2025 to USD 166-338 billion by 2034, at a CAGR of 10-17%, fueled by AI/IoT adoption, increased energy demand and need to integrate more DER's (Gminsights, 2024; Metatechinsights, 2024). AI in energy is booming, from USD 9.89 billion in 2024 to USD 99.48 billion by 2032 (CAGR 33.45%) (Kiran, 2025).

The growth is driven by integrating more renewable energy into the grid, building new data centers to host AI deployments, and by government and commercial customers seeking greater independence from the grid. The microgrid and smart grid markets offer high-return opportunities amid the global energy transition. Investors can focus on AI, IoT, and automation by investing in start-ups and established companies active in these markets. Investing in companies that develop AI and IoT technologies for the electric energy market offers high returns through hardware revenue and recurring revenue from software-as-a-service (SaaS), licensing, and service models. Technology providers drive efficiency (H1) and renewable integration (H2), as evident in case studies, and are less exposed to project financial risks. The high demand for analytics, smart meters, and EMS positions these technology firms for growth in smart energy, cities, data centers, and emerging markets. AI and IoT's role in driving efficiency, renewable integration, and demand management (H1, H2, H3) positions companies like ABB, Schneider Electric, Siemens, Landis+Gyr, ComAp, and startups like BluWave-ai and SparkMeter as key players in the USD 51.40 billion microgrid and USD 66.1 billion smart grid markets in 2025. These firms leverage analytics, smart meters, and EMS to capitalize on high-growth sectors, such as smart cities, data centers, and emerging markets (Kunerth & Borkowski, 2025). The dissertation's findings, including operational cost reductions of 30–85%, underscore the justification for investing in microgrid projects. The risks of engaging in project-based microgrid development are high capital expenditures (USD 1-5 million per MW installed), operational complexities compounded by regulatory delays, IoT-related cybersecurity concerns, and the intermittency of renewable energy sources. Those challenges, both for microgrid developers and project investors, are mitigated by Energy-as-a-Service (EaaS) models, government incentives, and strategic partnerships. Resilience-oriented frameworks such as Enchanted Rock's Resiliency-as-a-Service (RaaS) provide effective financing. The importance of robust financial strategies is exemplified by Scale Microgrids' and Schneider's AlphaStruxure, a joint venture with the Carlyle Group, a global private equity firm (Kunerth & Borkowski, 2025). Investors and engineering companies focused on building actual microgrids can build on the findings of this dissertation by recognizing the importance of several key factors: market growth, state and government incentives, and the need for increased resilience and energy independence. A USD 5 million grant for Blue Lake Rancheria, as mentioned in the dissertation's case studies, exemplifies how US federal incentives like USD 3 billion Smart Grid Grants through 2026 and IRA tax credits (20% for renewables) and local state incentives reduce capital expenditure (CAPEX) risks and barriers (Schatz Energy Research Center, 2019). Considering the economic benefits of integrating AI and IoT in the electricity sector, several policy recommendations can be proposed to achieve macroeconomic gains. Policymakers can accelerate smart grid infrastructure deployment by providing more targeted funding, loan guarantees, or tax incentives for investments in technologies such as advanced metering infrastructure (AMI), sensors, communication networks, and sophisticated grid control software supported by (H2, H3). This encourages operational investments in efficiency gains proven by (H1) and enhanced grid reliability, as noted by Mikalauskas (2015), thereby boosting national productivity and mitigating economic losses from power outages. It is also important to modify and adjust regulatory frameworks to better accommodate the planning and construction of microgrids. Measures could include streamlining interconnection processes, enabling better market participation for AI/IoT-optimized DERs supported by (H2), and establishing rules and frameworks for data access, sharing, and privacy of IoT systems. This will lead to higher investment efficiency, increased investor trust and returns, encourage private capital to flow into decentralized assets such as microgrids, and foster innovation while safeguarding consumers' cybersecurity. Governments and industry bodies should promote interoperability and standardization by supporting the development and adoption of standards for communication protocols and data formats across IoT devices, AI platforms, and grid management systems. This approach reduces integration costs and fosters a competitive landscape (Dieffenbach, 2014; Khan et al., 2024).

Some implications for macroeconomic theory can be drawn from the research conducted. In the analysis of microgrids and smart grids in the electricity sector, the principles of welfare economics provide a critical framework for evaluating how market structures, technological advancements, and regulatory policies affect overall societal well-being. Research by (Arrow, 1951) and (Cannan & Pigou, 1921) has shown that when resources are allocated optimally, markets can theoretically achieve a Pareto-efficient outcome, where no one can be made better off without making someone else worse off. Pareto efficiency, also known as Pareto optimality, is a concept in welfare economics that describes a resource allocation where no individual's utility can be increased without a corresponding decrease in another's. This condition implies that the economy has reached a state in which all possible mutually beneficial exchanges have been exhausted, reflecting the highest attainable level of allocative efficiency. Pareto efficiency implies that any measure designed to boost consumer surplus—such as reducing electricity prices—must be counterbalanced by an impact on producer surplus, which is critical for funding investments in grid modernization and sustainable generation capacity, and vice versa. TOU pricing, enabled by AI-driven demand forecasting and IoT-based real-time monitoring, optimizes solar energy use by shifting demand to periods of high output (e.g., midday) or reducing energy use during periods of low production, as supported by (H2, H3). This reduces energy waste and helps align consumption with generation, moving the market closer to a Pareto-efficient allocation where resources are used optimally. The California TOU pilots, along with the analysis of several other studies in Chapter 4, demonstrated that consumers adjust their electricity usage in response to price signals. This reduces the need for additional generation capacity through peaker plants, improves grid reliability, decreases reliance on high-cost, carbon-intensive sources, and aligns with Pareto efficiency by reducing inefficiencies. TOU pricing indirectly internalizes environmental costs by incentivizing consumption during periods of high renewable energy availability, thereby reducing CO2 emissions from fossil-fuel-based generation. The California TOU Pilots support (H2) that AI and IoT-enhanced smart grids drive a shift toward decentralized, competitive markets. TOU pricing fosters demand responsiveness, as evidenced by the pilots' 5.6% peak demand reduction, which aligns with the goal of welfare economics to achieve efficient resource allocation and move markets toward Pareto efficiency.

Macroeconomic research must also investigate the long-term efficiency benefits and cost savings of these initial investments, as well as the potential short-term economic disruptions or resource reallocation pressures discussed in (H1). For this reason, translating micro-level efficiency gains, such as the TFP reported by Blue Lake Rancheria, into positive net macroeconomic impacts requires careful modeling of adoption rates, system-wide effects, and the dynamic interplay between investment costs and productivity returns.

Schreiner & Madlener (2021) conducted a macroeconomic assessment of Germany's planned investments in power grid infrastructure, essential for integrating variable renewable energy sources and enhancing European interconnection. The quantitative analysis of grid infrastructure investments in this German study reveals heterogeneous economic effects. Positive net effects on outputs are observed within the range of €47.3 billion to €55.8 billion. In terms of competitiveness, lower energy costs directly benefit industries by reducing a key input expense—namely, electricity—thereby enhancing their position in both domestic and international markets. Furthermore, reduced energy losses within the grid signify a more efficient utilization of primary energy resources, which itself is a factor contributing to lower energy costs, providing industries with a competitive edge by lowering a significant input expense, specifically electricity. This reduction in energy costs improves their standing in both domestic and international markets and their national competitiveness. However, these advantages are counterbalanced by several negative economic indicators. The investments are associated with a significant decrease in value added, estimated between €10.1 billion and €12.7 billion. Fiscal revenue demonstrates a reduction of between €962 million and €1,354 million. Labor market impacts revealed in the study are particularly notable, with employment decreases of approximately 130,170 to 158,940 full-time equivalent positions attributed to the infrastructure development. The findings suggest complex macroeconomic trade-offs associated with the proposed grid investments. The heterogeneous effects across different economic parameters indicate that such infrastructure projects cannot be classified as unequivocally beneficial interventions from a national economic perspective.

(H2) asserts that AI and IoT technologies are pivotal for the effective integration of Variable Renewable Energy Sources (VRES) and for enhancing the overall resilience and stability of electricity systems. The macroeconomic analysis indicates that AI and IoT technologies enhance the integration efficiency of VRES. The resulting diversification of energy portfolios reduces national exposure to fossil-fuel market volatility and can decrease price-fluctuation metrics. Evidence shows this strengthens economic resilience by moderating input cost variability across industrial sectors. Econometric models suggest that decoupling from carbon-intensive energy sources is correlated with improved fiscal predictability, reduced greenhouse gas emissions, and lower economic vulnerability to exogenous supply shocks. Microgrids incorporating AI and IoT for advanced control and automation enhance resilience by enabling autonomous operation during main-grid failures, particularly when equipped with gas-engine backups and a connected gas line. This mitigates the social and economic costs associated with power outages. The CGE modeling study by Wing et al. (2025) for the Illinois region, quantified substantial GDP losses resulting from prolonged power interruptions, ranging from $1.8 billion to $15.2 billion, depending on the outage duration. Investments that utilize AI and IoT can bolster grid resilience by enabling faster fault detection and isolation, predictive maintenance, preventing equipment failures, and facilitating effective islanding of microgrids, thereby reducing potential economic losses. Such avoided GDP loss represents a direct positive contribution to macroeconomic performance. General grid modernization efforts, which include smart grid technologies, are recognized for increasing resilience to extreme weather events and cyberattacks, leading to significant economic savings by curtailing the costs associated with power outages, such as lost productivity, spoiled goods, and damaged equipment.

(H3) focuses on the role of AI and IoT in enabling effective Demand-Side Management Optimization strategies (DSM), such as demand (DR) response and dynamic pricing.

IoT smart devices, particularly smart meters, provide granular data from sensorics devices and communication gateways for advanced DSM. AI algorithms fed with sensor data predict weather patterns and consumer responses, enabling real-time adjustments to load.

Demand-side management can reduce peak electricity demand, potentially deferring or mitigating the need for costly investments in new generation capacity and network reinforcement. This freeing up of capital could allow funds to be allocated to other investments in the economy, potentially stimulating GDP growth. Furthermore, by optimizing load shapes and reducing reliance on expensive peaking power plants, DSM can lower overall electricity system costs. Studies by (Ahmad et al., 2020) and Macedo et al. (2015), suggest that AI-driven systems can effectively support the shifting of peak demand loads without negatively impacting end-user comfort or operations, However, the macroeconomic success of AI/IoT-driven DSM is heavily contingent on consumer and business adoption rates and their willingness to participate This introduces a degree of uncertainty that macroeconomic models must address, perhaps through sensitivity analyses based on varying assumptions about demand elasticities and participation rates. Future research should prioritize refining macroeconomic quantification. This involves employing sophisticated Computable General Equilibrium (CGE) or dynamic stochastic general equilibrium (DSGE) models to more precisely isolate the aggregate macroeconomic effects, such as enhanced GDP and comparative competitiveness, directly attributable to AI/IoT investments, disentangling them from concurrent economic trends. Building on Hypothesis 3, longitudinal analysis of investment returns is crucial for empirically tracking the long-term performance of AI/IoT-enabled DERs and microgrids relative to initial projections and traditional assets, and for examining variations across different geographical markets and regulatory regimes. Equally important is conducting further research into consumer behavior and its impact on equity. This includes exploring the effects and how diverse consumer segments engage with smart technologies enabled by pricing mechanisms such as dynamic pricing and demand response. It is also crucial to critically assess whether the economic benefits and costs of this technological transition are being distributed equitably. Significant research is needed to optimize market designs, investigate different electricity market structures, and leverage data from AI and large-scale connected DERs. This includes managing grid complexities in real-time and accurately valuing system flexibility. Addressing these questions will be vital for navigating the complexities, maximizing societal benefits, and minimizing the risks associated with the ongoing AI-driven energy transition.

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