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PROMOTING DISTRIBUTED ENERGY DEPLOYMENT AND DIFFUSION FOR SUSTAINABLE CIVIL INFRASTRUCTURE USING MULTI-AGENT BASED MODELING AND QUANTITATIVE ANALYTICS

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PROMOTING DISTRIBUTED ENERGY DEPLOYMENT AND DIFFUSION FOR SUSTAINABLE CIVIL INFRASTRUCTURE USING MULTI-AGENT BASED MODELING AND QUANTITATIVE ANALYTICS

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ABSTRACT

Distributed Solar Generation (DSG) using small-scale Photo-Voltaic (PV) is an evolving technology with increasingly growing market penetration due to its significant benefits to consumers and broader power systems. DSG is sustainable, provides reliability, and is cost-effective where solar energy is abundant. However, the increasingly growing adoption of DSG creates uncertainties in forecasting electric power demand and market behavior. It also causes concerns of a "*utility death spiral*". To this end, the goal of this research is to critically analyze the diffusion and benefits of DSG in the electric power infrastructure as a complex System-of-Systems (SoS). Specifically, this dissertation addresses the following five objectives: (1) investigating the relationship between the electric power sector and socio-economic parameters; (2) developing a complex simulation of electric power infrastructure and market impacted by the adoption of DSG; (3) exploring dynamic pricing by generating companies and the occurrence of a utility death spiral; (4) studying the impact of incentives on the adoption of DSG using complex sensitivity analysis; and (5) examining the benefits of DSG in reducing the vulnerability of the power infrastructure against natural disasters. As such, and as shown from the results, this research provided a novel holistic investigation of the complex relationship between DSG adoption and the electric power market and infrastructure in a multidisciplinary approach that combines infrastructure engineering, electric power engineering, economics, social science, machine learning, and computer modeling. The findings should benefit researchers, power system operators, and policy makers towards a sustainable DSG diffusion.

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NOMENCLATURE

a_g	Generator (g) Parameter $\left(\$/_{MW.h}\right)$
b_g	Generator (g) Parameter $\left(\$/_{MW^2.h}\right)$
P_g	Generator Commitment (MW)
P_j	Demand (MW) at LSE j
P_{km}	Power Flow (MW) in a transmission line between nodes (k) and (m)
Cap_g	Capacity (MW) for Generator (g)
π	Penalty Constant
δ_k	Phase Angle at node (k)
r	Rate of Interest (%)
$\boldsymbol{a}$	Action Set
$\boldsymbol{q}$	Propensity Set
$\boldsymbol{p}$	Probability Set
r	Reward
w	Weights
η	Learning Rate
ϕ	Forgetting Parameter
T	Gibbs-Boltzmann Cooling Factor

1. INTRODUCTION

1.1. OVERVIEW

Electric power is an essential aspect of modern life. Uninterrupted supply of electric power is even critical for many industries and infrastructures such as medical facilities for example. As such, there is a huge demand for electric power, which was estimated to be 3.8 trillion kWh in the US in 2020 (EIA, 2021a). The electric power infrastructure is a major element of national economies and is associated with highly-developed nations (Ali & El-adaway, 2020). However, there are concerns that electric power infrastructure in the US is aging and struggling to reliably meet demand. The American Society of Civil Engineering (ASCE) rated the energy infrastructure in the US with a C- in their most recent 2021 "*Report Card for America's Infrastructure*" (ASCE, 2021). The previous report card, which was in 2017, had a higher rating of D+ (ASCE, 2017). The electric power infrastructure in the US is aging. Most of the electrical transmission and distribution lines were built in the '50s and '60s with a life expectancy of 50 years. The deterioration of the electric power infrastructure in combination with other causes such as severe weather events and acts of vandalism was among the causes of 3,571 reported power outages in 2015, with an average duration of 49 minutes (ASCE, 2017). Weather-related events cause a major threat to the electric power grid. To add, although investment in the power grid has increased recently, there is a huge investment gap needed to reach a reliable system. This gap is estimated to reach \$209 billion by 2029 and increase to \$338 billion by 2039 (EBP US, 2020). To sum up, there is a need for research that investigates technologies that can support and modernize the electric power infrastructure.

1.1.1. Distributed Solar Generation (DSG). Distributed Energy Resources (DER) or Distributed Generation (DG) refers to small-scale power-generating units that are located near or at end-consumers. DER or DG can offer many advantages which may include being cost-effective and offering reliability as a backup system. DG systems are even essential for off-grid applications where there is no access to the grid. Distributed Solar Generation (DSG) refers to small-scale solar Photo-voltaic (PV) systems which are increasingly popular and accounted for 36% of the total solar generation capacity in the US in 2021, as shown in Figure 1.1 (EIA, 2022a, 2022b).

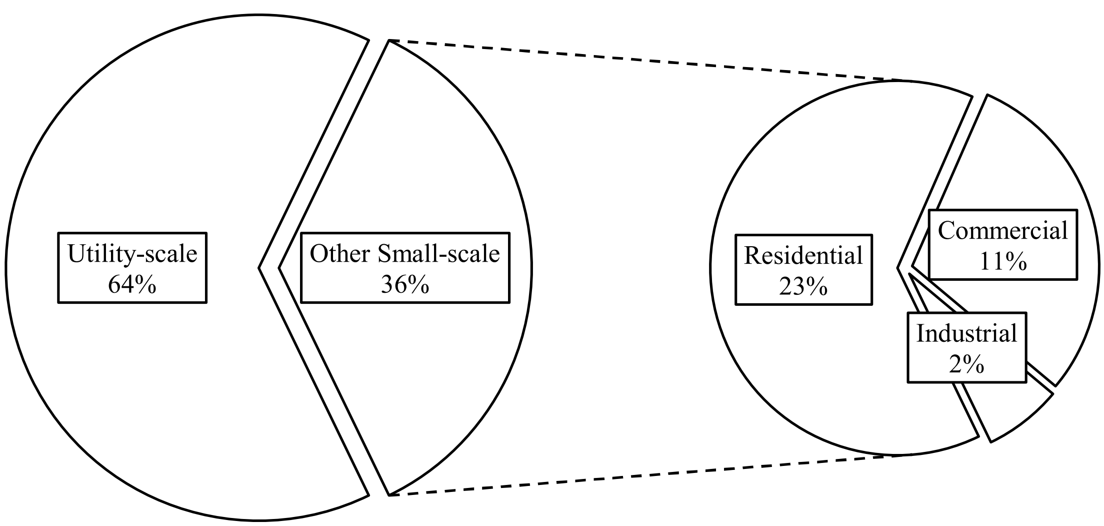


Figure 1.1. Distribution of solar PV generation capacity in the US in 2021.

1.1.2. Benefits of DSG. DSG offers many benefits, as shown in Figure 1.2, that have been a driver for their increasing adoption. To begin, electric power generated from solar resources is renewable and sustainable, which is a major motivator for their growth among increasing global concerns about the environmental impact of fossil fuels and global warming. Second, DSG can increase the reliability of the electric power grid. This is a major advantage where electric power from the conventional electric grid is unreliable, i.e., there are frequent power outages. It is also important in locations that are threatened by natural disasters. As such, DSG can improve the resilience of the electric power grid (Driesen & Katiraei, 2008). Finally, installing DSG can be a feasible financial decision. The cost of solar PV has been decreasing gradually over the years, which increases their economic feasibility (Barbose & Darghouth, 2019). In addition, the cost of batteries has also been decreasing in the past years which enables storing power in absence of sunlight (Goldie-Scot, 2019). DSG systems can be especially feasible in locations where (1) sunlight is abundant; (2) the cost of conventional power from the grid is expensive compared to the cost of purchasing and maintaining a DSG system; and (3) there may be federal or governmental incentives that may help relieve the financial burden of purchasing and installing a solar system (Crago & Chernyakhovskiy, 2017). A combination of those reasons has led to increased adoption in some locations such as California for example (EIA, 2015). To conclude, DSG can have many benefits to consumers and can also have many broader economic benefits (Pitt & Michaud, 2015). Those benefits have been a motivator for their increasing adoption.

1.1.3. Barriers Caused by DSG Adoption. Despite its many benefits to consumers and broader motivators, the increasing adoption of DSG creates several concerns, , as shown in Figure 1.2, that are worth investigating. To begin, the adoption of DSG has created uncertainty in estimating future demand, whether on a day-ahead basis or in the long term. As such, system operators are faced with the problem of estimating future demand. Independent System Operators (ISOs) are regional organizations that coordinate and optimize generation across wide generation areas by matching generation and demand considering system capability and the stakeholders in the electric power market (Greer, 2012). The integration of DSG creates technical problems as concerned from the electrical engineering aspect (Milano et al., 2007; Mori et al., 2017). On the broader level, the growing adoption of DSG creates uncertainty in estimating future demand for ISOs to manage the electric power grid and the market. Also, the uncertainty in estimating future demand creates uncertainty in estimating long-term demand growth which is needed to plan for future grid expansion plans regarding generation, transmission, and distribution. Understanding the potential problems created by the increasing adoption of DSG requires an understanding of how wholesale power markets operate.

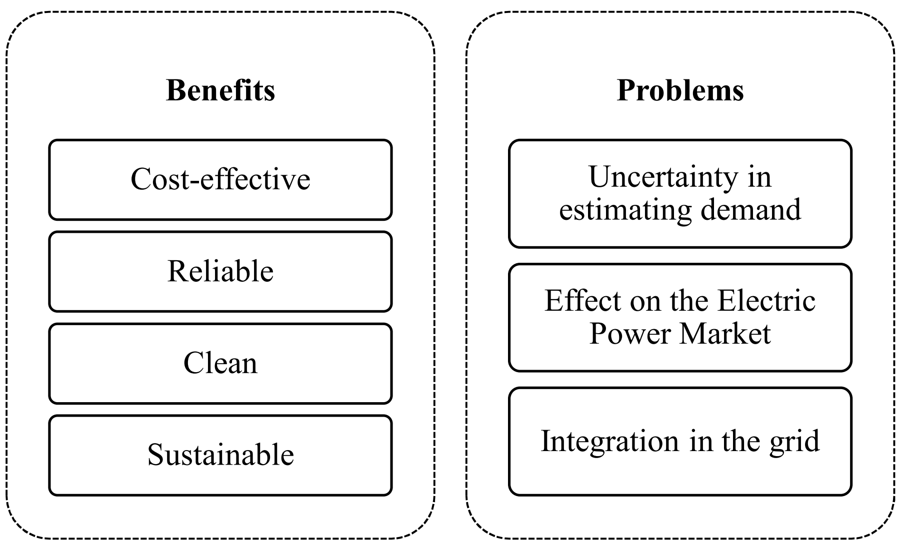


Figure 1.2. Benefits and problems associated with DSG.

1.1.4. Wholesale Power Market. In many geographic regions in the US, the wholesale power market is managed by ISOs or Regional Transmission Operators (RTOs), as shown in Figure 1.3. These markets include California Independent System Operator (CAISO), Midcontinent (MISO), New England (ISO-NE), New York (NYISO), PJM, Southwest Power Pool (SPP), and Texas (ERCOT). Other regions, which are the northwest, southwest, and southeast power pools are operated as traditional wholesale power markets. In such cases, the utilities operate the electric power system and provide power to consumers, i.e., the utilities own the generation, transmission, and distribution systems.

Figure 1.3. Wholesale power markets in the US (FERC, 2021).

The creation of ISOs was proposed and provided by the Federal Energy Regulatory Commission (FERC) in 1996 to manage the operation of the electric power market and provide non-discriminatory access to the grid for generators and customers (Greer, 2012). The ISOs manage and optimize the planning and transactions between sellers and buyers in the wholesale power market as illustrated in Figure 1.4.

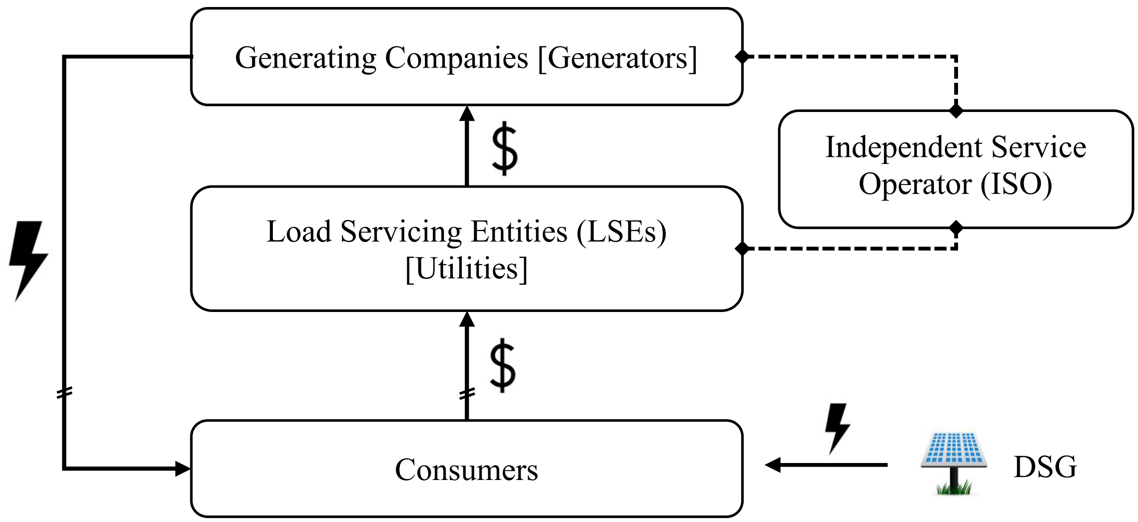


Figure 1.4. Illustration of a wholesale power market with DSG adoption.

Sellers are generating companies. Buyers are utilities or Load Servicing Entities (LSEs) that buy power from generating companies – and/or generate power at their owned generators – and sell electric power to the end consumers at homes, commercial customers, factories, etc. ISOs or RTOs operate by relying on Locational Marginal Prices (LMPs) at the location of injection or withdrawal from the electric power grid (Sun & Tesfatsion, 2007b). In other words, the price of power payable by LSEs or owed to generating companies depends on their location on the electric grid and the time of generation or consumption. This regional management and optimization task is managed by ISOs. Addressing the concern of the impact of the DSG on the electric power grid required an investigation of how DSG is integrated and interacts with the wholesale power market considering that consumers have the option to install DSG as shown in Figure 1.4.

1.1.5. Utility Death Spiral. With the growing adoption of DSG, concerns were made regarding the possibility of a "*Utility Death Spiral*", which refers to a continuous loop where companies would need to repeatedly increase electricity rates to cover the overhead cost of generation and transmission with lower demand for electric power (Denning, 2013). An illustration of the death spiral loop is shown in Figure 1.5.

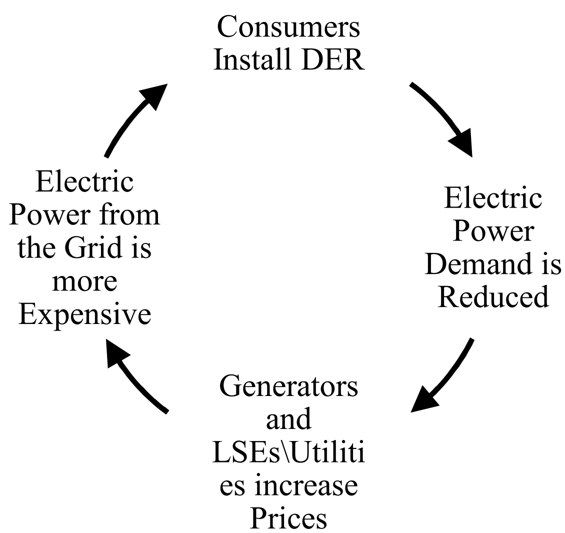


Figure 1.5. Illustration of a utility death spiral.

A utility death spiral is specific to market structures that rely on volumetric sales to cover the cost of operation and maintenance (Felder and Athawale 2014). As such, the concern is that the increasing penetration of DSG would be bi-directionally causing a continuous increase in electric power rates.

It is argued that a catastrophic death spiral would require a combination of high DSG adoption rates, increasing utility prices, and favorable consumer financials that is unique and not the general case (Laws et al 2017). Previous research has shown that the effect can be managed and is even unlikely to become catastrophic. For example, an agent-based simulation by Muaafa et al. (2017) showed that the sudden impact of a utility of a death spiral may be overblown and the DSG adoption is likely to increase smoothly rather than suddenly. Based on findings in previous research, it is expected that utilities will likely have enough time to revise their business models with innovative pricing structures controlling the rate of DSG adoption.

1.1.6. Effect of Pricing Mechanisms. In that matter, electric power companies are encouraged to replan their financials and consider innovative pricing mechanisms to consider and direct DSG adoption. With appropriate mechanisms and policy interventions such as time-of-use pricing and net metering, for example, the possibility of a death spiral can be circumvented and the rate of DSG adoption can be made sustainable and valuable to the resilience of the electric power grid (Castaneda et al., 2017; González & Rendon, 2022). Interestingly, pricing structures such as net metering which reward DSG adopters can reduce undesirable defection rates and the associated risk of a death spiral, while other pricing structures that do not compensate DG may accelerate defection from the grid (Laws et al., 2017).

A concern related to the increasing prices associated with the increasing DSG adoption is that customers who do not have DSG will be most affected as their electric bills would reflect a larger portion of the electric grid fixed fees, if calculated by demand volume, compared to DSG adopters. As such, non-adopters may be severely impacted by a utility death spiral. Other research suggests imposing buyback prices and subscription fees on consumers operating DSG to share the fixed cost of the electric power grid effectively alleviating the burden on utilities and slowing down or stopping a death spiral (Farajbakhsh Mamaghani & Çakanyıldırım, 2021). Fixed income-based charges and connection fees are also considered to improve energy equity while policy incentives such as net metering may increase disparity by favoring higher-income communities that can afford DSG systems (Chen et al., 2022).

1.2. PROBLEM STATEMENT

Many previous research efforts have investigated many aspects related to the electric power infrastructure and wholesale power markets with an emphasis on the effect of the increasing adoption of DSG. Research in that domain is guided by many different research fields and disciplines. However, there is still a need for a holistic exploration of the impact of DSG on the electric power infrastructure and how to capitalize on its benefits. Addressing this research need requires a multidisciplinary approach that combines infrastructure engineering, electric power engineering, economics, social science, and computer modeling. The following specific problem statements are addressed in this research.

1. There is a need to investigate the relationships and causality between electric power consumption and socioeconomic parameters such as Gross Domestic Product (GDP), human development, and corruption. Addressing this need would support the fact that the electric power infrastructure is a major element of the socio-econometrics of nations. Improving the condition of the electric power infrastructure is an important target for the nation.
2. There is a need to investigate the impact of DSG on the electric power infrastructure and markets as a complex System-of-Systems (SoS). The increasing adoption of DSG means that customers can choose to install DSG based on an economic decision comparing the price of conventional electric power from the grid vs the

cost of purchasing and installing solar resources. There is a need to simulate this relationship as a complex system, which would enable the exploration of DSG adoption and allow for further experiments.

3. There is a need to study how the increasing adoption of DSG interacts with pricing mechanisms by generating companies, and if this interaction may develop into a concerning utility death spiral. The concern is that a feedback loop may occur where, as consumers choose to install DSG systems, generating companies and utilities may need to increase electricity rates in response to reduced demand, which would motivate more DSG adoption. This behavior can be studied by simulating this complex relationship considering the profit-seeking behavior of generating companies.
4. There is a need to investigate how incentives that promote the installation of DSG affect their adoption rates, and how to capitalize on their benefits. The interaction between wholesale power market economics and DSG adoption is a complex relationship that may create behavior that is not necessarily simple or intuitive. As such, the effect of incentives can be studied using a complex simulation to study the locational effect of different incentives.
5. Finally, there is a need to investigate the benefits of DSG in decreasing the vulnerability of the electric power system to natural disasters. DSG can improve the reliability of the grid because it can supply power to consumers impacted by electric power interruption following natural disasters. Specifically, this part addresses the possibility of optimizing the location and size of DSG resources to mitigate the impact of natural disasters on transmission lines.

1.3. RESEARCH SIGNIFICANCE AND OUTLINE

This research is distinctive from similar research regarding focus, methods, and purpose. The framework proposed and applied in this research is intended to provide a holistic understanding of the effect of the adoption of DSG on the power infrastructure by developing a complex SoS that simulates agents in the electrical power infrastructure and market. This research combines multi-disciplinary perspectives from infrastructure engineering, electrical engineering, the economics of supply and demand, social sciences, complex systems simulation using ABM, optimization, and machine learning. The outcomes of this framework can assist researchers, system operators, and decision-makers in exploring the complex effect of DSG on the wholesale power market and infrastructure and promoting its sustainable diffusion. The research outline is divided into five parts as explained thoroughly in Table 1.1.

Table 1.1. Research objectives, methodologies, and outcomes.

Objective	***Methodology***	***Outcome***
Objective 1: Investigate the relationship between the electric power sector and socio-economic parameters.	Statistical Analysis using Panel Regression, Correlation Analysis, and Granger Causality Testing.	Developing an understanding of the relationships and causality between electric power consumption and socioeconomic parameters such as Gross Domestic Product (GDP), human development, and corruption.
Objective 2: Study the holistic effect of the adoption of DSG on the power infrastructure and market as a complex system.	Agent-Based Modeling (ABM) combined with Supply and Demand Economics and Optimal Power Flow Analysis.	Creating a complex System-of-Systems simulation that creates the emergent behavior of the impact of the penetration of DSG on the power infrastructure and markets.
Objective 3: Explore dynamic pricing in power market utilities considering the effect of the adoption of DSG and the emergence of a *Death Spiral*.	ABM and Machine Learning (ML) using Reinforcement Learning (RL).	Enabling the agents in the ABM model to dynamically price electric power and understanding the risk of a *Death Spiral* on electric power markets and infrastructure.
Objective 4: Examine the effect of policy incentives on the adoption of DSG.	ABM combined with Sensitivity Analysis of policy incentives to install DSG.	Analyzing and understanding the effect of policy incentives on consumer decision to adopt DER and its effect on the power infrastructure.
Objective 5: Inspect the benefits of DER in improving power system reliability against natural disasters.	ABM combined with Evolutionary Optimization and Reliability Testing.	Performing reliability testing and optimization of the amount and location of DER to mitigate the effect of natural disasters.

2. BACKGROUND

2.1. RELATIONSHIP BETWEEN THE ELECTRIC POWER SECTOR AND SOCIOECONOMIC INDICATORS

The International Energy Agency (IEA, 2020) estimates the electricity consumption of the world has increased from 10 GWh in 1990, to 24 GWh in 2018, which represents a huge increase of about 127%. Electric power is a critical commodity in the modern world. An interrupted supply of power is even indispensable for many industries and critical infrastructures such as medical facilities. Population growth, development, industrialization, and technological advancements are all some of the factors that magnify the growing demand for electric power. Several socio-economic factors are bi-directionally affected by the performance of the power sector. The following sections focus on three aspects: Economic Growth, Human Development, and Corruption.

2.1.1. Economic Growth. Many research efforts have shown that there is a relationship between electric power consumption and economic growth, represented by the Gross Domestic Product (GPD), and National Income. However, the findings are mixed regarding the relationship between them. For example, Shiu and Lam (2004) found that there is a unilateral causality between electricity consumption and the Gross GDP in China between 1971 and 2000. Ozturk and Acaravci (2010) found that there is no co-integration between energy consumption and the GDP in Albania, Bulgaria, Hungary, and Romania. Mozumder and Marathe (2007) showed a unilateral relationship between GDP and electricity consumption per capita in Bangladesh. Ghosh (2002) found a unidirectional causality between economic growth and electricity consumption in India. Altinay and Karagol (2005) found a unidirectional relationship between electricity consumption and income in Turkey. To summarize, many researchers discovered a link between electrical power consumption and economic growth. However, the outcomes of their causality are mixed.

2.1.2. Human Development. Numerous studies have looked into the connection between electrical energy use and human development and have discovered evidence of long-term causality. For example, Niu et al. (2013) conducted an analysis of panel data for 50 countries from 1990 to 2009, using proxies for human development, such as GDP per capita, consumption expenditure, urbanization rate, life expectancy at birth, and adult literacy rate. It was found that electricity consumption and human development cause each other in the long run, with varying trends for each indicator depending on the income of the country. In another research, Ouedraogo (2013) also found a long-term relationship between energy, electricity, and human development, after studying data from 15 countries between 1988 and 2008. Overall, previous research indicates that there is a long-term connection between electric power use and human development. Low-income nations appear to be significantly impacted by this relationship, whereas high-income nations may have adopted higher standards of human development and levels of electricity consumption that are less interdependent.

2.1.3. Corruption. Another area of research studied corruption and crime in the electric power sector. According to some estimates, a sizeable amount of electricity is produced but not billed because of fraud and theft and is instead recorded as power loss. Researchers have studied the effect of corruption in several countries around the world, such as Nigeria (Olukoju, 2004), Bangladesh (Alam et al., 2004), China (Yeh & Lewis, 2004), Lebanon (Abdelnour, 2003), and India (Min & Golden, 2014). For example, In Uttar

Pradesh, one of India's most populated cities, it is reported that a third of the electricity is never billed, summing up to about 300 million MWh. It is suggested that politicians benefit from relaxed power losses to win elections (Min & Golden, 2014). Although research indicates that there are theft-related power losses everywhere in the world, it is predictable that these losses are closely correlated with political instability, government inefficiency, and accountability (T. B. Smith, 2004).

2.2. PREVIOUS RESEARCH ON DER AND DSG

A significant amount of previous research from different perspectives and disciplines has been directed toward the uncertainties associated with DER, DSG, and related topics such as Microgrids and Virtual Power Plants (VPP) (Mahmud et al., 2020; Nosratabadi et al., 2017). Research from the electric engineering perspective has studied topics such as scheduling, grid control, and performance. Due to the increasing use of DSG, several optimization algorithms have been introduced to address the modified generation and consumption, using stochastic and deterministic formulations. Such models were developed to solve problems related to scheduling, uncertainty, demand response, emissions, and other aspects that are aggravated due to the adoption of DER and DSG (Nosratabadi et al., 2017; Pudjianto et al., 2007). Other research efforts focused on the aspects related to energy policies. Burger and Luke (2017) presented an empirical review of business models for deploying DER. The review shows that regulations and policies play a significant role in the viability of DER business models. The review advised avoiding regulatory and policy dependence. Many countries and states have some incentives that promote the installation of distributed solar resources. However, many policies and incentives are not perfectly implemented to achieve their intended goals. For example, the adopters in the US can benefit from the Federal Solar Investment Tax Credit, which is the main federal policy that supports Solar PV in the US (IRS, 2021a). However, most solar developers lack the tax liability requirement to fully utilize this tax credit (S. Zhang, 2016). Also, the broader policies and regulations related to electric power markets can be interdependent with the penetration of DSG such that the outcomes are unexpected. Electric power markets are currently designed for centralized power generators and distributors. However, DSG represents a shift to distributed local management, automation, and control, instead of centralized control requiring careful forecasting and planning of future DSG diffusion and its effect on the electric power market and infrastructure.

2.3. SIMULATION OF COMPLEX SYSTEMS USING ABM

Agent-Based Modeling (ABM) is one of the techniques for creating complex SoS simulations. An agent is defined as a simple system that (1) follows simple rules and behavior protocols, (2) interacts and affects the other agents in the SoS, and (3) adapts and learns (M. S. Eid & El-adaway, 2017c, 2017c, 2017e). The system results in complex emergent behavior that evolves from the interaction of the simple rules implemented into the agents. This enables a bottom-up approach to simulate complex SoS interdependency. ABM excels in creating an emergent behavior of the system as a whole from the bottom-up approach of defining multiple agents. This behavior can describe non-linearity, is not controlled by a single element, and is not necessarily easily deducted from the single components of the system (Siegfried, 2014).

ABM has proven applications in many fields, including systems engineering, social studies, economics, and many others. Previous papers have successfully integrated ABM to address research needs in several disciplines. An overview of research examples is provided in Table 2.1. ABM has also been proven as a technique to simulate wholesale power markets (Sun & Tesfatsion, 2007a, 2007b). In a wholesale power market, the electricity between the Generating Companies (GenCos) and the Load Servicing Entities (LSEs) is managed by an Independent System Operator (ISO). ISOs facilitate open access to transmission, operate the transmission system, and foster competition for electricity generation among the wholesale market participants. In other traditional wholesale power markets, utilities are responsible for system operations, management, and, typically, providing power to consumers (FERC, 2021). The shift to a decentralized, distributed, generation represents the shift towards a more complex system of systems, which can be simulated using ABM (Clausen et al., 2017; Howell et al., 2017).

Table 2.1. Example of previous ABM-related research in civil engineering.

Research Area	***Objective***	***References***
Infrastructure Management	Simulate and assess integrated management of infrastructure networks	(Batouli & Mostafavi, 2014; Bernhardt & McNeil, 2008; Pereyra et al., 2016)
	Test innovative financial structures for infrastructure projects	(Mostafavi, Abraham, & DeLaurentis, 2012; Mostafavi, Abraham, Delaurentis, et al., 2012; Mostafavi et al., 2014; Mostafavi & Abraham, 2010)

Table 2.1. Example of previous ABM-related research in civil engineering (cont.).

Research Area	***Objective***	***References***
Energy Conservation and Simulation	Model occupant behavior in buildings	(Abraham et al., 2018; Azar & Menassa, 2012)
	Study energy conservation in buildings	(Azar & Al Ansari, 2017)
	Model the interaction between occupants and appliances	(Carmenate et al., 2016)
	Investigate the effect of lightning sensors on energy use	(Norouziasl et al., 2019)
Transportation Engineering and Urban Planning	Create traffic simulations	(L. Zhang et al., 2013)
	Simulate roundtrip bus transit lines	(Huang et al., 2019)
	Study the interaction between travel behavior and urban forms	(Du & Wang, 2011)
	Study the effect of driverless vehicles on energy use, emissions, and parking use	(Harper et al., 2018)
	Assess walkability in cities	(Yin, 2013)
	Optimize road surface maintenance management based on travel time and maintenance costs	(B. Yu et al., 2019)
	Simulating electric vehicles such as investigating the patterns of electric vehicle ownership and driving activity to enable strategic deployment of charging infrastructure	(Sweda & Klabjan, 2015)
Water Management	Simulating water resources planning problems	(Berglund, 2015)

Table 2.1. Example of previous ABM-related research in civil engineering (cont.).

Research Area	***Objective***	***References***
Water Management	Investigate the effect of various factors such as demographics, household characteristics, and social influence on the adoption of residential water conservation technology	(Rasoulkhani et al., 2017, 2018)
	Assess the behavior of users for water demand management in river basins	(Xiao et al., 2018)
Project Scheduling, Performance, And Productivity Analysis	Simulate compensatory management to achieve distributed coordination of schedule changes	(Kim & Paulson, 2003)
	Study the impact of crew composition and project schedule on knowledge sharing and task durations	(Kiomjian et al., 2020)
	Simulate the interactions between construction crews for decision-making and performance analysis	(Kedir et al., 2020)
	Investigate the interaction of human and organizational factors to study construction performance	(Du & El-Gafy, 2012)
	Simulating randomness and uncertainty in crew performance and motivation	(Raoufi & Fayek, 2018, 2020)
	Evaluate collaboration between inter-organizational teams	(Son & Rojas, 2011)
	Simulate construction sites to evaluate labor efficiency	(Watkins et al., 2009)
	Evaluate the uncertainty and performance of integrated project management in complex projects	(J. Zhu & Mostafavi, 2015, 2016, 2018)

Table 2.1. Example of previous ABM-related research in civil engineering (cont.).

Research Area	*Objective*	*References*
Construction Safety	Simulating workers' unsafe behavior to study socio-cognitive processes and their interaction with the environment in shaping safety behaviors	(Choi & Lee, 2018)
Bidding	Study bidding strategies, interactions between bidders, and learning capabilities	(Ahmed et al., 2016; Asgari, 2016; Awwad et al., 2015; Elsayegh et al., 2020)
	Simulate negotiations in public-private partnership projects	(L. Zhu et al., 2016)
Disaster Management and Evacuation of Buildings	Investigate disaster recovery strategies and economic resilience	(Ahmed et al., 2016; M. S. Eid & El-adaway, 2017a, 2017b, 2017d, 2018)
	Study the impact of infrastructure service losses due to disasters on households	(Esmalian et al., 2019)
	Simulate the emergency response of ambulances during disasters	(Koch et al., 2020)
	Analyze building evacuation	(Z. Liu et al., 2016; Pan et al., 2012; J. L. Smith & Brokaw, 2012)

2.4. POLICY INCENTIVES FOR DSG IN THE US

There are many utility-wide, state-wide, and federal financial incentive programs in the US that are aimed to promote the installation and operation of renewable energy resources (EIA, 2013). Several incentives and examples are shown in Table 2.2. Federal incentives include production and investment tax credits. Production credits motivate the construction of power generation facilities that produce electricity using renewable energy resources. They grant qualified renewable energy generators a corporate tax credit amount per kWh. For example, electricity from wind, geothermal, and closed-loop biomass resources can receive tax credits up to 2.5 cents/kWh (EIA, 2020). Investment tax credits on the other hand allow for claiming tax credits for a percentage of the cost of installing a qualified renewable energy system. The federal residential solar energy credit implemented in the US provides a 26% tax credit for systems installed between 2020 and 2022, and 22% for 2023. The tax credit program will expire in 2024 unless it is renewed by congress again (Solar Energy Technologies Office, 2020). There are other types of rebates and tax credits that are offered in some states. These may include exemptions of DSG systems from property tax, or exemptions for the sale tax of DSG systems, which also ultimately reduce the cost of a DSG system. This research focuses on tax credits because they are easily available and can directly reduce the cost of a DSG system.

Table 2.2. Incentives applicable to DSG.

Type of Incentive	***Description***	***Example***
Production Tax Credit	Allows a taxpayer to claim against the production of power on a per-kilowatt-hour (kWh) basis using a qualified generating system by subtracting it from the federal or state taxes.	Federal Renewable Energy Production Tax Credit (IRS, 2021b)
Investment Tax Credit	Allows a taxpayer to claim an amount of the cost of the system by subtracting it from the federal or state taxes.	Federal Investment Tax Credit (IRS, 2021b)
Tax Exemption	Certified renewable energy systems may be exempt from property taxes.	New Jersey Property Tax Exemption for Property certified as renewable energy system (New Jersey Revised Statutes: Taxation, 2018)

Table 2.2. Incentives applicable to DSG (cont.).

Type of Incentive	***Description***	***Example***
Sales Tax Exemption	State sales tax exemptions for the purchase of renewable energy systems.	Sales and Use Tax Exemption for Renewable Energy Equipment in Washington State. (*Engrossed Second Substitute Senate Bill 5116*, 2019)
Net Metering	Allows consumers who generate excess electric power to "*credit*" or "*roll*" their extra generation to be used at another time such as the following month. Also, it may allow for cash reimbursement.	Net metering is allowed in the State of New York (N.Y. Pub. Serv. Law, 2012)
Feed-in Tariffs	Long-term purchase agreement to sell power generated at a guaranteed price.	The Renewable Market Adjusting Tariff (ReMAT) offered by the California Public Utilities Commission (CPUC, 2021)
Power Purchase Agreement	Long-term contract between a homeowner and an installer where the installer that owns the system, installs it on the homeowner's property and maintains it. The installer may be a third party. The owner buys power from the installer.	Offered as a financing option by several companies such as Siemens for example (Siemens USA, 2018).
Low-interest loans	Loans with low interests and innovative payment options to install DSG.	On-Bill Recovery, Smart Energy, and Companion loans offered by New York State Energy and Research and Development Authority (NYSERDA) (Hausman, 2016)
Community Solar	Solar programs or projects such as an offsite array can benefit many customers by buying or leasing a portion of it.	Washington DC's "Solar for All" Program which targets low to moderate income families (DOEE, 2022).

Table 2.2. Incentives applicable to DSG (cont.).

Type of Incentive	***Description***	***Example***
Renewable Energy Certificates (RECs)	Tradable certificates proving that 1 MWh of electricity was generated from renewable sources. They can be voluntary or a mandatory requirement for some electric companies.	RECs can be used to demonstrate compliance with renewable energy goals for Renewable Portfolio Standards (EIA, 2021b).

Two other forms of incentives are net metering and feed-in-tariffs, which are offered in some states or local utilities. Both allow owners of DSG systems to capitalize on power generation from their systems. The first type, net metering, allows the consumer to send their excess generation back into the grid. The excess generation is credited on a per kWh basis. The customer finally pays the net usage; receives credits that are rolled to the next month; or may receive payment for the excess power, depending on the applicable rules. The second, feed-in-tariffs, are agreements to sell power from a DSG system for a guaranteed price. These agreements are typically long-term and last several years. For example, 20-year feed-in-tariff agreements are offered in Florida (Queiroz et al., 2017). Another form of long-term agreement is Power Purchase Agreements (PPA), which are available for residential homes but is common in larger power generation projects. In a residential PPA, a third-party organization buys, installs, and maintains a generation system at the homeowner. The installer owns the system while the homeowner buys power generated by the system from the installed at a competitive rate according to a long-term contract. Accordingly, the homeowner is relieved from the burden of installing and maintaining the system. Low-interest loans with flexible payment plans are also offered by several organizations. For example, the New York State Energy and Research and

Development Authority (NYSERDA) offers On-Bill Recovery Loans up to $50,000 at 2.5% interest rates with monthly payments added to the electric bills. Another option offered by the NYSERDA is Participation Loans, where NYSERDA would fund 50% of the requested loan amount up to a maximum of $50,000 at 2% interest (Hausman, 2016; NYSERDA, 2021).

2.5. EFFECT OF INCENTIVES ON THE ADOPTION OF DSG

Initially, early adopters of DSG were motivated mainly by environmental and technical aspects; however, as the cost of PV systems has decreased significantly in the previous years, installing DSG is becoming a financially feasible option (Barbose & Darghouth, 2019). Incentives that promote the installation of DSG further motivate the decision to install DSG by reducing their costs. For example, in an empirical review of business models for deploying DER in general conducted by Burger and Luke (2017), it was found that regulations and policies play a viable role in the viability of business models for deploying DER, in addition to cost declines and technological innovations. In a survey conducted in Australia, it was found that 82% of the respondents installed a solar system for financial reasons (Simpson & Clifton, 2017). As such, incentives fortify a change from deciding to adopt DSG primarily for environmental reasons to a financial decision that is motivated by the savings from installing a DSG system.

Financial incentives can also improve the penetration of DSG in low-and-medium-income homes. In a study of four cities in the US (Riverside and San Bernardino, California, Washington, DC, and Chicago, Illinois), it was found that low-and-medium-income homes have high solar rooftop potential. However, they unsurprisingly have lower penetration of DSG compared to high-income households (Reames, 2020). Another study focused on California found that adoption rates are largely affected by race and income in addition to other factors such as political leaning, electric power consumption, and solar radiation (Bennett et al., 2020). Targeted financial incentives can thus reduce the disparity in access to DSG resources.

However, some obstacles are hindering incentives from achieving their ultimate policy goals. Research evaluating the effectiveness of over 400 state and utility incentives has shown that approximately 67% of them, which is nearly 1.9 billion USD spent over 11 years, did not increase the adoption of PV installations (Matisoff & Johnson, 2017). Incentives that offer a reduction in price at the point of purchase are more effective than incentives delivered over long-terms, require an administrative burden, or are not collected until taxes are paid (Matisoff & Johnson, 2017). In another study, it was found that states offering cash incentives, such as rebates, were more effective at increasing the adoption of PV systems compared to other states that do not offer cash incentives. Also, states that offer tax incentives did not necessarily have better rates of adoption compared to other states (Sarzynski et al., 2012). In another study focused on the northeastern states in the US, it was found that rebates had the highest effect of increasing the adoption of PV systems compared to other incentives (Crago & Chernyakhovskiy, 2017). In summary, incentives that directly decrease the cost of PV at purchase are more effective. Accordingly, this research considers rebates and tax incentives that directly reduce the cost of DSG. Also, the interest percentages on loans are considered since it reduces the financial burden of upfront costs.

2.6. DISASTER MANAGEMENT APPLICATIONS OF DER

The interrupted availability of infrastructure services is a necessity in the modern world. Some services and entities are especially critical, such as hospitals and communication for example. There are a variety of events that may disrupt the infrastructure, e.g., equipment failure, operational errors, or even sabotage. However, many catastrophic events are natural disasters, Acts of God, such as earthquakes, hurricanes, storms, tsunamis, etc. For example, Table 2.3 shows a summary of the frequency of blackouts, created by Hines et. al. (2008) using data from the Disturbance Analysis Working Group (DAWG) at the North American Electric Reliability Corporation (NERC, 2020); it can be seen that a substantial number of blackouts are caused by natural causes. Accordingly, the resilience and reliability of infrastructure is an ongoing pursuit of designers, operators, and researchers.

Many researcher efforts have been directed in the area of disaster management from various aspects, such as leveraging the use of Unmanned Aerial Vehicles (UAVs) (Erdelj et al., 2017), big data analysis (M. Yu et al., 2018), and social media analytics (Z. Wang & Ye, 2018). Researchers in electrical power engineering have investigated the reliability of the power infrastructure using DER, both pre-and-post- disaster. The concept is also associated with microgrids, which are networks that operate in parallel to the conventional power grid but can also be disconnected to operate in an "*island mode*". Thus, microgrids provide an effective method to reduce the consequences of natural disasters (Abbey et al., 2014; Nosratabadi et al., 2017; Y. Wang et al., 2016; Yuan et al., 2009). Nosratabadi et al. (2017) present a comprehensive literature review on the subject.

Table 2.3. Frequency of blackouts by category (Hines et al., 2008).

Cause	***Percentage of Events***	***Size of Blackout in MW***	***Number of Customers Affected***
Earthquake	0.8	1,408	375,900
Tornado	2.8	367	115,439
Hurricane/Tropical Storm	4.2	1,309	782,695
Ice Storm	5.0	1,152	343,448
Lightning	11.3	270	70,944
Wind/rain	14.8	793	185,199
Other Cold Weather	5.5	542	150,255
Fire	5.2	431	111,244
Intentional Attack	1.6	340	24,572
Supply Shortage	5.3	341	138,957
Other External Cause	4.8	710	246,071
Equipment Failure	29.7	379	57,140
Operator Error	10.1	489	105,322
Voltage Reduction	7.7	153	212,900
Volunteer Reduction	5.9	190	134,543

3. METHODOLOGY

The outline of this research is divided into five parts as previously shown in Table 1.1. To start, Part 1 is intended to establish the impact of electrical power markets on socio-economic parameters. In the following Part 2, an ABM model will be developed to simulate the effect of the adoption of DSG on the electrical power market. The ABM model created in Part 2 will form the basis for the following parts. Each part is intended to address a gap in knowledge concerning the effect of DSG on electrical power infrastructure and the wholesale power market by extending the capabilities of the ABM. A full description of the research plan for each objective follows.

3.1. RELATIONSHIP BETWEEN THE ELECTRIC POWER SECTOR AND SOCIOECONOMIC INDICATORS

This objective studies how the electric power sector development (i.e., electrical power consumption per capita and electrical losses during distribution) is associated with socio-economic indicators of economic growth, human development, and corruption, as shown in Figure 3.2. Statistical tests - including Pearson correlation analysis, linear regression, panel analysis, polynomial regression, and Granger-causality testing – are performed to investigate the aforementioned relationships. Ultimately, the relevant relationships that affect electrical power consumption and losses are identified. The findings should provide a holistic understanding of the complexity of the connection between the electric power sector and socio-economic parameters. The following subsections provide more details about the methodological steps in this research.

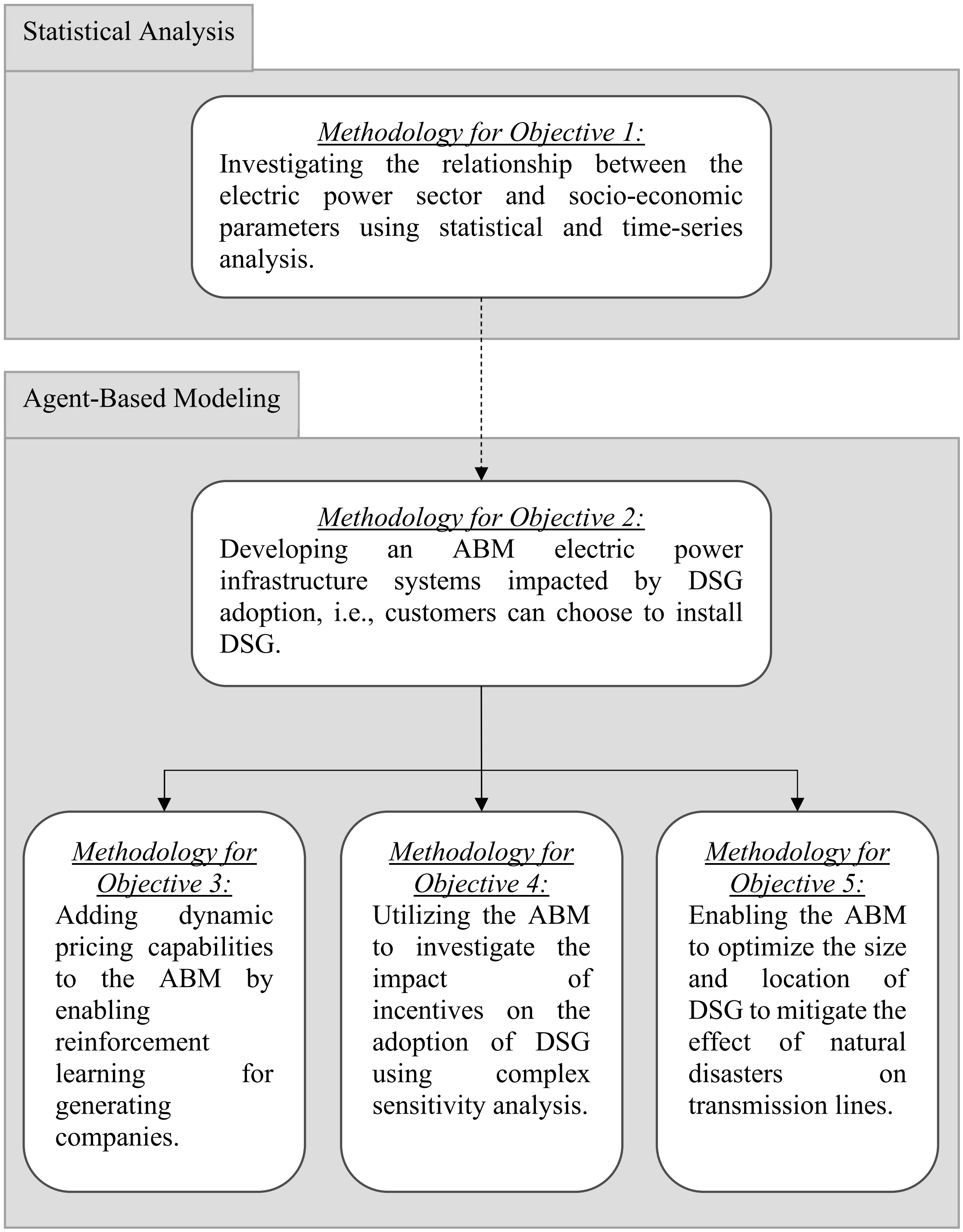


Figure 3.1. Flowchart of objectives and methodologies.

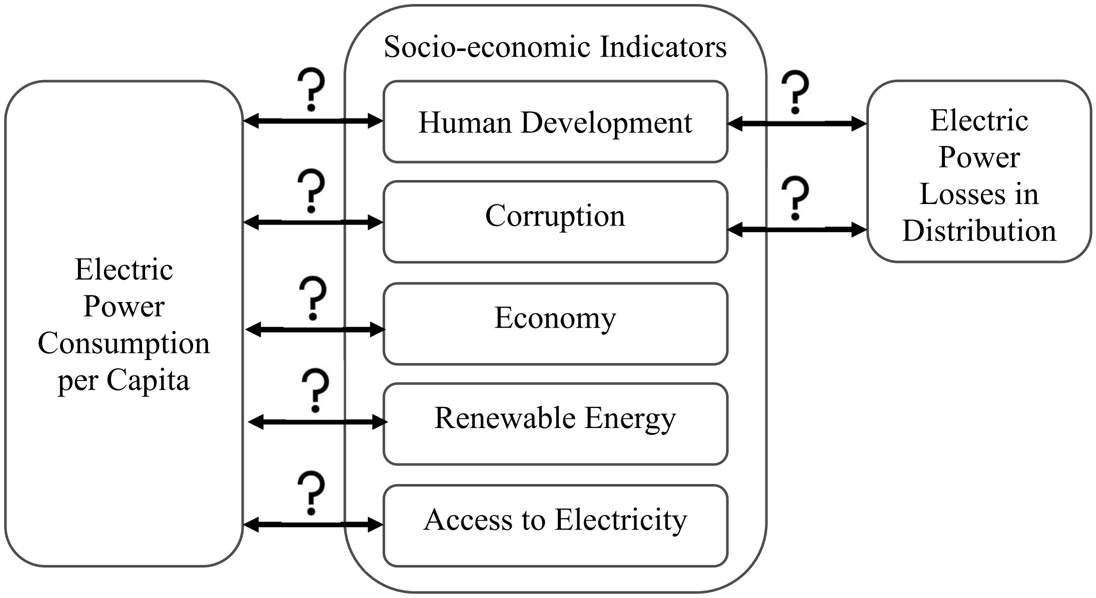


Figure 3.2. Socio-economic relationships examined.

3.1.1. Data Collection. The metrics included in the analysis cover the economy, development, and corruption. The data is publicly available online. The following are the metrics used in this research:

1. Electric Sector:
    1.1. Electric power consumption (kWh per capita) (The World Bank, 2019e)
    1.2. Electric power transmission and distribution losses (% of output) (The World Bank, 2019f)
    1.3. Renewable electricity output (% of total electricity output) (The World Bank, 2019j)
    1.4. Electricity production from renewable sources, excluding hydroelectric (kWh) (The World Bank, 2019g)
    1.5. Access to electricity (% of population) (The World Bank, 2019a)
2. Economic Performance:

2.1. GDP PPP Current International (The World Bank, 2019i)

2.2. GDP per capita (current US$) (The World Bank, 2019h)

2.3. Adjusted net national income per capita (current US$) (The World Bank, 2019b)

3. Human Development:

3.1. Human Development Index (HDI) (United Nations Development Programme, 2019) (Retrieved from the World Bank)

4. Corruption:

4.1. Corruption Index: (Transparency International, 2018)

4.2. CPIA transparency, accountability, and corruption in the public sector rating (1=low to 6=high) (The World Bank, 2019d)

4.3. Control of Corruption (Kaufmann et al., 2011; The World Bank, 2019c)

3.1.2. Correlation Analysis. Correlation analysis tests if any two variables have a linear relationship. The correlation results range between $+1$ and -1, where a value of $+1$ means that the variables have a perfect linear relationship, and a value of -1 means that the values have a perfect negative linear relationship. A value of zero means that there is no relationship between the variables. Correlation analysis was used in many research publications. Examples include correlating between initial capital costs and lower long-term life cycle costs for private financial initiative projects in the UK (N. Wang, 2014), studying the success factors in design-build projects (Chan et al., 2001), examining the relationship between organizational learning styles and project performance (Wong Peter Shek et al., 2009), among many others.

3.1.3. Regression Analysis. A thorough regression analysis is conducted using a variety of panel data analysis techniques. Panel data, or longitudinal data, is a multidimensional approach that combines cross-sectional and time-series data (Greene, 2018). The data set used in this research is collected across different countries and years. The general structure of the panel data is shown in Table 3.1. To take advantage of the panel data, this research applies (1) Pooled OLS, (2) Random Effect Model, (3) Fixed Effect Model with Time Effect, (4) Fixed Effect Model with Entity Effect, and (5) Fixed Effect Model with Time and Entity Effect. The results of each model are compared to each other in order to determine the relationship between each of the variables and the dependent variable. A more detailed explanation of panel analysis concepts follows.

Table 3.1. Structure of the panel data.

Country	*Year*	X_1	X_2	Y
Country 1	Year 1	…	…	…
	Year 2	…	…	…
	…	…	…	…
Country 2	Year 1	…	…	…
	Year 2	…	…	…
	…	…	…	…
…	…	…	…	…

3.1.3.1. Pooled OLS. Pooled Regression using Ordinary Least Square Method is the simplest form of regression for panel analysis. It is performed with a single intercept (α) and slope (β) for all the data. Therefore, it does not take into consideration variations across time or entities. The formula for Pooled OLS is shown in Equation (3.1).

$$y_{it} = \alpha + \beta\, x_{it} + \epsilon_{it} \tag{3.1}$$

For entity i; time t

3.1.3.2. Fixed Effects Model (FEM). If there are unobserved variables affecting the model, and these effects are correlated with x_{it}, then the Fixed Effects Model (FEM) is more suitable for analyzing a dataset. This model takes into consideration the unobserved fixed effect as an entity-specific effect by including α_i as shown in Equation (3.2), or time-specific by including γ_t as shown in Equation (3.3), or both entity and time effects as shown in Equation (3.4). It should be noted that a fixed effect model without the inclusion of any effect would be reduced to the previously mentioned Pooled OLS. The meaning of time-specific effects, for the scope of this research, are effects that change over the years for all countries, like for example introduction of new technologies, world economic conditions, etc. On the other hand, entity-specific effects would mean unobserved factors that are unique to each country like political, cultural, or geographical parameters, for example. The equations for fixed effects model with different effects are as follows:

- Fixed Effect with Time Effect

$$y_{it} = \gamma_t + \beta\, x_{it} + \epsilon_{it} \tag{3.2}$$

For entity i; time t

- Fixed Effect with Entity Effect

$$y_{it} = \alpha_i + \beta\, x_{it} + \epsilon_{it} \tag{3.3}$$

For entity i; time t

- Fixed Effect with Time and Entity Effect

$$y_{it} = \gamma_t + \alpha_i + \beta\, x_{it} + \epsilon_{it} \tag{3.4}$$

For entity i; time t

3.1.3.3. Random Effects Model (REM). The Random Effects Model (REM) is suitable in case the unobserved heterogeneity is uncorrelated with x_{it}. The REM assumes that the unobserved parameters affecting the model are random. The main difference between REM and FEM is therefore whether the unobserved heterogeneity is uncorrelated or correlated, respectively. The formulation in this research uses a one-way REM, which has the same formulation as the FEM with entity effects as shown in Equation (3.3).

3.1.4. Granger-Causality Testing. The goal of the Granger-causality test which was created by C. Granger (1969) is to find whether a time series has a causality effect on another time series. In other words, it tests whether a change in a time series causes a change in another time series. The general representation, for two time series $y_{1,t}$ and $y_{2,t}$, and lag order p is shown in Equation (3.5) (Lütkepohl et al., 2004). If $\propto_{12,i} = 0$, then this confirms the null hypothesis of the Granger-Test that y_{2t} does not Granger-cause y_{1t}.

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \sum_{i=1}^{p} \begin{bmatrix} \propto_{11,i} & \propto_{12,i} \\ \propto_{21,i} & \propto_{22,i} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + u_t \qquad (3.5)$$

Where: $i = 1,2, \dots, p$; and,

$\propto_{12,i} = 0$ if y_{2t} *does not Granger cause* y_{1t}.

Granger causality testing was used in many previous research applications. Examples include stock analysis (Hiemstra & Jones, 1994), forecasting the Engineering News Record Construction Cost Index (Shahandashti S. M. & Ashuri B., 2013), predicting raw material prices (Lee Chijoo et al., 2019), residential and non-residential investment's relationship with the GDP (Green, 1997), and others. It is suitable for the econometric analysis of the time series in this research part.

3.2. DEVELOPMENT OF THE ABM

The methodology of Objective 2 revolves around developing the ABM. In the following objectives 3, 4, and 5, different additions are built onto the ABM to enable the capabilities needed for each objective. The methodology in this section is focused on how the ABM is developed.

3.2.1. Overall Model Development Process. The complex SoS simulation was developed based on concepts from ABM combined with DC-OPF. Such integration attempted to attain important capabilities including power market settlement as a deregulated wholesale power market with hourly-based Locational Marginal Prices (LMPs) and consumer behavior based on the economic feasibility of installing DSG. As such, the development of the model followed a multi-step methodology, as shown in Figure 3.3, that comprised: (1) creation of the ABM model and DC-OPF solver; (2) calculation of the demand parameters for the LSEs; (3) calibration of the model to reduce the gap between the results of the model and historical real-life data; and (4) formulation of the consumer decision algorithm to adopt DG.

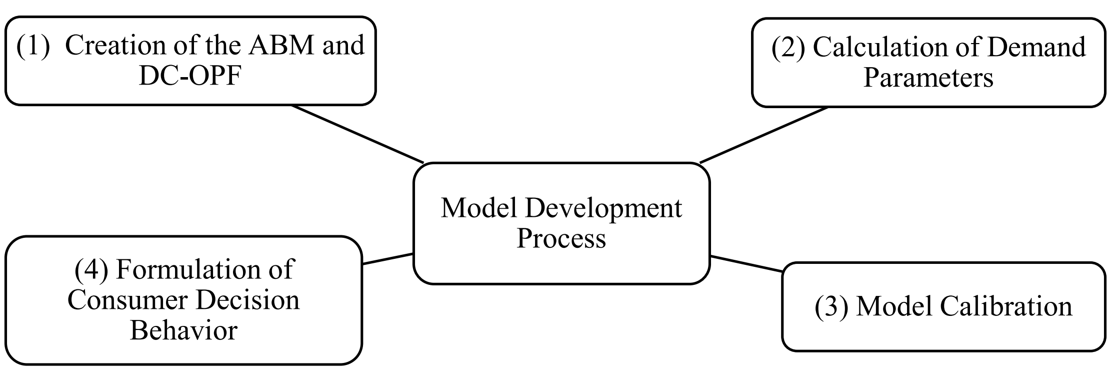


Figure 3.3. Model development process.

3.2.2. Application Domain. A case study is used as the application domain for the model to achieve the following objectives: (1) verify that the model can achieve the required functionalities; (2) ensure that the model can be applied to other specific cases after modifying its input parameters; and (3) disseminate the results to demonstrate the effect of incentives on electric power grids and markets. The configuration of the grid is a modified IEEE 6-bus system as shown in Figure 3.4 (Khurshaid et al., 2019; Tungadio et al., 2015). Previous research has used 6-bus systems as a case study for many topics such as optimizing reactive power (Mantawy & Al-Ghamdi, 2003; Sharma et al., 2012) and resilience evaluation (Panteli & Mancarella, 2017; Yang et al., 2018), among others. They were also used in cases specifically related to distributed generation such as optimizing reactive power flow for electric power distribution systems with integrated distributed generation (Leeton et al., 2010); or energy management of integrated power infrastructure and gas networks with renewable energy sources (Nazari-Heris et al., 2020). As such, a 6-bus system is considered a feasible case study for this research. A 6-bus system enables an easier understanding of the results while avoiding unneeded complexity. Still, the model can be easily scaled to larger networks by adding more nodes, transmission lines, LSEs, and generators.

The locations and types of generators are designed to diversify their effect on the market. The generation parameters are calculated from data acquired by the authors from the Tennessee Valley Authority (TVA). Electric power consumption published by the US Energy Administration Agency (EIA, 2020) is used to define electric power demand amount and cost per customer. The calculations of the size and cost of DSG systems are explained in later sections and are based on multiple sources and publications including the National Renewable Energy Laboratory (NREL, 2021), Barbose et al. (2019), BloombergNEF (Goldie-Scot, 2019), Hyder (2021), McCloy (2019), Haruna et al. (2011), and Sarre et al. (2004). It should be noted that the case study (1) does not represent a limited geographic location; (2) represents an average US electric power market based on the data used to create the model; (3) is primarily intended to verify that the model can achieve the required functionalities and provide indicative results showing the effect of incentives on electrical power grids and markets; and (4) can be modified to other electric grids in targeted geographic locations and market conditions.

The configuration of the grid is shown in Figure 3.4. It includes six nodes, five generators, six LSEs, and seven transmission lines. The transmission lines connecting the nodes have a maximum capacity of $450\ MW$ each and reactance of $35\ \Omega$. The reactance values affect the flow of power in the lines, more specifically reactive power losses. The LSEs and the generators are each connected to a node. Each LSE initially has 400,000 customers that do not have DG. Customers may detach from their LSEs if they decide to install DG, which affects the cumulative customers and demand requirements at the LSE level. The parameters for the demand are based on real data published by the EIA (2020) and are elaborated in a subsequent section. The parameters for the generators are shown in Table 3.2. The parameters a_g and b_g define the cost function of the generations as will be explained in a subsection in the methodology about the DC-OPF formulation. The parameters are based on the types of the generators such as natural gas, coal, or nuclear. The parameters are based on data acquired by the authors from the Tennessee Valley Authority (TVA) and calibrated as explained in a respective sub-section of the methodology. The calculation of the power flow in the network is performed using DC-OPF, which is explained in a respective subsection later.

Table 3.2. Initial generation parameters.

Generator	***Type***	a_g $(\$/MW.h)$	b_g $(\$/MW^2.h)$	***Max Capacity (MW)***
1	Natural Gas	175.048	0.000967361	700
2	Coal	80.623	0.001198895	450
3	Nuclear	22.054	0.000095802	2,000
4	Coal	80.623	0.001198895	240
5	Natural Gas	175.048	0.000967361	700

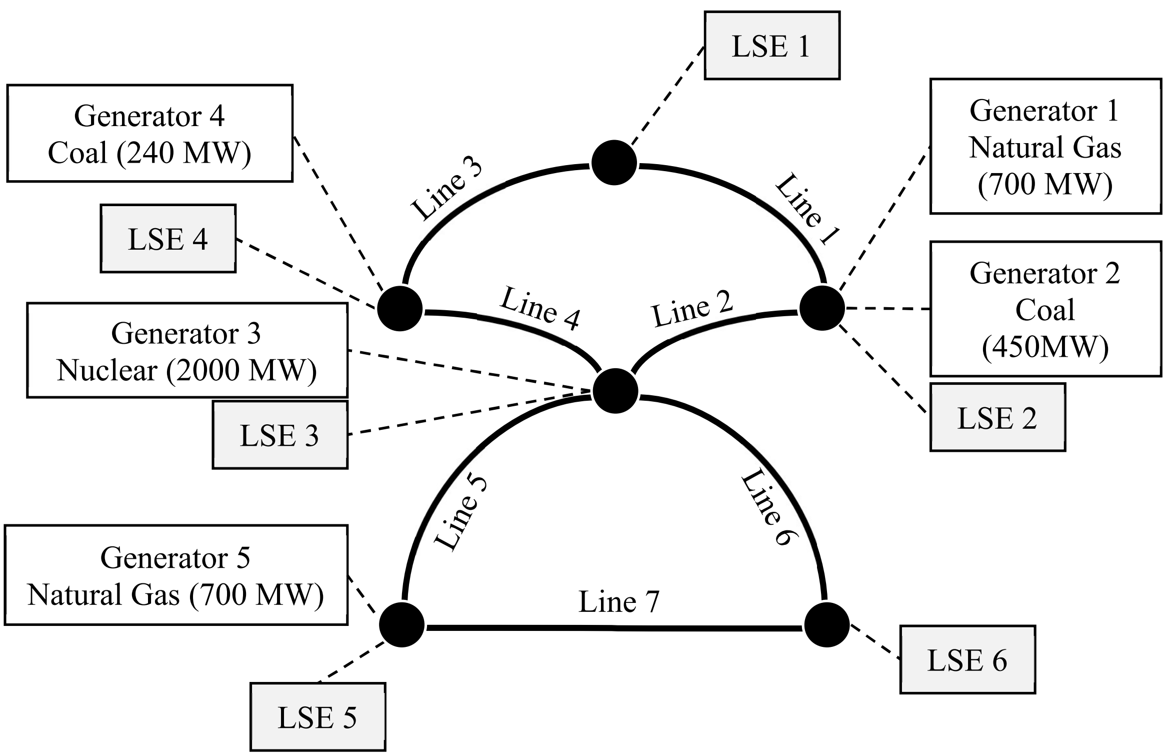


Figure 3.4. Grid layout.

3.2.3. Main Model Components. The framework created in this research simulates a complex SoS. The framework relies on several sub-systems which together result in complex emergent behavior, as shown in Figure 3.5. At the center of the framework is the ABM. Agents, or classes, include (1) Nodes, which represent buses in the electric network; (2) Generators, which supply power to the network; (3) Load Servicing Entities (LSE), which represent the utilities that buy power for their customers; and (4) Transmission Lines which are connected to the nodes.

To create the dynamic response of the market considering the adoption of DSG, the LSEs are connected to three modules, shown in the bottom right part of Figure 3.5; (1) Sub-functions to update the demand parameters of the LSEs depending on the number of customers that are still connected to the grid; and, (2) Investment Decisions: a module that defines investment decision rules that enable consumers at LSEs to decide whether to install DSG depending on the current locational price of electric power and cost of the alternative opportunity, which is to install DSG; and, (3) Price of Solar Panels: a module where the investment to install DSG is calculated through a separate sub-model that predicts the cost of PV systems using historical data.

At a higher level, an optimization problem is formed to calculate the optimal power flow through the network. At every hour of the simulation time, the "*interface*" transforms the parameters of the ABM into parameters that are fed into the power flow solver (DC-OPF) and then feeds back the results of the solver into the agents in the ABM. The following sections describe each part of the framework in depth.

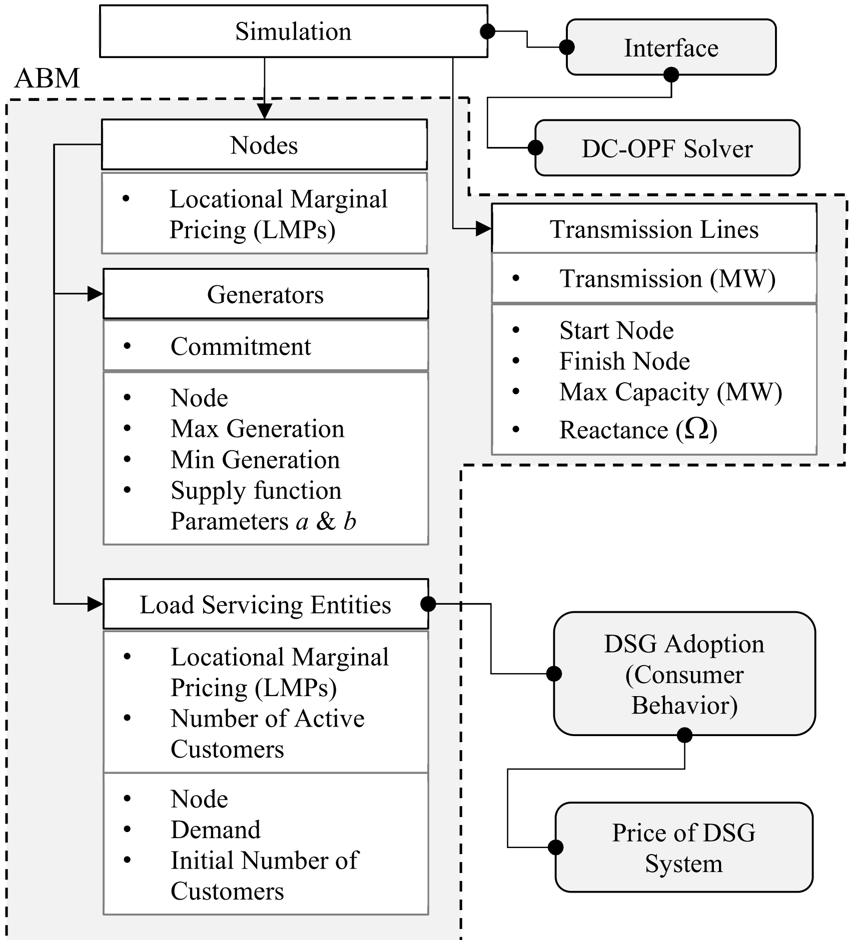


Figure 3.5. Main components and agents in the ABM.

The agents in the ABM are classes that represent the main "*players*" in the wholesale power market. The agents are connected so that they can communicate and access the parameters of each other. The parameters of each agent are shown in Figure 3.6. By using simple rules for each agent, the simulation results in emergent behavior, allowing for a bottom-up approach to simulate the complex system. The types of agents include (1) Nodes (or buses), (2) Generators, (3) Load Servicing Entities (LSEs), and (4) Transmission Lines. Nodes represent end locations for electrical power transmission, i.e. a city or town.

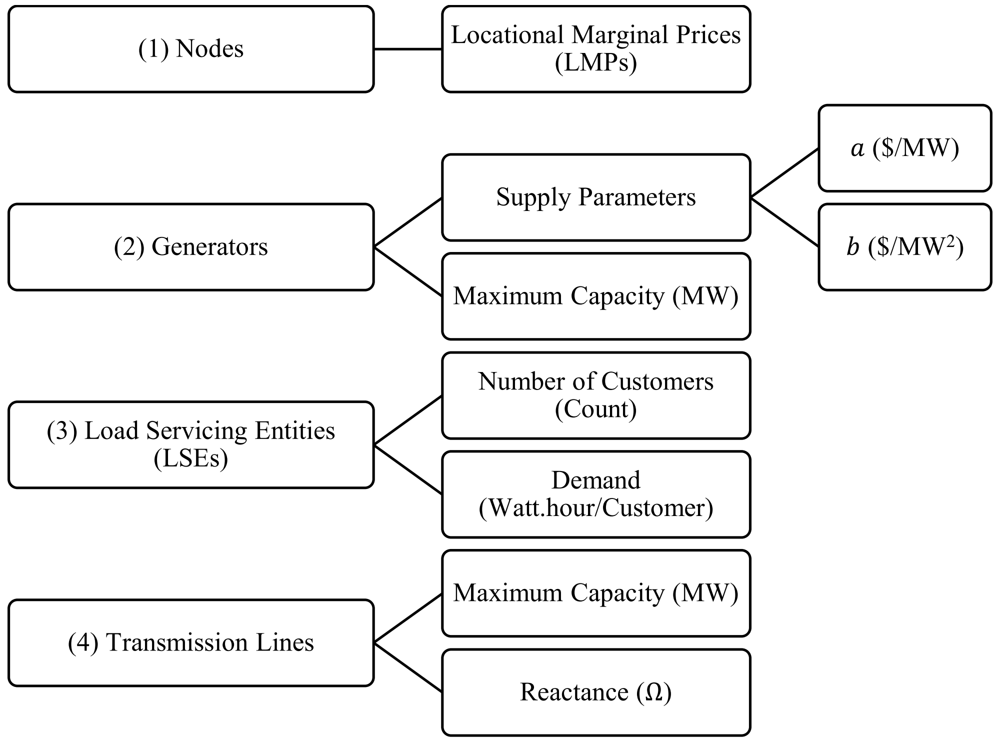


Figure 3.6. Model parameters.

By calculating the DC-OPF solver, which is described in a later section, Locational Marginal Prices (LMPs) are calculated based. The reason that LMPs are used in the wholesale power market is that they account for transmission congestion and rules of supply and demand according to the location of injection or withdrawal. Therefore, each node may have different LMPs depending on grid parameters (connectivity and capacity), power demand (which changes during the day), and supply. Generators represent generating companies, which sell power to the grid. Each generator has a supply function, defined in the model by parameters a and b, which determine its willingness to sell electric power, i.e. the variable price of power generated. Each generator also has minimum and maximum generation capacities. LSEs represent local utilities, which buy electric power from generators and supply it to end-users. Each LSE has a demand function, defined by parameters c and d, which, opposed to generators, define their willingness to buy electric power. Each LSE has an initial number of customers, who are connected to the grid and buy power from the LSE. During the simulation, the number of customers at each LSE is affected by the customers' decision to install DSG and detach from the grid, effectively ceasing to buy power from the LSE. As such, the demand functions of the LSEs are updated according to the number of active customers. Each LSE also has variable demand boundaries which are also affected by the number of active customers. Finally, transmission lines connect the nodes. Each line has two main parameters; the reactance (Ω) and maximum capacity (MW). Both parameters affect the flow of electricity in the network and ultimately impact the LMPs at the nodes.

As previously mentioned, the agents are connected, communicate, and adapt. In this model, the number of active customers is affected by their decision to adopt DSG and detach from the grid. This decision is affected by the LMPs at the node agents. The number of customers affects the demand parameters of the LSE agents. The collective parameters of the agents, including the supply, demand, and transmission parameters, are used in the DC-OPF solver. The agents are updated based on the results of the solver, and the loop is repeated until the simulation is stopped.

3.2.4. Grid Layout Agents and Economic Agents. The agents in the ABM developed in this research are defined according to the design of a wholesale power market. As shown in Figure 3.7, the economic entities are the stakeholders in a wholesale power market and the main agents in the ABM. Those agents include the generators and the LSEs. The generators represent the supply part of the economic market. They have pre-defined supply parameters that represent the cost they expect for generating power into the electric grid and their maximum generation capacity. The parameters of the generators depend on their types, e.g., coal, natural gas, or nuclear. The LSEs represent the demand side of the market. Each LSE has a pre-defined initial number of customers that do not have DSG systems and therefore rely on electric power from the grid. The demand from LSEs is the cumulative demand of their customers who have not installed DSG and defected from the grid yet. It is assumed that each month, customers will decide whether to purchase and install a DSG system and defect from the grid. Accordingly, the demand from the LSEs will reduce and consequently affect the entire grid. More details regarding those algorithms are presented in subsequent sections.

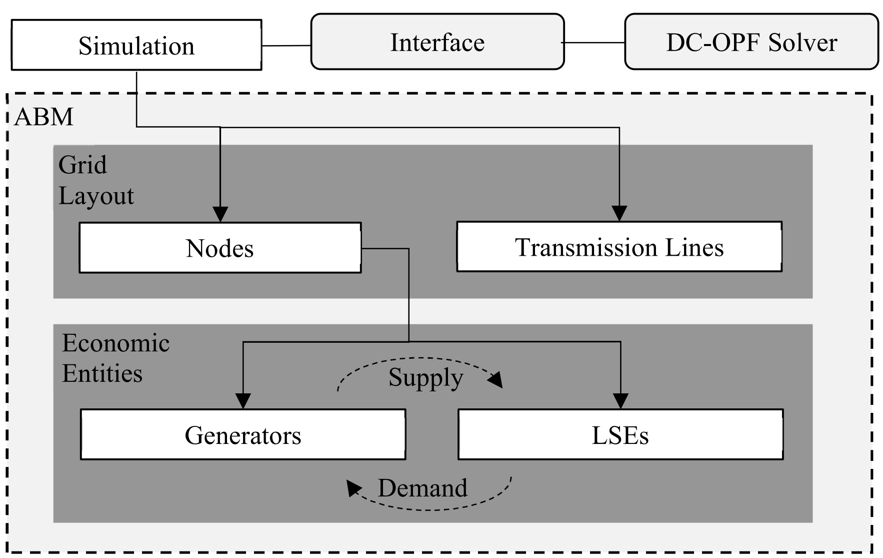


Figure 3.7. Relationships between the agents.

The second agent type includes grid layout agents, which are the nodes and the transmission lines. Nodes represent locations on the grid such as cities or towns. The nodes are connected by transmission lines. Each transmission line has a reactance and maximum capacity. The values of the reactance affect the flow of power through a transmission line, specifically they affect the flow of active and reactive power. Ultimately, the simulation is connected to a DC-OPF through an interface that encodes the data in the ABM into parameters for the DC-OPF, solves for the cost-minimizing flow of power and LMPs in the network, and feeds back the results into the ABM at every iteration, which represents an hour in real-time.

3.2.5. Power Flow Optimization. Planning and managing electric power grid resources requires the optimization of resources and is covered by a plethora of research (Frank & Rebennack, 2016; Padhy, 2004; Sheblé, 1999). A simple can be formulated as an Economic Dispatch (ED) problem. It optimizes the allocation of generators considering their generation cost by minimizing overall network costs. However, there may be a need to consider many additional constraints depending on the planning horizon and the required level of complexity. For example, there may be a need to consider when to start and shut down generators considering the associated minimum uptime/downtime time and startup costs, which extends to a Unit Commitment (UC) problem. There are also additional generation constraints that can be considered such as ramp rates which define the maximum change of generation output over time. There is also a need to consider transmission properties and constraints. At the least, there may be a need to consider the maximum operational capacity of transmission lines. There is also a need to consider transmission losses. Such requirements for more detailed analysis develop into Optimal Power Flow (OPF) problems which also have many variations in formulations (Wong, 2011). In this research, a DC Optimal Power Flow (DC-OPF) formulation adopted by Sun and Tesfatsion (2006) is used because it fits the requirements of the developed model for the following reasons: (1) It determines the optimum allocation of generators considering their cost parameters and maximum capacities; (2) It calculates the power flow in transmission lines considering their maximum capacities and reactance which is important to study the effect of transmission line failure during natural disasters; (3) It minimizes losses using a penalty function; (4) there is no need to consider time-dependent constraints such as ramp rates; and (4) it is computationally fast enough considering that large numbers of iterations are required for the DSG optimization performed in this research.

3.2.6. Formulation of DC-OPF. DC-OPF is an optimization problem used to calculate the commitment of each generator, the flow through the transmission lines, and the LMPs at the nodes. It is a simplification of the more tedious AC-OPF problem, which makes it less computationally expensive and suitable for long-term simulations of wholesale power markets. The DC-OPF formulation used is adapted from Sun and Tesfatsion (2007a, 2007b). The objective function of the DC-OPF is to minimize the total generation cost, as shown in Equation (3.6). In practice, a wholesale power market is settled through an Independent Service Operator (ISO) using the supply and demand offers received from the generating companies and the LSEs, respectively. The objective function is shown in Equation (3.6) also minimizes the phase angles (δ) between the nodes using a penalty constant (π) to minimize the reactive power losses in the system (Sun & Tesfatsion, 2007b). The equality constraint shown in Equation (3.7) represents the node balances where, for each node k, where P_j is the demand for each LSE, P_g is the commitment for each generator, and P_{km} is the power flow through all the lines connected to the node. The inequality constraints are the generation capacity for each generator as shown in Equation (3.8), and the maximum capacity of each transmission line km as shown in Equation (3.9).

Ultimately, the DC-OPF calculates the commitments of the generators (P_g) and the line flows (P_{km}). Also, the LMPs at each node are calculated using the Lagrangian of the equality constraint in Equation (3.7). The DC-OPF is solved using the Dual Stage Optimization method (Goldfarb & Idnani, 1983). The results of the DC-OPF are calculated at every hour of the simulation and fed back into the agents in the ABM.

$$Minimize\colon\ a_g \cdot P_g + b_g P_g^2 + \pi \left[\sum_{km} [\delta_k - \delta_m] \right]^2 \tag{3.6}$$

Subject To:

- Node Balance Constraints for each Node (k):

$$\sum_{j \in J_k} P_j - \sum_{g \in G_k} P_g + \sum P_{km} = 0 \tag{3.7}$$

- Generation Constraints for each Generator (g):

$$Cap_{g,min} \leq P_g \leq Cap_{g,max} \tag{3.8}$$

- Transmission Line Constraints for each Transmission Line (km):

$$|P_{km}| \leq P_{km_{max}} \tag{3.9}$$

3.2.7. Equilibrium of Supply and Demand. The demand parameters in the developed model assume that each customer has a fixed average demand represented by a vertical demand curve. This follows the logic that electric power is price-insensitive in the short term as proven by previous research (Burke & Abayasekara, 2018; Lijesen, 2007). The supply offers are calculated using the generation parameters for the generators, which are also calibrated as explained in detail in a later section. The equilibrium of supply and demand, determined using the DC-OPF problem, identifies the equilibrium amount of power and prices, as illustrated in Figure 3.8. The agent-based behavior continuously affects the equilibrium of supply and demand. First, on the supply side, the consumer decision to adopt DSG is based partially on the LMPs at each node and affects the cumulative demand requirements at the LSE level. As shown in Figure 3.8, a shift in demand will occur when consumers adopt DSG. The behavior of the supply side is determined by the Reinforcement Learning (RL) pricing algorithms used by the generators which learn from the market behavior and modify their supply offer curve as will be explained in another part of this dissertation. The shift in supply and demand is resulting in lower power generation and higher prices as shown in Figure 3.8. This feedback loop between the LSEs and the generators enables a complex system behavior and provides insight into how power markets are impacted by the adoption of DSG.

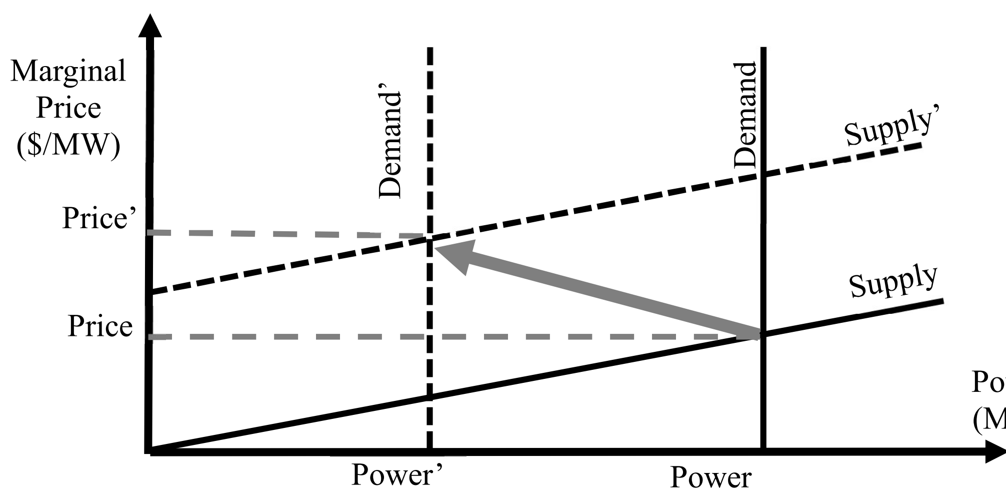


Figure 3.8. Equilibrium of supply and demand.

3.2.8. Demand Parameters. The amount of power consumed by each customer is calculated based on publicly available data published by the EIA (2020). The data includes monthly electricity demand quantities, electricity rates, and the number of customers. A histogram of the residential hourly sales per customer, calculated from the monthly sales and number of customers, is shown in Figure 3.9. The data for the residential sector in all states in the US was used to calculate the mean demand per customer, which was found to be 1.283 KWh/Hour/Customer. This translates to a monthly average of approximately 923 KWh/Month/Customer.

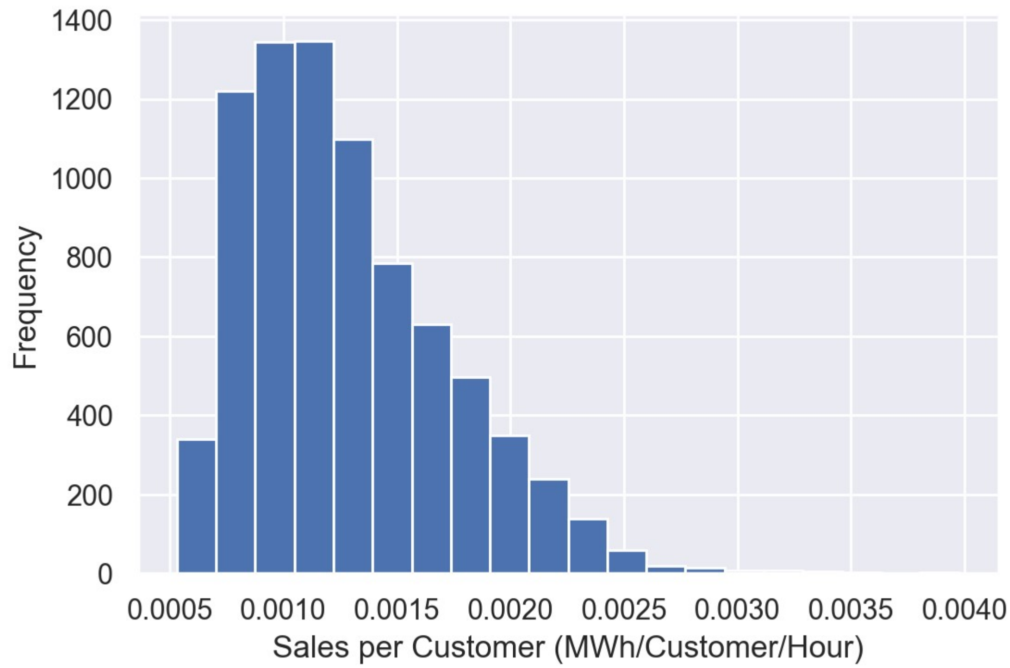


Figure 3.9. Hourly sales per customer.

The averages shown in Figure 3.9 represent hourly sales per customer without intra-day variations. To account for that, the function was fitted to create an hourly factor to convert the average daily demand into a more accurate real-time hourly demand. The function was fitted using data available from the EIA (2020) using a cosine function, shown in Equation 5 where h is the hour such as $0 \leq h \leq 23$. The fitted function has an R^2 score of 0.99. Accordingly, the function shown in Equation (3.10) and Figure 3.10 is applied to the numbers shown in Figure 3.10 to create intra-day variations in the demand. Finally, the average hourly consumption per customer, the intra-day hourly consumption curve, and the number of customers for each LSE are grouped into (3.11), where C_j is the number of active customers for each LSE j.

$$Factor_h = 0.240 \times \cos(0.261 \times h + 1.742) + 1 \tag{3.10}$$

$$P_{j,h} = 0.001283 \left[\frac{MW}{Customer \cdot Hour}\right] \times [0.240 \times \cos(0.261 \times h + 1.742) + 1] \times C_j \tag{3.11}$$

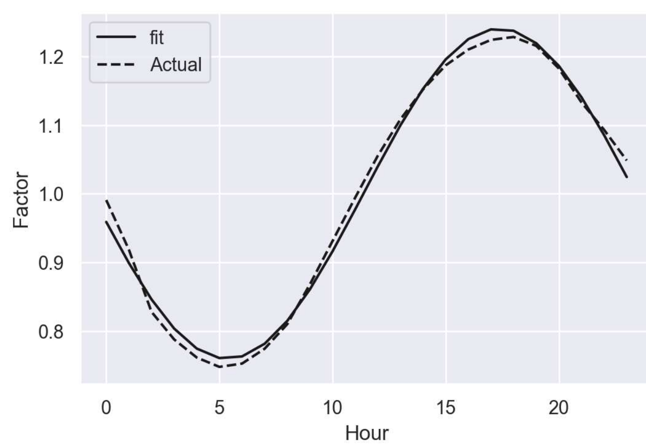


Figure 3.10. Intra-day variation in demand.

3.2.9. Calibration of the Supply. Simulations developed using ABM offer flexibility and complexity. However, there is often a need to conduct parameter calibration to close the gap between the results and real-world data. As ABM simulations grow in complexity, the task of calibrating its parameters can be tedious (Lamperti et al., 2018). In the model developed in this research, there is a need to reduce the gap between the LMPs calculated from the model and real-world electric power rates. This is a necessary step so that the subsequent consumer decision to adopt DSG can be based on realistic electric power rates. As such, the calibration step accounts for the difference between the costs incurred by the generators and the final prices paid by the customers. It is set up as an optimization problem such that the objective function is to reduce the squared difference between the average LMP for the grid and the target price. The decision variables are the generator supply parameters. The previously shown generation parameters in Table 3.2, estimated using data acquired from the Tennessee Valley Authority (TVA), only represent the cost of generation. However, the parameters do not include additional costs that influence end-user prices such as transmission and distribution network charges and taxes, in addition to the actual cost of power (C. Eid et al., 2016; Pront-van Bommel, 2016). Such financial costs, as well as environmental impacts, are increasingly measured and controlled using cyber-physical systems (Mulrow et al. 2021). As such, the supply parameters are identified as the target of the calibration. The decision variable is assumed to be a single multiplier for the $\mathrm{a_g}\,(\$/\mathrm{MW.h})$ parameter for all generators while neglecting $\mathrm{b_g}\,(\$/\mathrm{MW^2.h})$. This assumption is made to increase the cost of power generation linearly per unit generation while maintaining the incremental costs associated with generator efficiency (heat rate). The actual power rates are calculated using data published by the EIA (2020) representing the year 2020. Figure 3.11 shows a histogram of the data used. It was found that the average retail electricity rate in 2020 was $13.64\ Cents/kWh$ which equals $136.47\ \$/MWh$. This number was used to determine a factor to increase the a_g parameter for each generator according to Equation (3.12) where x is the needed parameter. Accordingly, the calculated factor is used to linearly scale the a_g parameters of the generators to calibrate the cost per MW for the generators, as denoted by x in Equation (3.12). The objective function of the calibration is to determine the factor x to minimize the squared error of the difference between the average of the calculated LMPs at every node i and the historical average electricity rate, as shown in Equation (3.13). After running the optimization, it was found that the needed parameter value is 5.881. The final parameters are shown in Table 3.3. To conclude, it is important to note that the outcome of this calibration is critical to replicate a realistic rate of the adoption of DSG since the calculated LMPs are critical in the developed consumer decision algorithms.

$$a_{g_{new}} = x \times a_{g_{old}} \tag{3.12}$$

$$Objective\text{: } \min\left[\left(\frac{\sum_{i=o}^{I} LMP_i}{I} - 136.47\right)^2\right] \tag{3.13}$$

3.2.10. DSG Cost and Adoption Rules. The LSEs are assumed to have an initial number of customers who do not have DSG and rely on their respective LSEs for their entire electrical power needs. It is assumed that customers will consider batteries for their DSG systems such that they can fulfill their full-day needs. PV systems with lithium-ion battery storage can be more economically feasible than PV alone especially considering their decreasing cost over the previous years (Tervo et al., 2018). Over the duration of the simulation, customers at each LSE will consider installing DSG systems with battery storage based on an economic decision as shown in Figure 3.12. Customers will compare two alternatives: (1) Paying a monthly loan for a DSG system consisting of PV cells and batteries; and (2) Paying their regular monthly electric bills that are calculated according to their power consumption and LMP at their location.

Table 3.3. Calibrated generator parameters.

Generator	***Type***	$a_{original}$ $\left(\$/_{MW.h}\right)$	$a_{calibrated}$ $\left(\$/_{MW.h}\right)$	b $\left(\$/_{MW^2.h}\right)$	$Capacity$ $(_{MW})$
Generator 1	Natural Gas	29.765	175.047975	0.000967361	700
Generator 2	Coal	13.709	80.622629	0.001198895	450
Generator 3	Nuclear	3.75	22.05375	0.000095802	2,000
Generator 4	Coal	13.709	80.622629	0.001198895	240
Generator 5	Natural Gas	29.765	175.047965	0.000967361	700

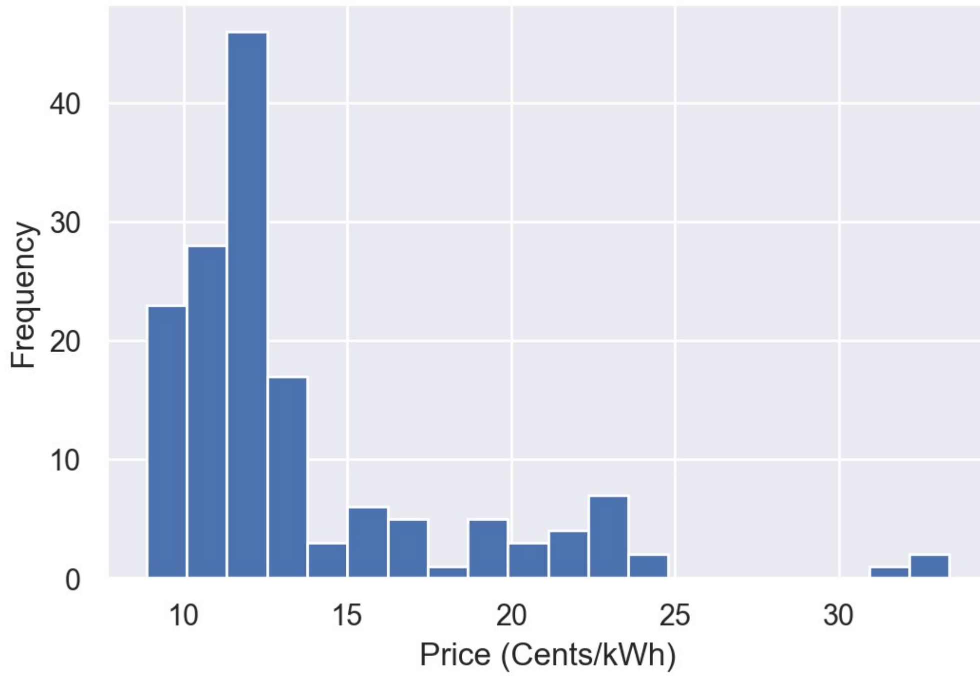


Figure 3.11. Histogram of electricity rates in the US in 2020.

Determining the value of monthly payments to buy and install a DSG system is achieved in five steps as shown in Figure 3.13: (1) The size of the PV cells is determined such that it can fulfill the electric power requirements of a consumer's house for a full day considering their efficiency and the number of daily sun-hours; (2) The size of battery storage capacity is determined considering the full day needs and the efficiency of the batteries; (3) The cost of the PV cells is determined using a forecast of historic data; (4) The cost of batteries is also determined using a forecast of historical numbers; (5) The cost of the system is calculated; (6) The monthly payment for a loan to buy the system is calculated; finally (7) the monthly payment amount is compared with the electric grid in a stochastic process to calculate the DSG adoption rate at each LSE. The following subsections explain the methodology for each step.

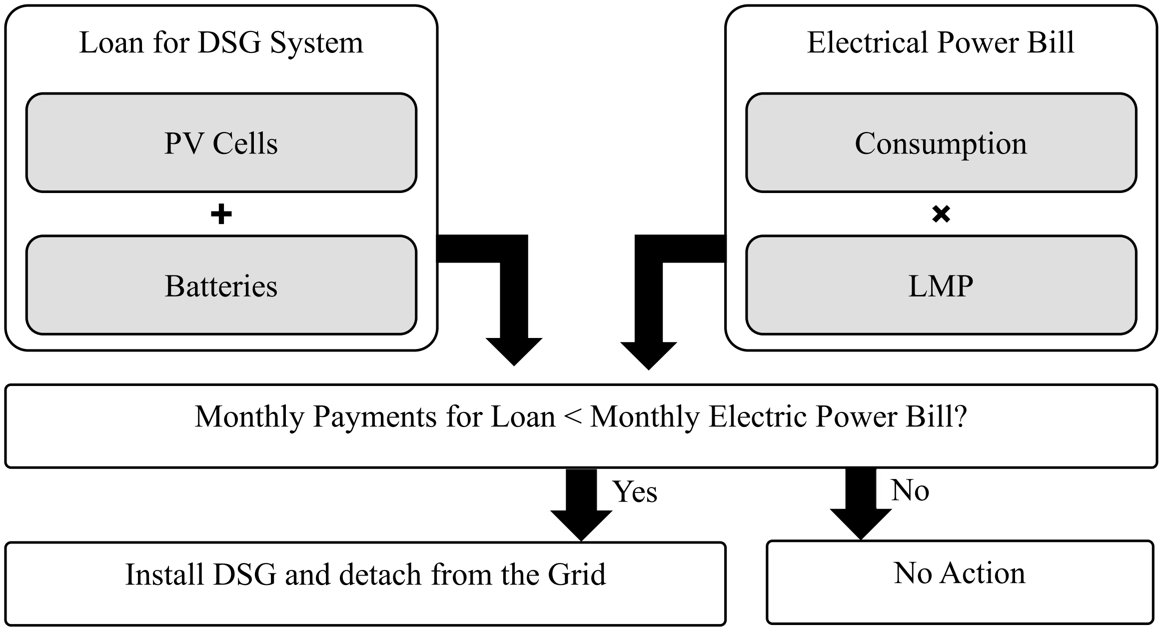


Figure 3.12. Consumer decision algorithm.

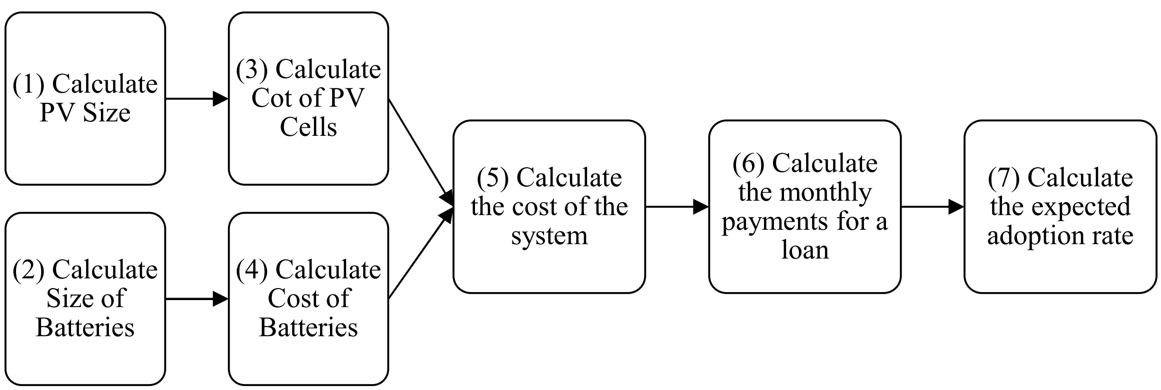


Figure 3.13. Steps to calculate the monthly loan for a DSG system.

3.2.10.1. Step 1: Calculate the size of PV cells. In the developed model, it is assumed that customers are considering DSG systems that can fulfill their electric power needs for a full day. Accordingly, the size of PV cells is determined according to three factors: (1) the full energy needs of a customer; (2) the daily peak sun-hours; and (3) the efficiency of the system. The first item is easily determined using the consumer demand estimated in the previous section.

The second item is the daily peak sun-hours which quantifies the number of hours per day when solar irradiance averages 1 kW/m^2 (DOE, 2022). The number of peak sun hours depends on the location and time of year. It is estimated to be 4 $hours/day$, which is the average number of peak sun-hours in most states in the US based on historic data (Hyder, 2021).

The third item is the efficiency of the PV cells, which quantifies their usable power output compared to their theoretical capacity. It accounts for losses such as the effect of the weather, dust, inefficiencies in the system, degradation, and other potential losses. This value is estimated to be the recommended value of 14.08% according to the *PVWatts® Calculator* published by the National Renewable Energy Laboratory (NREL, 2021).

The three variables are used to calculate the size of the PV systems in W as shown in Equation (3.14). The results are used to calculate the cost of the PV cells as explained in step 3.

$$Size_{PV}\ (W) = \frac{Daily\ Demand\ (Wh)}{4\ \left(\frac{Peak\ Sun\ Hours}{Day}\right) \times 86\%\ \ (Efficiency\ \%)} \tag{3.14}$$

3.2.10.2. Step 2: Calculate the size of batteries. The size of batteries is determined such that they can provide enough storage for a full day's power needs. It is assumed that customers will consider installing Lithium-Ion batteries. PV systems with lithium-ion battery storage can be more economically feasible than PV alone (Tervo et al., 2018).

The size of the batteries is estimated in Wh as shown in Equation (3.15). It includes (1) the daily demand, which is estimated similarly to the previous step, and (2) an efficiency factor which consists of the estimated maximum charging capacity of the batteries compared to their full potential to consider aging and degradation (Omar et al., 2015). The resulting battery size is used to calculate the cost of batteries as shown later in step 4.

$$Size_{Batteries}\ (Wh) = \frac{Daily\ Demand\ (W)}{75\%\ (Efficiency\ \%)} \tag{3.15}$$

3.2.10.3. Step 3: Calculate the cost of PV cells. The cost of PV cells may be estimated as a cost per unit of power generated in $\$/W$ (Barbose & Darghouth, 2019). This value has been decreasing substantially in the previous years. Therefore, there is a need to forecast the cost of PV cells in the future to include them in the ABM considering that those simulations span many years or decades.

To achieve that, an exponential function is used to calculate the cost of PV for any year (y) as shown in (3.16). The function includes a constant (c) such that the forecasted price never reaches zero. The equation is fitted to historical prices published by Barbose et al. (2019) as shown in Figure 3.14. The fitted function achieved a R^2 of 0.86. The total cost of the PV cell is calculated by multiplying the result of Equation 8 by the size of the PV cells calculated in Step 1.

$$Cost_y\ (\frac{\$}{W}) = e^{a+b\times y} + c \tag{3.16}$$

3.2.11. Step 4: Calculate the cost of batteries. The cost of Lithium-Ion batteries is calculated similarly to the methodology shown in step 3 for the PV cells. The cost of lithium-ion batteries has also been decreasing over the previous years, as shown in Figure 3.15. An exponential function, as shown in Equation 8, is used to forecast the future cost of Lithium-Ion batteries. The function is fitted to data published by BloombergNEF (Goldie-Scot, 2019) which includes historic data between 2010 to 2018 and expected values for 2024 and 2030. The fitted function reached an R^2 of 0.98. The output of the fitted function is in cost per energy, or $\frac{\$}{Wh}$, which is used to calculate the cost of the batteries by multiplying it by the size of the batteries calculated in Step 2.

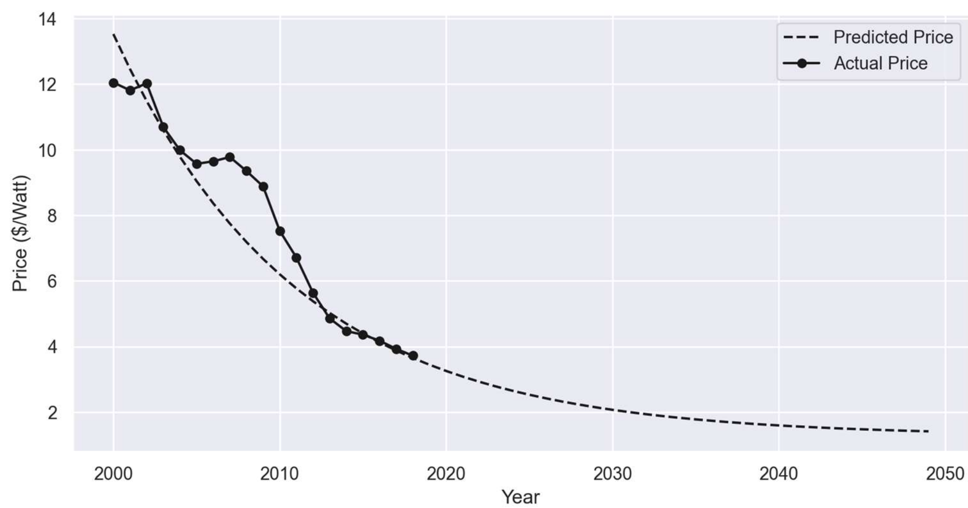


Figure 3.14. Price of PV systems.

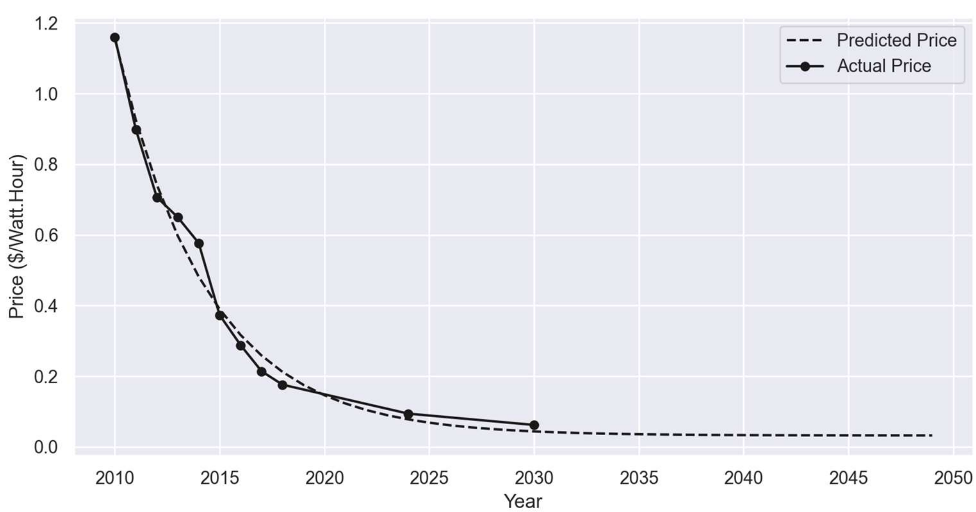


Figure 3.15. Price of Lithium-Ion batteries.

3.2.11.1. Step 5: Calculate the lifetime cost of the system. In the previous steps, the cost of the PV cells and the batteries were calculated separately. In this step, those two costs are combined to calculate the expected total present value of the system as shown in Equation (3.17). It is estimated that PV cells have a lifetime of 25 years which is the typical warranty period offered by manufacturers (McCloy, 2019). Batteries are assumed to have an average life of 10 years (Haruna et al., 2011; Sarre et al., 2004). Accordingly, Equation (3.17) uses a multiplier of 2.5 for the cost of batteries to get an investment value for the complete DSG system over 25 years.

$$Cost = \tag{3.17}$$

$$Size_{PV}\ (W) \times Cost_{y,pv}\left(\frac{\$}{W}\right)$$

$$+\ 2.5 \times Size_{Batteries}(Wh) \times Cost_{y,batteries}(\frac{\$}{Wh})$$

3.2.11.2. Step 6: Calculate the monthly payments for a loan. After calculating the initial loan amount for the complete system including PV cells and battery, it is assumed that prospective buyers will consider a loan with a duration matching the lifetime of the system which is 25 years. The monthly payments for that loan are calculated according to Equation (3.18) where the present value of the loan is the system cost calculated in Step 5. The yearly interest can be reasonably estimated to be 6% considering that the interest rates for loans for PV systems range between 4.5% to 7.1% depending on factors such as credit scores and market changes (Feldman & Schwabe, 2018). The interest rate value is tested in this research to understand the effect of loan-related policy incentives.

$$A = \frac{Cost \times r \times (1+r)^n}{(1+r)^n - 1} \tag{3.18}$$

$where$:

- $n = 25\ years \times 12\ months$
- $r = \frac{APR\ \%}{12\ months} = \frac{6\ \%}{12\ months}$

3.2.11.3. Step 7: Calculate the expected adoption. The final step is to make a comparison and decide between two economic alternatives: (1) pursue a loan to install a DSG system and pay the associated monthly payments; or (2) take no action and keep incurring the monthly cost for electric power from the grid, i.e., the regular monthly electric power bills calculated by multiplying the average monthly electrical power consumption per customer and the LMPs associated with the LSE. This decision process is made on the LSE level to calculate the overall adoption rate governing all the customers in an LSE. However, there is a need to induce a stochastic element in that process. Otherwise, the comparison would yield a binary decision where the entire LSE would adopt DSG at the same time, which is not realistic. As such, a stochastic element is needed to capture the uncertainty in the parameters of the adoption decision which includes the (1) variability in the cost of the DSG system; (2) variability in the financial terms of the loan to purchase the DSG system; and (3) variability in the electrical consumption across the customers. To mimic that effect, a lognormal distribution, as shown in Equation (3.19), is used to characterize the monthly cost of power where (x) is the average monthly electric bill and (σ) is assumed to be 0.2 as a reasonable estimate for the variance in monthly electric bills. The distribution is scaled to have its mean as the monthly electrical power bill cost incurred by the customers attached to the targeted LSE. Customers may adopt when the monthly payment from the loan is less than their monthly electric bill. As illustrated in Figure 3.16, based on this simple adoption rule, the percentage of customers who will choose to install

DSG at any time is found by evaluating Equation (3.19) at the current monthly loan payment. It should be noted that although the model was calibrated for an average power rate for the entire US, it can be re-calibrated to match the power rates at any location.

$$f(x) = \frac{1}{\sigma\, x\, \sqrt{2\pi}}\, e^{-\frac{\log^2(x)}{2\sigma^2}} \tag{3.19}$$

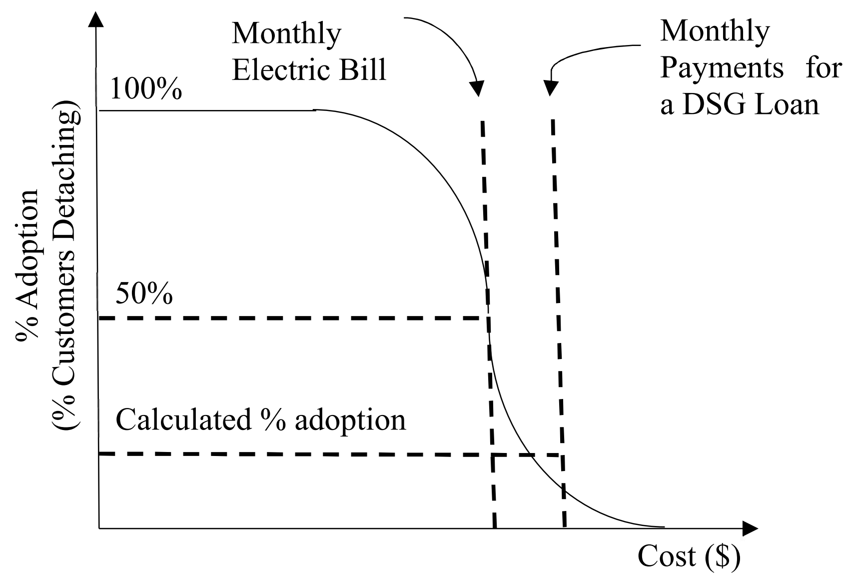


Figure 3.16. Stochastic process to calculate adoption.

3.3. DYNAMIC PRICING USING REINFORCEMENT LEARNING (RL)

3.3.1. Overview of Learning Algorithms Used. The following subsections discuss each RL algorithm used in this research: (1) Basic Learning, (2) Multiplicative Weights, (3) Roth-Erev, and (4) Modified Roth-Erev. Also, (5) a Gibbs-Boltzmann Cooling Factor method is attempted for each of the RL algorithms.

3.3.1.1. Basic learning algorithm. A basic learning algorithm, as discussed by Roth and Erev (1998; 1995), follows a set of steps as shown in Figure 3.17. First, an Action

Set ($\boldsymbol{a}$) is defined according to a possible number (N) of actions (a_i). Also, a Propensity Set ($\boldsymbol{q}$) is initiated. The Probability Set ($\boldsymbol{p}$) is calculated according to Equation 14. Then, a loop is repeated using steps 1 through 4 as shown in Figure 3.17: (1) An action (a_k) is selected from the Action Set ($\boldsymbol{a}$) using the respective probabilities of the actions provided in the Probability Set ($\boldsymbol{p}$). (2) The reward $R(a)$ is calculated according to the resulting outcome of choosing the action (a_k). The reward function may for example be the profit resulting from that action. (3) Based on the reward (r), the Propensity Set ($\boldsymbol{q}$) is updated for each action (a_i) according to Equation (3.21). Finally, (4) The Probability set ($\boldsymbol{p}$) is updated based on the new Propensity Set ($\boldsymbol{q}_{\mathbf{t+1}}$) according to Equation (3.20). Then the loop is repeated in every iteration starting with step 1.

$$\boldsymbol{p_i} = \frac{\boldsymbol{q_i}}{\sum \boldsymbol{q}} \tag{3.20}$$

$$\boldsymbol{q}_{t+1} = \begin{cases} q_t + r & for \;\; a_i = a_k \\ q_t & for \;\; a_i \neq a_k \end{cases} \tag{3.21}$$

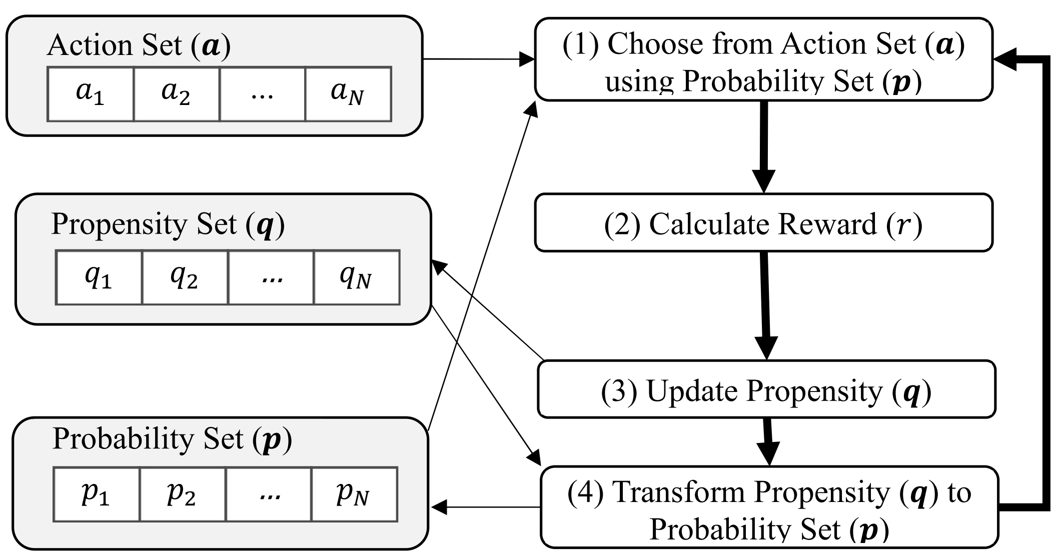


Figure 3.17. General outline of a learning algorithm.

3.3.1.2. Multiplicative weights algorithm. The multiplicative weights method is a simple yet effective meta-algorithm that has been used in many applications such as machine learning, optimization, and game theory (Arora et al., 2012). Compared to the basic RL shown in the previous section, the multiplicative RL algorithm extends the basic learning algorithm by adding a *Learning Rate* (LR) parameter (η), as shown in Equation (3.22). The LR controls the effect of the reward on updating the weights in the RL.

$$w_{t+1} = w_t \times (1 + \eta r) \tag{3.22}$$

3.3.1.3. Roth-Erev RL algorithm. The Roth-Erev (1998; 1995) algorithm is similar in steps to the basic RL method. However, it introduces two variables: ϕ which is a "*forgetting*" parameter and ϵ which is an "*experimenting*" parameter. The two variables are used to update the propensities as shown in Equation (3.23). Compared to the basic RL, the Roth-Erev algorithm updates all the actions instead of simply increasing the propensity of the chosen action only based on a direct addition of the reward. This modification improves the learning behavior to better mimic human learning by adding: (1) a forgetting behavior where the agents slowly forget the rewards from previous actions, and (2) enabling the agents to experiment with new actions and discover the rewards associated with them. The probability set is updated in the same manner as the basic RL, according to Equation (3.23).

$$\boldsymbol{q}_{t+1} = \begin{cases} q_t \times (1-\phi) + r \times (1-\epsilon) & for\ a_i = a_k \\ q_t \times (1-\phi) + \dfrac{r \times \epsilon}{N-1} & for\ a_i \neq a_k \end{cases} \tag{3.23}$$

3.3.1.4. Modified Roth-Erev algorithm. The modified Roth-Erev algorithm, proposed by Nicolaisen et al. (2001), includes a change to the formulation for calculating the propensity set. The modification is shown in Equation (3.24) (Pentapalli, 2008; Sun &

Tesfatsion, 2007a). It should be that the Roth-Erev algorithm, shown in Equation (3.23), uses a function of the reward (r) to update the propensities of the actions that were not chosen (i.e., $a_i \neq a_k$), while the modification in Equation (3.24) relies on the previous propensities (q_t) instead. The probability set is updated in the same manner as the basic RL which is shown in Equation (3.20).

$$\boldsymbol{q}_{t+1} = \begin{cases} q_t \times (1-\phi) + r \times (1-\epsilon) & for\ \ a_i = a_k \\ q_t \times (1-\phi) + \dfrac{q_t \times \epsilon}{N-1} & for\ \ a_i \neq a_k \end{cases} \tag{3.24}$$

3.3.2. Gibbs-Boltzmann Cooling Factor. In the previously shown algorithms, the propensities or weights were converted to probabilities using the formulation shown in Equation (3.20). One other option is to use a Gibbs-Boltzmann cooling factor. This modification is used to update the probability set (p_i) as shown in Equation (3.25) (Pentapalli, 2008; Sun & Tesfatsion, 2007a). The equation introduces a new variable (T) called a Boltzmann Cooling Factor. The Gibbs-Boltzmann cooling factor was previously found to cause a significant effect on learning behavior (Pentapalli, 2008). A major benefit is that it can handle negative values, compared to the original method in Equation (3.20). An additional modification is made in this research where the $T = \text{avg}(|q|)$ so that it is dynamic. Otherwise, a fixed T would cause the difference between the probabilities to be reduced when the values in the propensity decrease.

$$\boldsymbol{p_i} = \frac{\boldsymbol{e}^{\frac{\boldsymbol{q_i}}{\boldsymbol{T}}}}{\sum \boldsymbol{e}^{\frac{\boldsymbol{q}}{\boldsymbol{T}}}} \tag{3.25}$$

3.3.3. Reward Function for Generator RL Algorithms. It is assumed generating companies can alter the parameters of their supply functions every day to mimic the mechanism of a wholesale power market where generators send supply offers to the generators daily (Sun & Tesfatsion, 2007a). The RL algorithms are used to enable the generators to decide their a_g parameter to increase their reward (r) which is discussed in the following paragraph. The decision of the a_g parameter modifies the supply curves of each generator, which changes the LMPs paid by the LSEs and ultimately the consumers' decision to install DSG and defect from the grid. In all the RL algorithms tested in this research, the action set for the generators is assumed to be in the range of [-0.50, +1.50] with an 0,1 interval, resulting in 21 actions. The markup for every generator during each hourly time tick (t) in the model is calculated according to Equation (3.26).

$$a_{g,t.RL} = markup_g \times a_{g,initial} \tag{3.26}$$

Where:
- $markup_{g,t} = 1 + action_{g,t}$
- $50\% \leq markup_{g,t} \leq 250\%$

The decision of the generating companies to increase or decrease their supply parameters is a profit-seeking behavior. The gross profit for a generating company is shown in Equation (3.27). The revenue for each generator (g) is calculated according to the LMP at the node where it is located, multiplied by its commitment (P_g). The variable cost of a generating company is the actual generating cost calculated according to its supply parameters a_g and b_g and its generated commitment P_g. The generators will attempt to improve their profits by altering the supply parameter a_g reported to the ISO. The calculation of the revenue however relies on the actual supply parameters $a_{g,Actual}$ and $b_{g,Actual}$ which are the initial parameters without the markup. The reward function for the RL is therefore the daily gross profit margin, as shown in Equation (3.28). The generators will update their supply parameters daily in accordance with the design of a wholesale power market where the generators supply their offers daily to the ISO (Sun & Tesfatsion, 2007a). The supply parameters will have a complex cascading effect on the entire network: (1) The demand may be committed to other less costly generating companies because of the dynamic wholesale power market behavior; (2) the LMPs will change throughout the nodes; and ultimately, (3) the rate of adoption of DSG will be affected. Therefore, an RL approach can be used to create an AI behavior that can determine the markups, learn from the outcomes of its actions, and adapt to the outcomes continuously.

$$Profit_g = Revenue_g - Cost_g \tag{3.27}$$

$$where: \quad Revenue_g = LMP_g \times P_g$$

$$Cost_g = a_{g,Actual} \times P_g + b_{g,Actual} \times P_g^2$$

$$r_{g,day} = Gross\ Profit\ Margin_{g,day} = \frac{\sum_{h=1}^{24} Profit_{g,h}}{\sum_{h=1}^{24} Cost_{g,h}} \tag{3.28}$$

3.3.4. Exploration/Exploitation and Hyperparameter Tuning. A key element of RL algorithms is their ability to explore actions and learn from the outcomes. In the developed model, generating companies have no inherent knowledge or expectations regarding the expected outcomes from each action. The actions decided by the generating companies affect the adoption of DSG dynamically and ultimately the outcomes of the actions. The RL approach in this research intends to mimic dynamic pricing by generating companies in wholesale power markets considering that customers can choose to install DSG. As such, the RL algorithms rely on exploration and exploitation to maximize the outputs, where the exploration aspect attempts new actions, while the exploitation aspect selects actions that previously resulted in desirable outcomes (Assaad et al., 2021). The tradeoff between exploration and exploitation is controlled using the hyper-parameters for each algorithm. The multiplicative weights algorithm relies on the LR parameter (η) and the Roth-Erev algorithm relies on the "*forgetting*" parameter (ϕ) and the "*experimenting*" parameter (ϵ). The Gibbs-Boltzmann cooling factor also affects the calculations of the probability sets which modified the learning behavior. As such, the RL hyperparameters are tested to balance exploration and exploitation. To perform hyperparameter tuning, the respective hyperparameters of each RL algorithm are tested in the range of 0.1 to 0.9 to create stable learning behaviors that result in the highest rewards for the generating company agents. The RL algorithms select actions and learn continuously for the duration of the simulation which is five years and terminate when the simulation ends. This behavior is intended to mimic the fact that the actions (markups) decided by the generating companies will have a direct impact on DSG adoption and their revenues. As such, they will interactively learn and adapt to a dynamic market. The termination time for the simulation is set to five years as a reasonable time horizon. However, it can be easily increased to create long-term simulations.

3.4. DSG POLICY INCENTIVES

The objective of this part is to study the effect of policy incentives on the adoption of DSG. The previous sections explain the steps to achieve a working model where a DSG adoption behavior emerges from the economic decision between (1) the electrical power bills impacted by the node-level LMPs, and (2) the cost of buying a DSG system reflected as a monthly payment for a loan. To achieve the main objective of this part, two incentive options are applied and compared as shown in Figure 3.18.: (1) tax credits and rebates which reduce the upfront cost of the system; and (2) DSG loans with lower interest rates which increases the long-term net benefits of a system. The purpose of this step is to investigate how different incentive scenarios affect the DSG adoption rate and the prices across the network. This is achieved in three steps: (1) Study the baseline case of the model, where it is assumed that there are no reductions in the initial cost of a DSG system and the interest rate is 6%; (2) Test the possible combinations of incentives at an LSE such that the interest rate $(i) \in [4\%, 5\%, 6\%, 8\%, 9\%]$ and the rebate $\in [0\%, 5\%, 10\%, 15\%, 20\%]$ to study the isolated effect on that LSE; and, finally (3) perform an exhaustive combination of scenarios using the aforementioned range of interest rates and rebates to study the relationship between incentives, DSG adoption rates, and electric power rates.

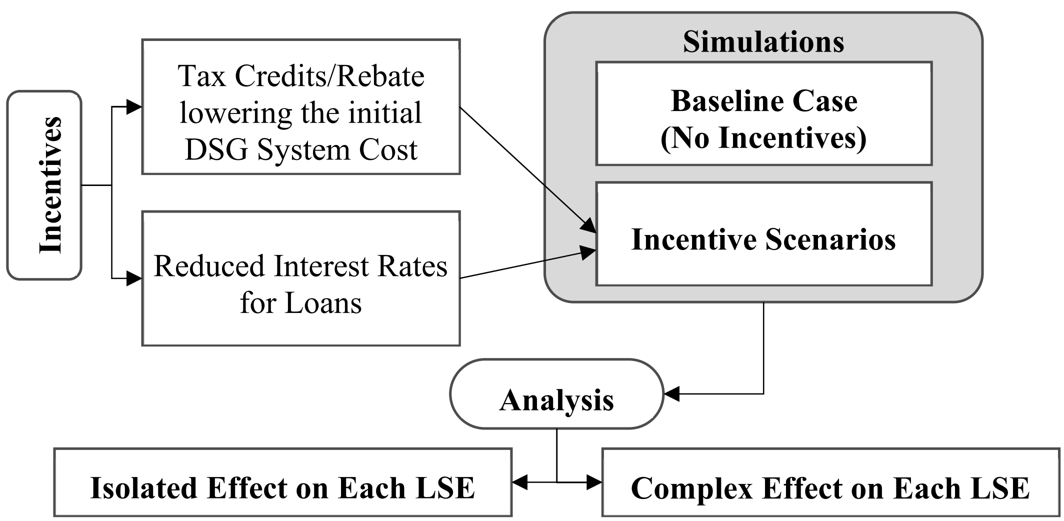


Figure 3.18. Overview of the methodology for DSG policy incentives.

3.5. REDUCING VULNERABILITY AGAINST NATURAL DISASTERS

3.5.1. Meta-Heuristic Optimization Methods. In this part, a Genetic Algorithm (GA) is used to optimize the size and location of DSG to reduce the vulnerability of electric power grids against natural disasters. GA is classified as a meta-heuristic optimization method. In general, meta-heuristic optimization methods are widely used for optimizing complex problems in many fields. Most meta-heuristic optimization methods are inspired by nature, involve stochastic behavior, do not require gradients, and have adjustable parameters (Boussaïd et al., 2013). There are many meta-heuristic methods such as Genetic algorithms (GA), Simulated Annealing (SA), Tabu Search (TS), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Harmony Search (HS), Artificial Bee Colony (ABC), Cuckoo Search Algorithm (CSA), Shuffled Frog Leaping Algorithm (SFLA), Shuffled Bat Algorithm (SBA), Plant Growth Simulation Algorithm (PGSA), Biogeography Based Optimization (BBO), Firefly Algorithm (FA), and Imperialist Competitive Algorithm (ICA), among other techniques and variations (Abdmouleh et al., 2017).

The GA is a heuristic optimization technique that is inspired by evolution and survival of the fittest. GAs have been used in countless applications and research such as water resources planning (Nicklow et al., 2010), construction planning and resource allocation (Hegazy, 1999), disaster management (M. S. Eid & El-adaway, 2017b), optimizing the maintenance cost of bridges (Ghodoosi et al., 2018), among many others. It was also used in many papers to optimize DG allocation problems under different considerations (Abdmouleh et al., 2017; Ganguly & Samajpati, 2015; Pisica et al., 2009). While GA is considered the most applied optimization technique in solving problems related to DG placing and sizing, many other optimization methods such as simulated annealing and particle swarm were applied to grid optimization and DG optimization (Abdmouleh et al., 2017). However, there is limited research that combines hybrid heuristic and OPF optimization to perform two-step optimization of DG allocation. Few papers presented hybrid GA and OPF methods to investigate the capacity of distributed systems for new DG systems (Harrison et al., 2007, 2008), and to minimize the cost of active and reactive power using DG (Mardaneh & Gharehpetian, 2004). In this part, GA is used because (1) it is a robust method that has been used in many applications; (2) it has been previously used as a hybrid method with OPF; and (3) there is a technical proximity between ABM and GA because solutions in GA are represented as chromosomes which can be easily linked to the parameters of the agents. This allows seamless integration and cross-validation between them (M. S. Eid & El-adaway, 2021). Still, there is a need for future research comparing hybrid meta-heuristic techniques as related to the problem presented in this research.

3.5.2. Optimizing Methods. The optimization approach in this research intends to determine the location and number of DSG. It is assumed that any transmission line can be damaged during natural disasters and therefore limit the power flow in the grid. When the grid is unable to meet the total demand, system operators may need to strategically reduce power to parts of the system instead of risking a complete blackout of the entire grid, which is a measure referred to as load *shedding,* or *rolling blackout,* or *brownout*, depending on the procedure (Agarwal & Khandeparkar, 2021; Y. Liu et al., 2015; Tofis et al., 2017). The method presented in this research proposes and compares two perspectives to allocate DSG at one node or several to mitigate the disruption caused by the failure of transmission lines.

3.5.2.1. Method 1: Optimizing at a single node. The purpose of the optimization approach in the first method of to calculate the minimum number of DSG to place at one node to (1) mitigate the effect of a damaged transmission line; (2) avoid a complete system blackout or the need for a targeted blackout at the problematic node. The outline of the algorithm for Method 1 is shown in Figure 3.19.

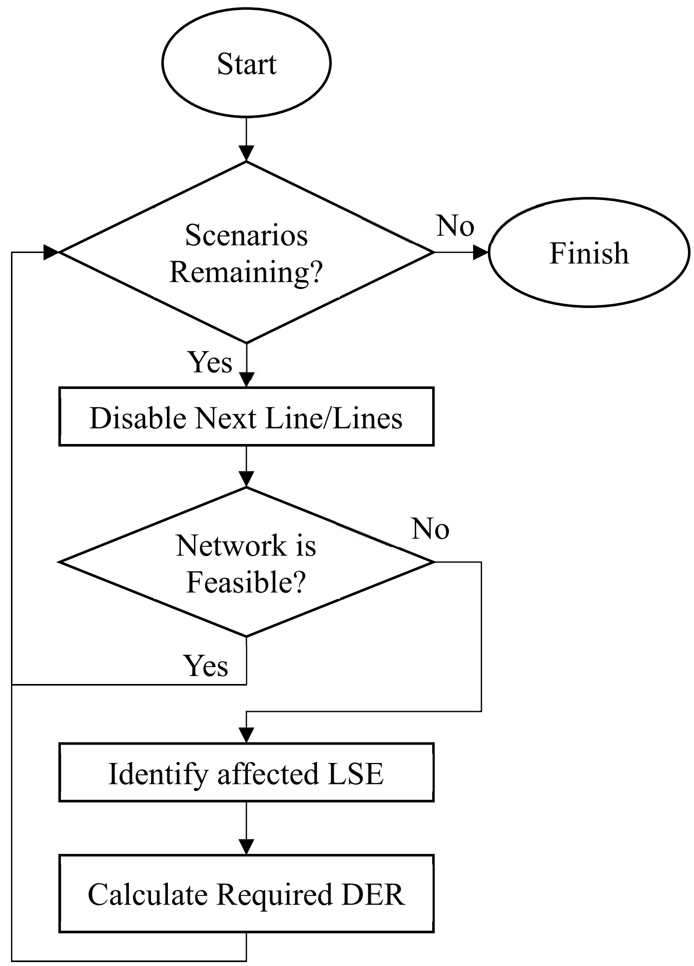


Figure 3.19. Outline of the algorithm for method 1.

The algorithm assumes that each transmission line is susceptible to failure in separate scenarios per line. In each scenario, a transmission line is considered completely damaged, and the electric network is recalculated to determine its feasibility, i.e., whether the demand from the LSEs can be satisfied. If the demand cannot be satisfied, the algorithm iterates each LSE to find which one would make the network feasible again if power to the determined LSE would be cut off to avoid a complete grid blackout instead. The algorithm then proceeds to search for the minimum number of DSG to allocate to the determined node in the previous step, which would satisfy the feasibility of the electric grid. The algorithm then proceeds to iterate over each transmission line to determine the required DSG to mitigate against the failure of the targeted line. Ultimately, the outputs of the scenarios are cross-referenced to determine the number of DSG at each node needed to avoid the failure of any transmission line at any time. It should be noted that the algorithm is integrated into the ABM model, which means that the allocation of DSG would affect the electric power market economics of the entire grid including the supply of all the generators, the demands from all LSEs, and the LMPs across the nodes.

3.5.2.2. Method 2: Network optimization using Genetic Algorithm (GA). The purpose of Method 2 is in the same direction as Method 1 concerning that it intends to mitigate against the failure of transmission lines subjected to natural disasters and avoid blackouts. However, in Method 2 the number of DSG is optimized across the entire grid, as shown in Equation (3.29) as opposed to a single node at-a-time. This can help achieve a lower number of DSG at the cost of spreading them across many locations. To achieve that objective, an ad-hoc solver was developed using GA and integrated into the ABM model.

$$Minimize: \sum_{i} DG_i \tag{3.29}$$

Where: $0 \leq DG_i \leq Customers_i$

A metaheuristic optimization layer using a Genetic Algorithm (GA) is integrated on top of the ABM and OPF. GA is a preferred method because there is a technical proximity between ABM and GA that allows seamless integration between them (M. S. Eid & El-adaway, 2021). Specifically, the parameters of the agents in the ABM can be easily integrated in a GA as chromosomes and optimized in an iterative evolutionary process. Collectively, ABM, OPF, and GA can be integrated in a multilayer DSG optimization approach that fulfills the need for simulating and optimizing dynamic electrical networks as opposed to a conventional static grid model (Abdmouleh et al., 2017). As shown in Figure 3.20, the general steps of a GA are as follows: (1) Initialization: An initial population of solutions is generated using *chromosomes* where each *gene* is a variable in a feasible solution of DSG allocation of Node i; (2) Selection: The best solutions in the population are kept and the rest of the solutions are omitted to mimic survival of the fittest; (3) Cross-over: The *genes* of the selected solutions are mixed in a *cross-over* to create new solutions with mixed genes from the best solutions similar to the inheritance of genes from parent to offspring; (4) Mutation: The variables in a few solutions are randomized to create new solutions outside of the search area of the current population of solutions to escape possible local minima and attain a global minimum. The mutation step is not performed on every iteration of the GA; it is performed according to a pre-set probability that is usually low and tweaked according to the problem. The loop is then repeated until a stopping criterion is reached, which can be a maximum number of epochs. The GA and ABM are integrated seamlessly at the agent level. The list of numbers of DSG for the LSEs in a grid represents a solution or a *chromosome* in the GA, as shown in Figure 3.20. GA optimization is performed for each transmission line in the electric grid as shown in Figure 3.21. Each transmission line is considered non-operational in a separate scenario similar to method 1. If disconnecting a line renders the network infeasible, then the optimization is performed to determine the number and location of DSG to make it operational again. The algorithm loops through all the scenarios and returns an optimized allocation of DG_i, for every node (i), that can effectively mitigate the failure of any transmission line.

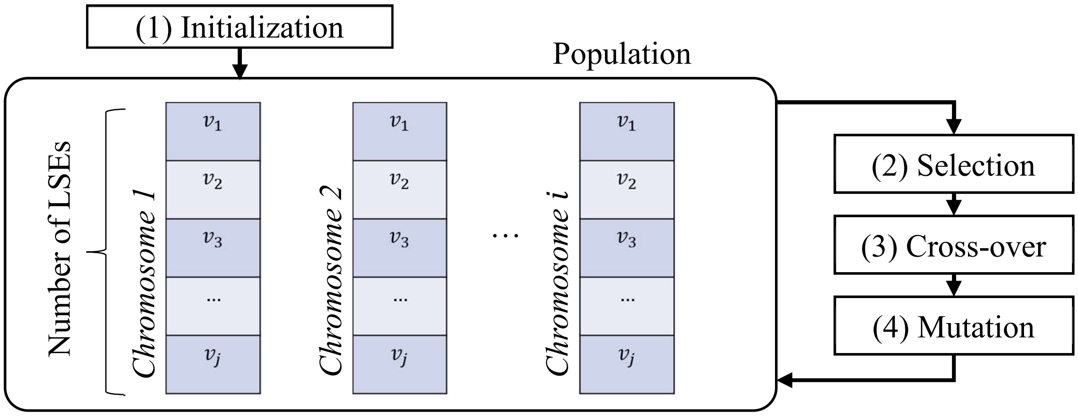


Figure 3.20. Outline of evolutionary algorithm.

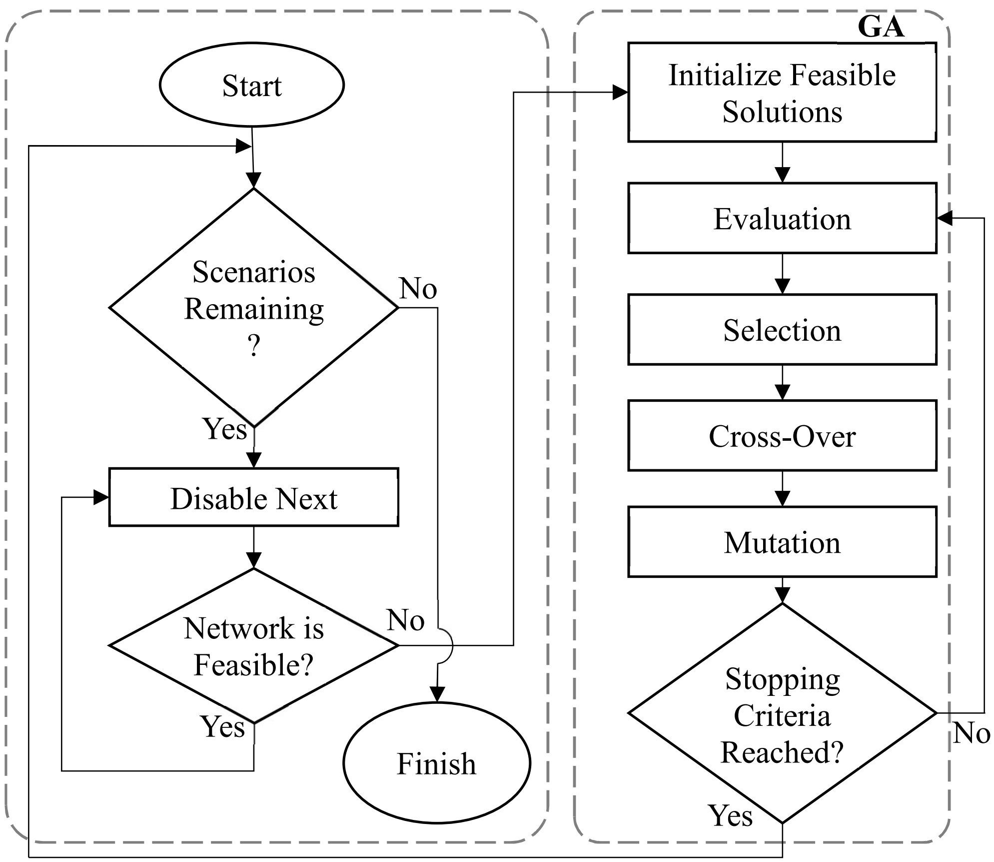


Figure 3.21. Outline of the algorithm in method 2.

3.6. TOOLS AND SOFTWARE USED

The model was developed entirely using the programming language Python, which is a popular and well-established environment for scientific and engineering applications (Millman & Aivazis, 2011; Oliphant, 2007). Several open-source packages are used, including; Numpy for numerical computation (Oliphant, 2006; Van der Walt et al., 2011), Matplotlib and Seaborn for plotting and visualization (Hunter, 2007; Waskom et al., 2018), Pandas for data structures and data manipulation (McKinney, 2011), Statsmodels and Linearmodels for statistical analysis (Seabold & Perktold, 2010; Sheppard, 2017), SciPy for scientific computing (Virtanen et al., 2020), Networkx for network analysis and visualization (Hagberg et al., 2008), Scikit-learn / Sklearn for machine learning (Pedregosa et al., 2011), and Numba (Lam et al., 2015). Development relied on free and open-source development environments such as Microsoft's Visual Studio Code and Jupyter Notebooks (Kluyver et al., 2016). A summary of the tools and software used is shown in Table 3.4.

Table 3.4. Tools and software used.

Name	*Description*	*Reference*
Python	Programming language	(Millman & Aivazis, 2011; Oliphant, 2007)
Numpy	Numerical methods	(Oliphant, 2006; Van der Walt et al., 2011)
Matplotlib/Seaborn	Visualization	(Hunter, 2007; Waskom et al., 2018)
Pandas	Data manipulation	(McKinney, 2011)
Statsmodels and Linearmodels	Statistical analysis	(Seabold & Perktold, 2010; Sheppard, 2017)
SciPy	Scientific computing	(Virtanen et al., 2020)
Networkx	Network analysis	(Hagberg et al., 2008)
VSCode and Jupyter	Coding	-

4. RESULTS AND ANALYSIS

4.1. RELATIONSHIP BETWEEN THE ELECTRIC POWER SECTOR AND SOCIOECONOMIC INDICATORS

4.1.1. Data Collection. Data was collected from the World Bank and Transparency International as specified in the Methodology. The dataset was refined by cross-referencing against the list of 195 dependent countries in the world and removing the countries that do not exist in that list. Table 4.1 shows the descriptive statistics of the collected data. It should be noted that the data was not collected for a specific range of date, but for all available years for each country and metric. This decision was made to enable the analysis of the unique relationship against each parameter without limitations to a time range. Otherwise, the data range would be very limited because some of the parameters have a limited time range. For example, the Corruption Perception Index had a major revision of its calculation method starting 2012, which made it inconsistent with its previously published values. In addition, some of the parameters are absent for some countries. Therefore, a decision to remove any country that has missing inputs for any metric or for any time range would severely limit the availability of data. As such, the number of observations, shown in Table 4.1, is different for each metric. A note should also be made that the negative values for the minimum Adjusted net national income per capita (current US$), shown in Table 4.1, is not a mistake; this value was negative in Angola (years 1992 and 1994) and Equatorial Guinea (between 2000 and 2005) (The World Bank, 2019b).

4.1.2. Analysis Against Electrical Consumption per Capita. The following shows the first part of the analysis where the relationship between the socio-economic parameters and the electric power consumption per capita is thoroughly analyzed.

4.1.2.1. Visualizing the data. Figure 4.1 to Figure 4.5 show scatter plots for each variable against the electrical power consumption per capita, in order to visualize the relationship between the dataset parameters. A linear regression line, with a confidence interval of 95% is added to each plot to show the trends of the relationships. Figure 4.1 shows the Electrical Power Consumption per capita against: (a) Adjusted Net National Income per Capita and (b) the GDP per Capita at PPP. The positive relationship between those parameters, although not consistent, is very apparent. It can therefore be concluded that the economy, represented by the GDP per capita and the national income per capita, has a positive relationship with electrical consumption per capita. This trend is not surprising; a country that has a healthier economy is expected to have a higher electrical power consumption per capita.

Figure 4.2 shows the Electrical Power Consumption per capita against the Human Development Index. The trend that there is a positive relationship between the HDI and the Electrical Power Consumption per capita. Another observation is that the trend decreases as the HDI and electrical power consumption increase. In other words, the relationship has a higher positivity in less developed countries and fades in more developed countries. The reason may be that developed country may have already achieved high levels of human development and it can only be increased with in smaller intervals. The underlying indicators if the HDI, which are life expectancy (health), knowledge, and income per capita have already been pushed to the best possible expectations in advanced countries and further improvements are smaller.

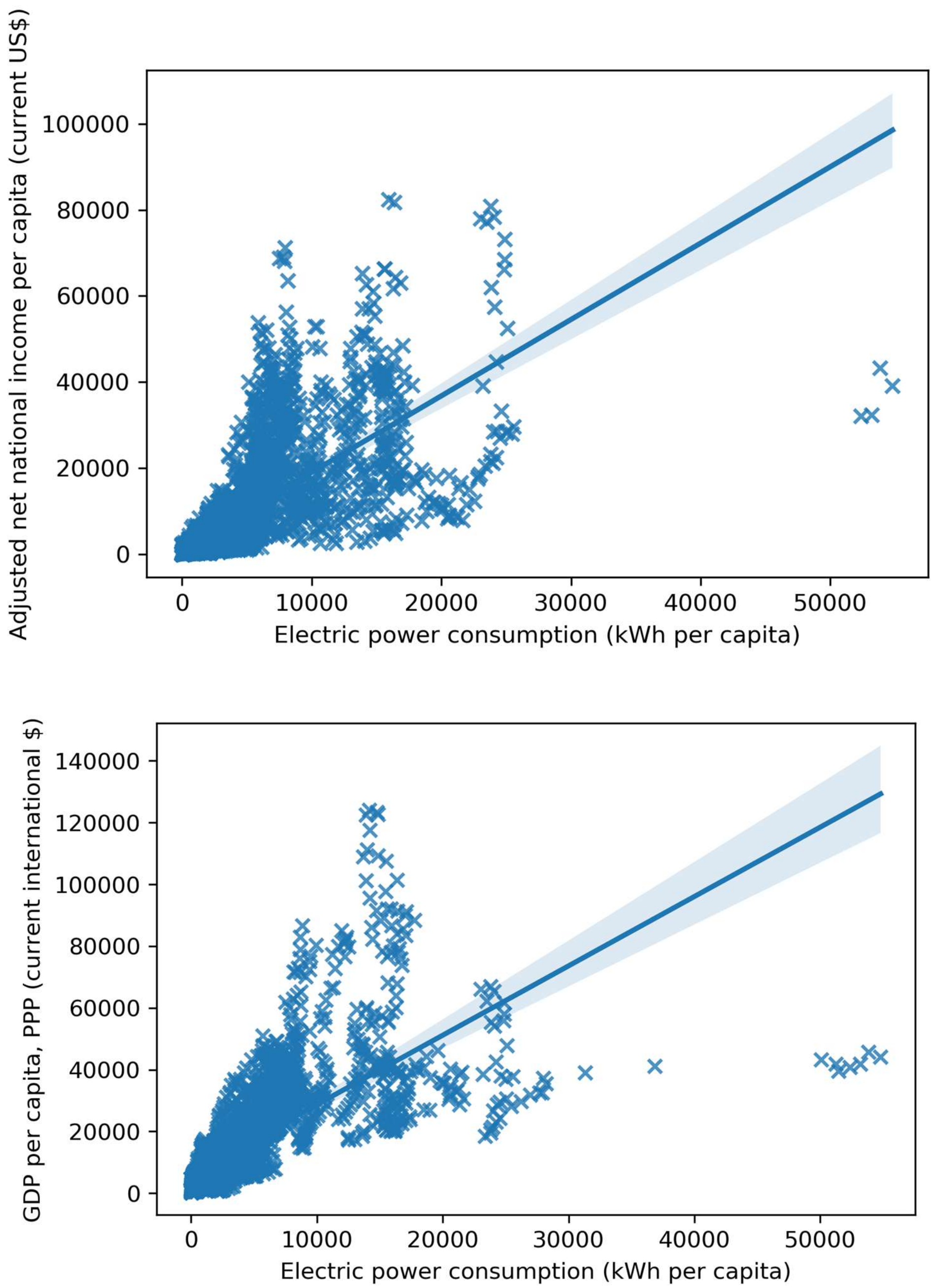


Figure 4.1. Scatter plot of the electrical power consumption per capita against (top) adjusted net national income per capita and (bottom) the GDP per capita at PPP.

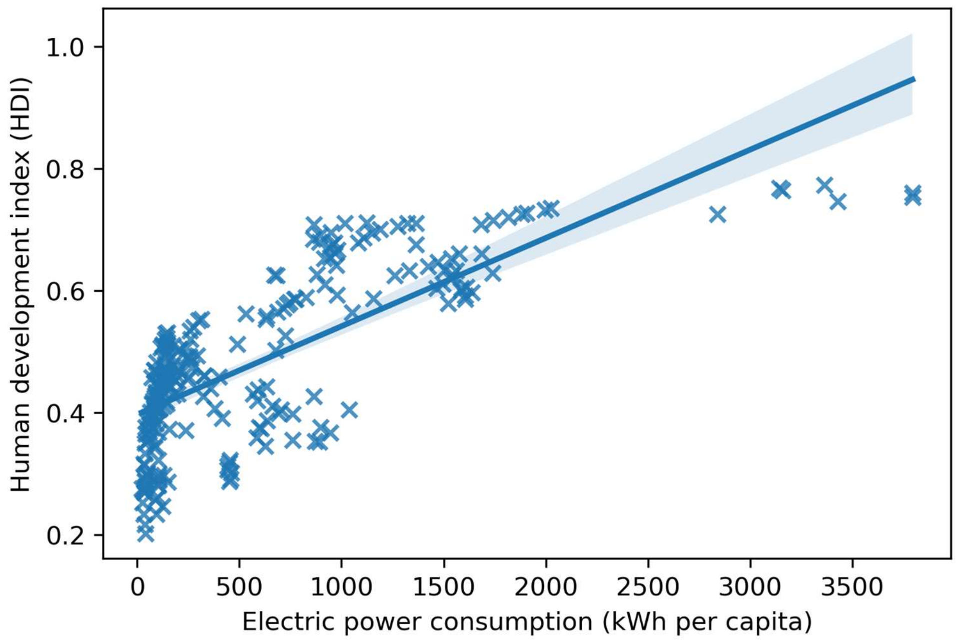


Figure 4.2. Scatter plot of the electrical power consumption per capita against the HDI.

Figure 4.3 and Figure 4.4 show the Electrical Power Consumption per capita against the Corruption Perception Index and the Control of Corruption, respectively. For both indicators of corruption, a higher value means that there is lower corruption. Therefore, as expected, the electrical consumption per capita is higher when the corruption is lower. Again, as observed in the previous visualization of the HDI, the relationship between electrical consumption and corruption starts to fade as corruption decreases. It should be noted that the maximum value for the CPI is 100 and the Control of Corruption Index is a standardized measurement. Figure 4.5 shows the plot CPIA transparency, accountability, and corruption in the public sector rating. However, this index does not show the expected relationship. Overall, it can be concluded that there is a relationship between lower corruption and higher electrical power consumption per capita.

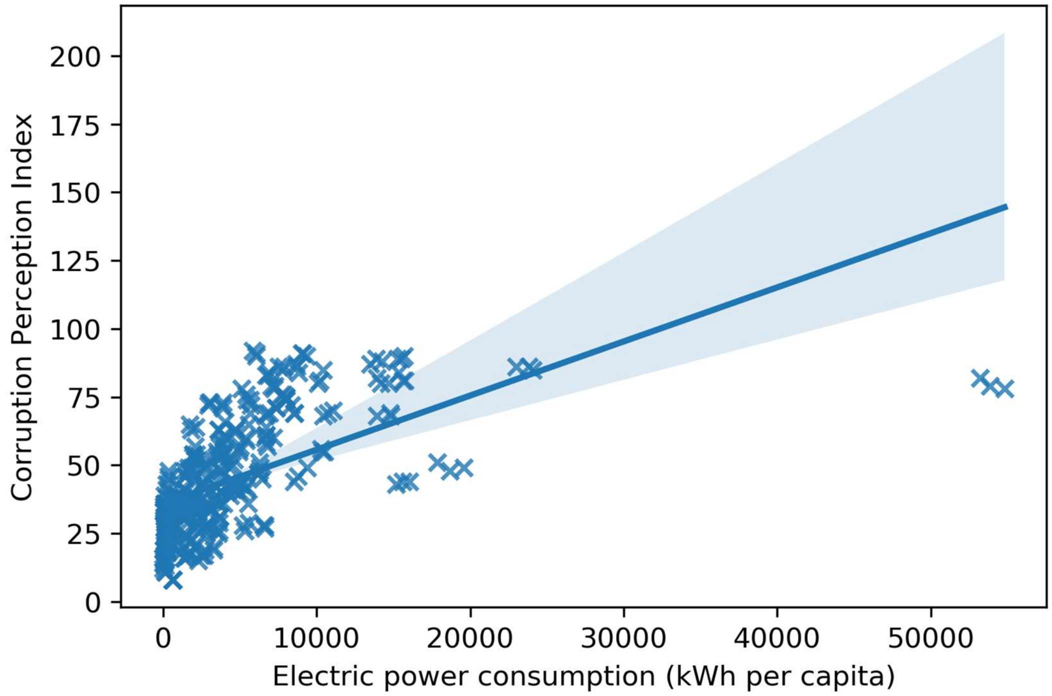


Figure 4.3. Scatter plot of the electrical power consumption per capita against the corruption perception index.

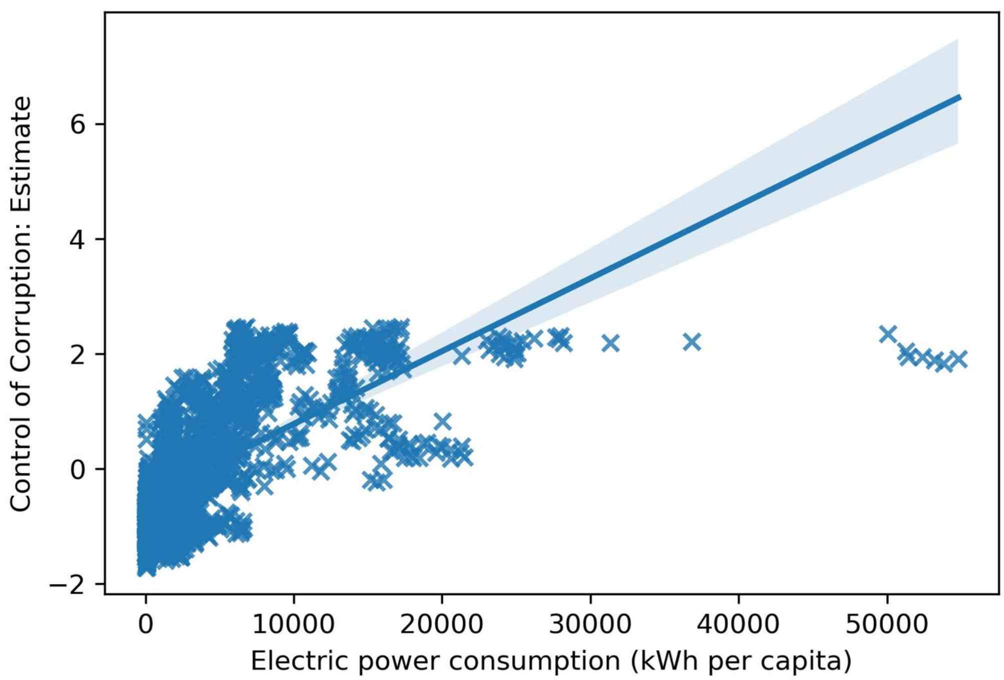


Figure 4.4. Scatter plot of the electrical power consumption per capita against the control of corruption.

Table 4.1. Description of data.

	Number of Observations	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Electric power consumption	5,471	3,160.63	4,577.02	0	54,799.17
Adjusted net national income	6,125	6,292.82	10,667.75	-595.518	82,487.47
Human development	408	0.449	0.135	0.176	0.804
GDP per capita (current US$)	8,451	7,653.00	15,961.57	34.79	189,170.90
GDP per capita, PPP (current	4,790	13,632.02	16,787.35	247.7657	126,597.60
Access to electricity (% of	4,105	78.125	31.196	0.01	100
Renewable electricity output	4,628	31.886	34.449	0	100
Electricity production from	5,591	2.311	5.626	0	65.443
CPIA transparency,	934	2.859	0.658	1	4.5
Control of Corruption:	3,290	-0.048	1.013	-1.868	2.469
Corruption Perception Index	1,129	42.767	19.757	8	92

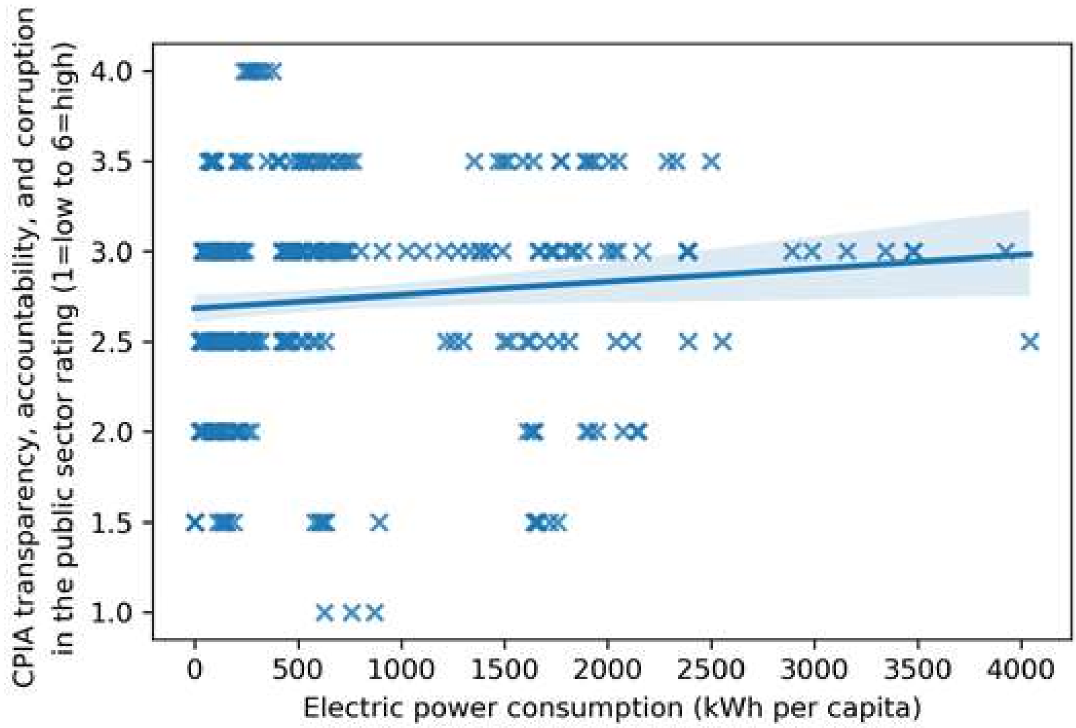


Figure 4.5. Scatter plot of the electrical power consumption per capita against the CPIA transparency, accountability, and corruption in the public sector rating.

4.1.2.2. Correlation analysis. Pearson correlation analysis was performed on the data to determine the possible relationships between the parameters. Table 4.2 shows the results of the correlation. It can be seen that there is a high correlation between the electrical power consumption per capita and all of Adjusted Net National Income per Capita, Human Development Index, GDP per Capita, GDP PPP per Capita, and Control of Corruption indices. There is also a high inter-correlation between some of the parameters. The positive relationship between the national income and the GDP is, of course, not surprising, because they translate to the same underlying economic broad meaning. There is a positive correlation between corruption indicators and the GDP as well as the National Income, meaning that less corrupt countries have better economies. The positive correlation between electrical power consumption per capita and the corruption perception index suggests that low corruption is associated with higher the electrical consumption per capita. Similarly, the Control of Corruption Index proves the same relationship. There is also a good correlation between electric power consumption per capita and the Human Development Index. This is also expected, because a developed country is expected to consume more electricity than a less developed country.

4.1.2.3. Linear regression analysis. Linear regression analysis is performed on the dataset to test the relationship between each of the socio-economic variables under study and the electrical consumption per capita. This is performed by fitting a separate model between the electrical consumption per capita and each of the other variables individually, as shown in Equation (4.1) below:

$$ElectricalPowerConsumptionPerCapita \\ = \alpha \times Variable + Intecept + error \tag{4.1}$$

The results of the linear regression tests are shown in Table 4.3. The columns on the left shows the variable/parameter used to fit the model as the independent variable, where each row represents a separate test. The dependent variable in all the tests is the electrical power consumption per capita. By observing the R^2 results, the goodness of fit of the model can be evaluated. The R^2 value shows the proportion of the variance in the dependent variable that is predictable from the independent variable. The Human Development Index (HDI), adjusted net national income per capita, and GDP per capita, all have R^2 values ≥ 0.5. In addition, the Control of Corruption Index, and the Corruption Perception Index both have noticeable R^2 values.

Table 4.2. Correlation analysis for the dataset.

	Electric power consumption (kWh per capita)	**Adjusted net national income per capita (current US$)**	**Human development index (HDI)**	**GDP per capita (current US$)**	**GDP per capita, PPP (current international $)**	**Access to electricity (% of population)**	**Renewable electricity output (% of total electricity output)**	**Electricity production from renewable sources, excluding**	**CPIA transparency, accountability, and corruption**	**Control of Corruption: Estimate**	**Corruption Perception Index**
Electric power consumption (kWh per capita)	1	0.73	0.75	0.71	0.71	0.42	-0.07	0.13	0.09	0.66	0.6
Adjusted net national income per capita (current US$)	0.73	1	0.8	0.99	0.88	0.45	-0.13	0.21	0.38	0.78	0.82
Human development index (HDI)	0.75	0.8	1	0.68	0.73	0.85	-0.33	0.23	0.23	0.41	-
GDP per capita (current US$)	0.71	0.99	0.68	1	0.89	0.38	-0.09	0.23	0.41	0.72	0.79
GDP per capita, PPP (current international $)	0.71	0.88	0.73	0.89	1	0.49	-0.21	0.17	0.35	0.66	0.72
Access to electricity (% of population)	0.42	0.45	0.85	0.38	0.49	1	-0.26	0.11	0.29	0.47	0.47
Renewable electricity output (% of total electricity output)	-0.07	-0.13	-0.33	-0.09	-0.21	-0.26	1	0.14	-0.11	-0.08	-0.03
Electricity production from renewable sources, excluding hydroelectric (% of total)	0.13	0.21	0.23	0.23	0.17	0.11	0.14	1	0.11	0.33	0.44
CPIA transparency, accountability, and corruption in the public sector rating (1=low to 6=high)	0.09	0.38	0.23	0.41	0.35	0.29	-0.11	0.11	1	0.82	0.87
Control of Corruption: Estimate	0.66	0.78	0.41	0.72	0.66	0.47	-0.08	0.33	0.82	1	0.99
Corruption Perception Index	0.6	0.82	-	0.79	0.72	0.47	-0.03	0.44	0.87	0.99	1

Table 4.3. Linear regression tests.

Parameter	***Number of Observations***	***R^2***	***Adjusted R^2***	***Coefficient of Variable***	***P-Value of Variable***	***P-Value of Intercept***
Human development index (HDI)	246	0.562	0.563	3891.276	0	0
Adjusted net national income per capita	4479	0.533	0.533	0.3	0	0
GDP per capita (current US$)	5079	0.505	0.505	0.246	0	0
GDP per capita, PPP (current international $)	3103	0.504	0.504	0.225	0	0
Control of Corruption: Estimate	2057	0.431	0.431	3404.839	0	0
Corruption Perception Index	387	0.353	0.354	178.714	0	0
Access to electricity (% of population)	2718	0.176	0.176	84.059	0	0
Electricity production from renewable sources, ...	5455	0.016	0.016	107.541	0	0
CPIA transparency, accountability, and corruption ...	383	0.006	0.009	119.82	0.067	0.1
Renewable electricity output (% of total elect...	3205	0.004	0.004	-10.192	0	0

4.1.2.4. Panel analysis. Panel data analysis is performed using Pooled OLS, FEM, and REM, as previously specified in the methodology. The results are shown in Table 4.4. It should be noted that Pooled OLS is the same concept as the previous linear regression sub-section, and results in almost identical results. There are negligible differences due to using a different tool. The results of panel regression show that the Human Development Index, Adjusted Net National Income per capita, GDP per capita, and GDP per capita at PPP have relatively high R^2 values. There is however a drop in R^2 values when Entity Effects are considered. This is probably due to other unobserved variables that are country specific. Regarding the analysis of corruption related parameters, the Control of Corruption Estimate and the Corruption Perception Index have a significant R^2 values using the Pooled OLS and FEM with Time Effect. However, the regressions using Entity Effect and RE do not perform well and have low T-statistics values. This means that Control of Corruption and Corruption Perception Index have a relationship with Electric Consumption per Capita.

Table 4.4. Results of panel analysis for electrical power consumption per capita as the dependent variable.

Variable	***No. Obs.***	***Method***	***R-squared***	***P-value (F-stat)***	***Coef. Of Variable***	***T-Stat of Coef.***
Adjusted net national income per capita (current US$)	4479	[Pooled]	0.53	0.00	0.30	71.43
		[FE (Time Effect)]	0.54	0.00	0.32	71.39
		[FE (Entity Effect)]	0.45	0.00	0.13	59.74
		[FE (Time and Entity Effect)]	0.25	0.00	0.10	37.76
		[RE]	0.44	0.00	0.13	59.74

Table 4.4. Results of panel analysis for electrical power consumption per capita as the dependent variable (cont.).

Variable	No. Obs.	Method	R-squared	P-value (F-stat)	Coef. Of Variable	T-Stat of Coef.
Human development index (HDI)	246	[Pooled]	0.56	0.00	3891.30	17.74
		[FE (Time Effect)]	0.55	0.00	3943.70	17.07
		[FE (Entity Effect)]	0.42	0.00	2736.70	12.55
		[FE (Time and Entity Effect)]	0.29	0.00	3622.40	9.29
		[RE]	0.41	0.00	2154.60	13.01
GDP per capita (current US$)	5079	[Pooled]	0.51	0.00	0.25	72.00
		[FE (Time Effect)]	0.51	0.00	0.26	72.43
		[FE (Entity Effect)]	0.38	0.00	0.14	55.00
		[FE (Time and Entity Effect)]	0.15	0.00	0.10	28.98
		[RE]	0.39	0.00	0.15	56.63
GDP per capita, PPP (current international $)	3103	[Pooled]	0.50	0.00	0.22	56.16
		[FE (Time Effect)]	0.51	0.00	0.23	56.81
		[FE (Entity Effect)]	0.12	0.00	0.08	20.13
		[FE (Time and Entity Effect)]	0.04	0.00	0.07	11.72
		[RE]	0.16	0.00	0.10	24.12
Access to electricity (% of population)	2718	[Pooled]	0.18	0.00	84.06	24.10
		[FE (Time Effect)]	0.17	0.00	83.86	23.80
		[FE (Entity Effect)]	0.00	0.02	12.31	2.26
		[FE (Time and Entity Effect)]	0.01	0.00	-36.47	(-6.05)
		[RE]	0.03	0.00	34.06	9.68

Table 4.4. Results of panel analysis for electrical power consumption per capita as the dependent variable (cont.).

Variable	No. Obs.	Method	R-squared	P-value (F-stat)	Coef. Of Variable	T-Stat of Coef.
Renewable electricity output (% of total electricity output)	3205	[Pooled]	0.00	0.00	-10.19	(-3.79)
		[FE (Time Effect)]	0.00	0.00	-9.78	(-3.63)
		[FE (Entity Effect)]	0.00	0.01	-8.14	(-2.50)
		[FE (Time and Entity Effect)]	0.00	0.87	-0.51	(-0.16)
		[RE]	0.00	0.37	-2.80	(-0.90)
Electricity production from renewable sources, excluding hydroelectric (% of total)	5455	[Pooled]	0.02	0.00	107.54	9.38
		[FE (Time Effect)]	0.01	0.00	86.99	7.43
		[FE (Entity Effect)]	0.12	0.00	217.96	26.69
		[FE (Time and Entity Effect)]	0.04	0.00	117.87	15.64
		[RE]	0.12	0.00	218.70	26.89
CPIA transparency, accountability, and corruption in the public sector rating (1=low to 6=high)	383	[Pooled]	0.01	0.07	119.82	1.84
		[FE (Time Effect)]	0.01	0.14	99.40	1.47
		[FE (Entity Effect)]	0.00	0.80	8.61	0.25
		[FE (Time and Entity Effect)]	0.00	0.69	-13.58	(-0.40)
		[RE]	0.03	0.00	90.19	3.19
Control of Corruption: Estimate	2057	[Pooled]	0.43	0.00	3404.80	39.47
		[FE (Time Effect)]	0.43	0.00	3410.80	39.42
		[FE (Entity Effect)]	0.00	0.35	-153.13	(-0.94)
		[FE (Time and Entity Effect)]	0.00	0.51	-104.86	(-0.66)
		[RE]	0.00	0.11	245.33	1.58

Table 4.4. Results of panel analysis for electrical power consumption per capita as the dependent variable (cont.).

Variable	No. Obs.	Method	R-squared	P-value (F-stat)	Coef. Of Variable	T-Stat of Coef.
Corruption Perception Index	387	[Pooled]	0.35	0.00	178.71	14.54
		[FE (Time Effect)]	0.35	0.00	179.62	14.34
		[FE (Entity Effect)]	0.01	0.20	-9.90	(-1.30)
		[FE (Time and Entity Effect)]	0.00	0.28	-8.68	(-1.07)
		[RE]	0.08	0.00	37.47	5.65

4.1.2.5. Polynomial regression fitting. In order to find the best equation that describes the electrical power consumption per capita, an optimization problem was formulated to search for the best formula to fit a polynomial regression. This is performed by running an exhaustive enumeration search through all combinations of the independent variables with the goal on finding the formula with the lowest $Adjusted\ R^2$. The number of possible variables was limited to a selection of variables that are expected to be relevant to the dependent variable while attempting to avoid collinearity. The variables used for the test are the Human Development Index, GDP per capita at PPP, Access to Electricity Percentage, Control of Corruption Estimate, and Corruption Perception Index. The search is performed on the first and second order combinations for each selected variable. The best formula found by the search algorithm is shown Equation (4.2). This formula was found to have the have the highest $Adjusted\ R^2$ value, which is 0.837, and has R^2 value of 0.842. The number of observations is 202.

Table 4.5 shows the statistical parameters of the linear fit, including the values of the coefficients, standard errors, P-values, and Confidence Interval. It can be seen that the P-values are generally low for all the variables, except the Access to electricity.

$$\begin{aligned} & ElectricalPowerConsumptionPerCapita = \\ & \alpha_1 \times HumanDevelopmentIndex + \alpha_2 \times \\ & (HumanDevelopmentIndex)^2 \\ & + \alpha_3 \times ControlOfCorruption + \alpha_4 \times \\ & (ControlOfCorruptionEstimate)^2 \\ & + \alpha_5 \times AccessToElectricity\% \\ & + \alpha_6 \times \ (\text{GDPperCapitaAtPPP})^2 \\ & + Intercept + error \end{aligned} \tag{4.2}$$

Table 4.5. Statistical parameters of the linear model.

Variable	***Coefficient***	***Standard Error***	***P>|t|***	***Confidence Interval (0.95%)***	
				Lower	***Upper***
Intercept	1359.707	313.313	0	741.79	1977.624
Human Development Index	-5751.13	1364.569	0	-8442.34	-3059.92
Access to Electricity	0.7365	1.716	0.668	-2.648	4.121
Control of Corruption	327.9585	58.582	0	212.424	443.493
(Human Development Index)^2	7671.495	1568.062	0	4578.956	1.08E+04
(GDP per Capita at PPP)^2	2.62E-06	3.19E-07	0	1.99E-06	3.25E-06
(Control of Corruption)^2	153.7084	51.219	0.003	52.694	254.723

4.1.2.6. Time series: electrical power consumption. Figure 4.6 shows the time series of the worldwide electrical power consumption per Capita. The first and very apparent observation is that Iceland has the highest electrical consumption, with a strikingly higher value than any other country. The reason of this fact is the unique conditions of the electrical sector in Iceland. Electrical power in Iceland is generated almost exclusively from renewable resources and mostly sold to industrial users, which are generally Aluminum smelters. The electrical generator in Iceland was 18,798 GWh in 2015, divided into 73% from hydroelectric sources, 27% geothermal power, and less than 1% from fossil fuels. The jump in the electrical power in 2008 marks the operation of the Kárahnjúkar Hydropower Plant which produces 4,600 gigawatt-hours (ASKJA Energy, 2019). In second place, with a much less consumption per capita, comes Norway. Bahrain is third in rank. The US is also in the upper range, with an electrical power consumption per capita of 12,993 kWh in 2014. The worldwide average electrical power consumption per capita in 2014 was 3,130 kWh.

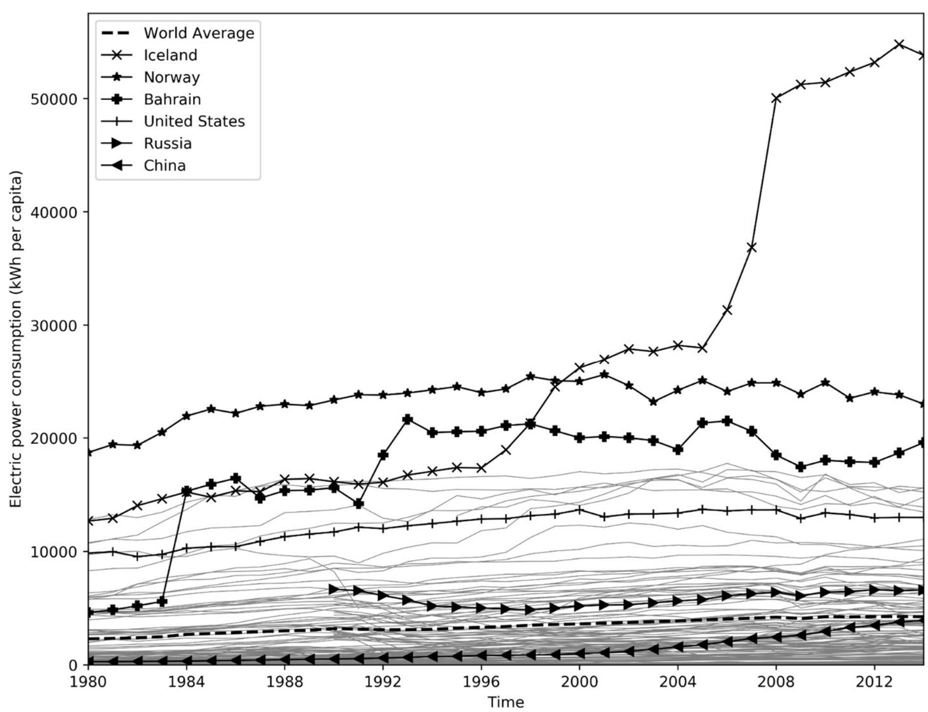


Figure 4.6. Electrical power consumption per capita.

4.1.2.7. Correlation analysis for each country. While correlation was done on the dataset in a previous part of this research, the correlation test in this section is performed for each country and variable separately. The correlation analysis done previously shows the relationship between the variables in the large dataset as a whole. However, the correlation in this section tests the relationship for each country separately. This approach presents a deeper understanding of how the relationships hold for each country separately and how ranges between them.

Table 4.6 shows the descriptive statistics of the recorded correlation results. Figure 4.7 shows a box plot of the same values for more convenient visualization. From the results, it can be observed the Adjusted Net National Income per Capita, the Human Development Index, the GDP per Capita, and the GDP per Capita at PPP all have very noticeable correlation against the Electrical Power Consumption per Capita, especially the Human Development Index. The Access to Electricity Percentage and the Percentage of Electricity from Renewables except Hydroelectric have much lower significant correlation results. Finally, the Renewable Electricity Output Percentage, CPIA Index, and the Corruption Perception Index have a very large range, which practically means the relationship could be negative in some countries and positive in others. It should be noted that the limitation of this analysis is the lack of relevant and consistent datasets across all countries and the same data range. Also, the approach of the correlation analysis shows the direct relationship between two variables without taking into consideration the simultaneous relationships between the entire variables. As such, another subsequent section will analysis the variables further using regression analysis including panel regression.

Table 4.6. Descriptive statistics of the correlation analysis for each of the variables against the electrical power consumption per capita, done for each country separately.

Variable	*# Countries Tested*	*Mean*	*Standard Deviation*	*Minimum*	*25%*	*50%*	*75%*	*Maximum*
Adjusted net national income per capita (current US$)	128	0.73	0.41	-0.97	0.74	0.89	0.94	1
Human development index (HDI)	27	0.73	0.42	-0.72	0.79	0.89	0.96	1
GDP per capita (current US$)	130	0.75	0.35	-0.69	0.73	0.89	0.94	0.99
GDP per capita, PPP (current international $)	129	0.71	0.43	-0.8	0.65	0.92	0.97	1
Access to electricity (% of population)	84	0.58	0.48	-0.93	0.28	0.81	0.93	0.98
Renewable electricity output (% of total electricity output)	125	-0.17	0.56	-1	-0.67	-0.24	0.33	0.89
Electricity production from renewable sources, excluding	104	0.44	0.43	-1	0.29	0.52	0.73	0.96
CPIA transparency, accountability, and corruption	28	0.01	0.66	-1	-0.59	-0.01	0.59	1
Control of Corruption: Estimate	130	-0.01	0.49	-0.9	-0.42	0.01	0.33	0.92
Corruption Perception Index	121	0	0.73	-1	-0.75	0	0.75	1

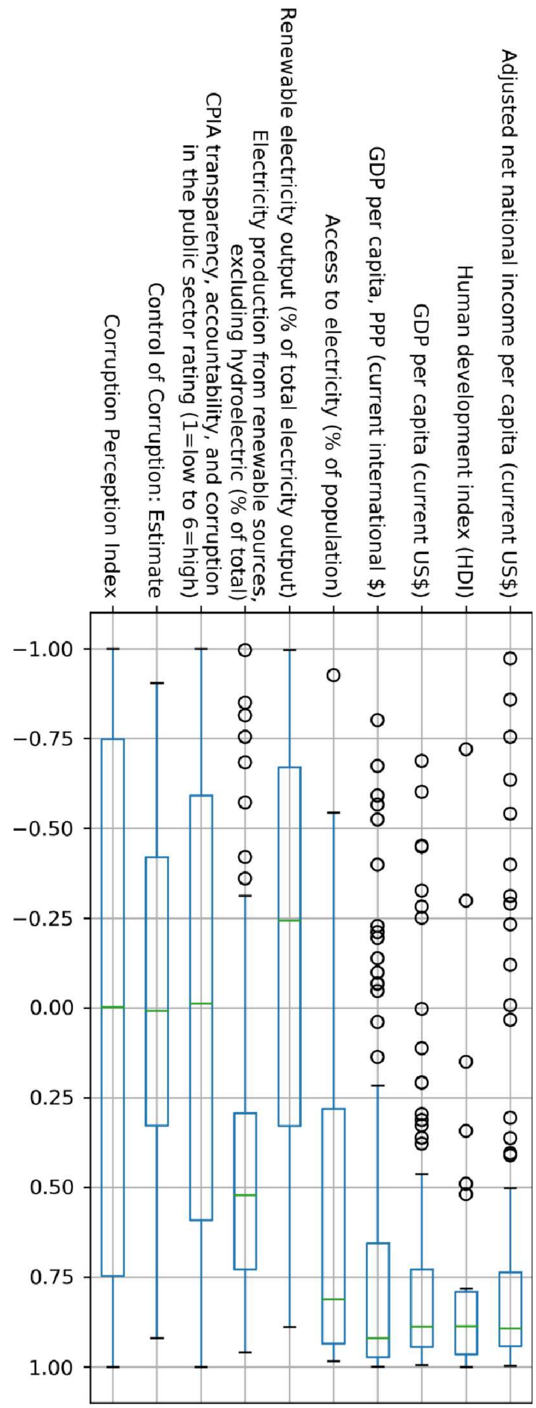


Figure 4.7. Box plot of the correlation against electrical power consumption per capita for each country.

4.1.2.8. Granger causality testing. Granger-causality testing is performed on two time series to test if one causes the other, i.e. that a change in one time-series causes change in the other. The null-hypothesis in this test is that the time series does not cause the other one. The observed outputs of this test that are the p-values. If the value is ≥ 0.05, the null hypothesis can be rejected and it can be concluded that a causality relationship exists. The test is performed in two directions: (1) test which of the variables causes the Electrical Power Consumption, and (2) test if the Electrical Power Consumption per Capita granger-causes any of the other variables. In both cases, the test is performed between the Electrical Power Consumption per Capita and each of the variables separately, and at the same time for each country separately. The test is performed with a max lag of two years. This low range of lag some of the variables lack enough available time range.

Causes of electrical consumption. In the first case, the test is performed to find which variables grange-case the Electrical Power Consumption per Capita. The descriptive statistics of all the granger-causality tests are shown in Table 4.7, and visualized as box plots in Figure 4.8. It can be seen from the results the mean values of the P-values are generally large. The null hypothesis should not be rejected if P-value $\geq$ 0.05. Therefore, it be concluded that none of the studied metrics has a noticeable causality effect on the electrical power consumption. This conclusion is at least valid for on the short-term since the test was performed with a maximum time lag of two years.

Impact of electrical consumption per capita. In this section, the granger-causality test is performed to find which variables the Electrical Power Consumption per Capita cases. The descriptive statistics of all the granger-causality tests are shown in Table 4.8, and visualized as box plots in Figure 4.9. Similar to the findings in the previous section of the Granger-causality testing, the results of the P-values in this test are also generally high and greater than 0.05. Therefore, the null hypothesis should not be rejected, and it can be concluded that, at least on the short-term, the electrical power consumption per capita does not cause any of the studied metrics.

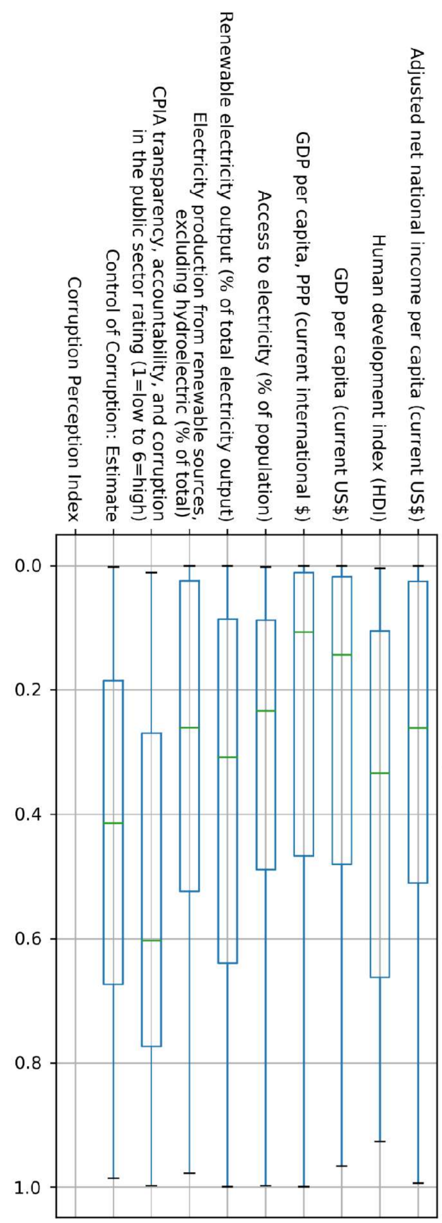


Figure 4.8. Box plot of the Granger-Causality against electrical power consumption per capita for each country.

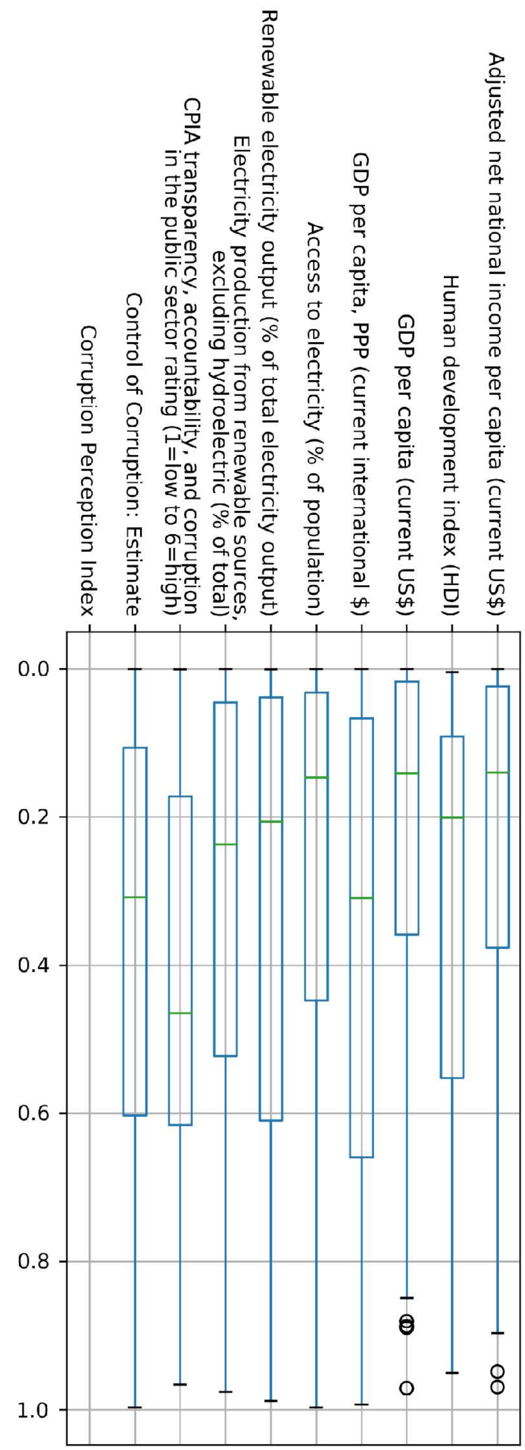


Figure 4.9. Box plot of the Granger-Causality against electrical power consumption per capita for each country.

Table 4.7. Descriptive statistics of P-values resulting from the Granger-Causality test, done for each country separately.

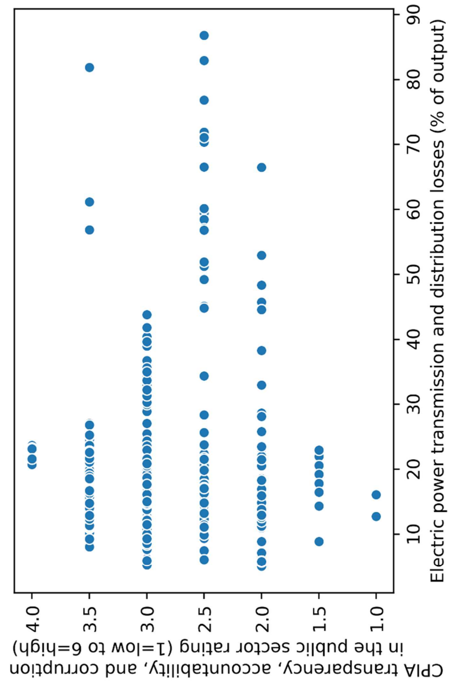
Variable	***# Countries Tested***	***Mean***	***Standard Deviation***	***Minimum***	***25%***	***50%***	***75%***	***Maximum***
Adjusted net national income per capita (current US$)	126	0.3	0.29	0	0.03	0.26	0.51	0.99
Human development index (HDI)	24	0.38	0.3	0	0.1	0.33	0.66	0.93
GDP per capita (current US$)	129	0.27	0.3	0	0.02	0.14	0.48	0.97
GDP per capita, PPP (current international $)	128	0.27	0.3	0	0.01	0.11	0.47	1
Access to electricity (% of population)	79	0.31	0.28	0	0.09	0.23	0.49	1
Renewable electricity output (% of total electricity output)	124	0.39	0.31	0	0.09	0.31	0.64	1
Electricity production from renewable sources, excluding hydroelectric (% of total)	102	0.32	0.31	0	0.02	0.26	0.52	0.98
CPIA transparency, accountability, and corruption in the public sector rating (1=low to 6=high)	22	0.53	0.31	0.01	0.27	0.6	0.77	1
Control of Corruption: Estimate	129	0.43	0.29	0	0.18	0.41	0.67	0.99
Corruption Perception Index	0	-	-	-	-	-	-	-

Table 4.8. Descriptive statistics of P-values resulting from the Granger-Causality test, done for each country separately.

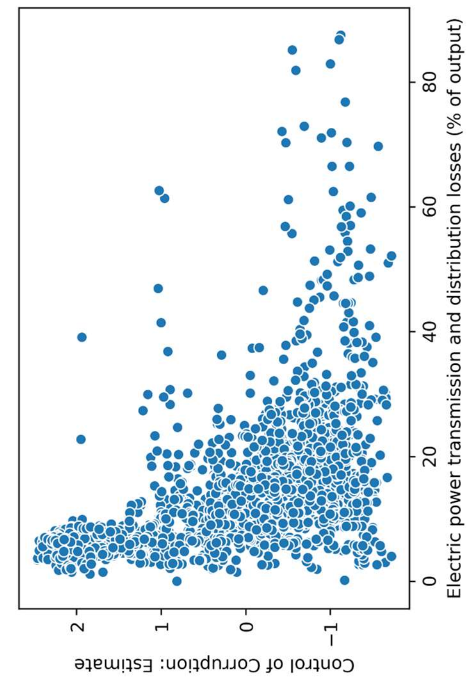
Variable	***# Countries Tested***	***Mean***	***Standard Deviation***	***Minimum***	***25%***	***50%***	***75%***	***Maximum***
Adjusted net national income per capita (current US$)	126	0.24	0.26	0	0.02	0.14	0.38	0.97
Human development index (HDI)	24	0.34	0.31	0	0.09	0.2	0.55	0.95
GDP per capita (current US$)	129	0.24	0.26	0	0.02	0.14	0.36	0.97
GDP per capita, PPP (current international $)	128	0.38	0.32	0	0.07	0.31	0.66	0.99
Access to electricity (% of population)	79	0.26	0.27	0	0.03	0.15	0.45	1
Renewable electricity output (% of total electricity output)	124	0.33	0.32	0	0.04	0.21	0.61	0.99
Electricity production from renewable sources, excluding hydroelectric (% of total)	103	0.3	0.28	0	0.05	0.24	0.52	0.98
CPIA transparency, accountability, and corruption in the public sector rating (1=low to 6=high)	22	0.43	0.3	0	0.17	0.46	0.62	0.97
Control of Corruption: Estimate	129	0.38	0.29	0	0.11	0.31	0.6	1
Corruption Perception Index	0	-	-	-	-	-	-	-

4.1.3. Analysis Against Electrical Losses in Distribution. The previous analysis showed that a relationship between electrical power consumption per capita, on one side, and metrics that represent economy, development, and corruption, on the other side. This section focuses on electrical power losses in distribution, instead of electrical power consumption per capita. Previous studies, covered in the literature review, highlighted that that illegal actions, theft, government inefficiency, and poor enforcement of the law result in large power losses, in the form of electricity that is generated, but not billed. In addition, it can be argued that the design, construction, and maintenance of an efficient power infrastructure is impacted by corruption. Therefore, the analysis in the following sections place a special interest on the effect of corruption on electrical power losses in distribution.

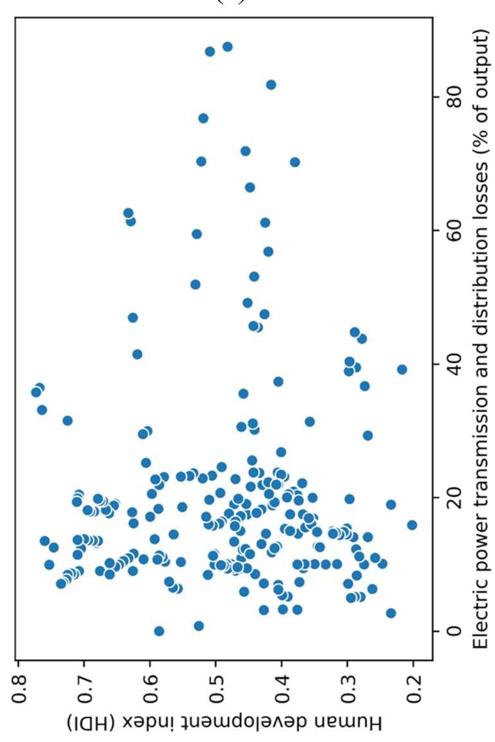
4.1.3.1. Data visualization. Figure 4.10 shows the scatter plots of (a) CPIA Index, (b) Control of Corruption, (c) Human Development Index, and (d) Corruption Perception Index, vs. electric power losses. The plots of the Control of Corruption and the Corruption Perception Index show visually apparent negative trends. It should be mentioned the corruption indices are high in less corrupt countries, and low in low in more corrupt countries. Therefore, the trend means that in less corrupt countries, the percentage of electricity losses is lower. The trend is less apparent when comparing to the Human Development Index against the electric power losses. This means that corruption may be more suitable than human development to reflect the losses in distribution in a country.



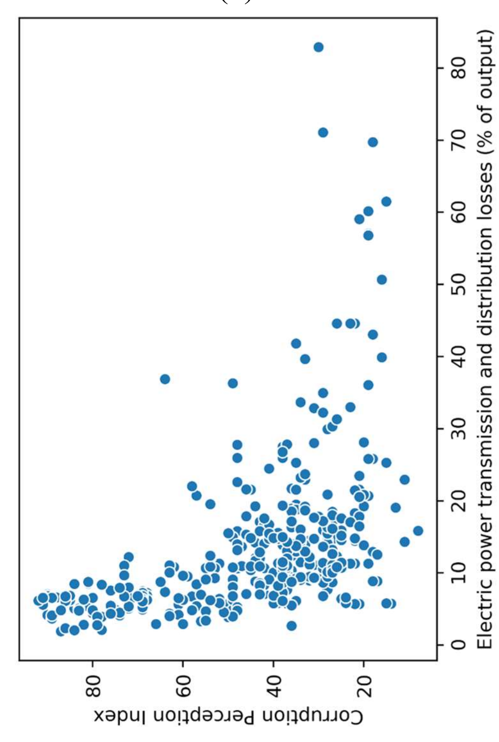
(a)



(b)



(c)



(d)

Figure 4.10. Scatter plots of the (a) CPIA index, (b) control of corruption, (c) human development index, and (d) corruption perception index, vs. electrical power consumption per capita.

4.1.3.2. Correlation analysis. The relationship between corruption and electrical losses can be further studied by performing correlation analysis. Table 4.9 shows the correlation analysis results. The correlation of the percentage of electricity losses against each of the studied variables can be seen in the first column.

The results show that there is a weak correlation between the percentage power loss and both the Control of Corruption Index and Corruption Perception Index. However, the correlations for those two indices are higher than that of the Human development Index. Therefore, it can be concluded from this test that corruption is somewhat correlated with electric power losses. However, there is a very weak correlation between human development and electric power losses. This, again, means that losses in distribution in a country may be more connected to corruption that human development. A country that has lower corruption has lower losses in distribution, and vice versa.

4.1.4. Regression Analysis. In this section, regression analysis is performed to find the best linear model that fits the percentage of electrical power losses. The test was performed by searching for the formula of a polynomial regression that produces the highest $Adjusted\ R^2$. The results of this optimization problem in shown in Table 4.10. From the results, it can be seen the Corruption Perception Index has the highest R^2 and $Adjusted\ R$^2, followed closely by the Control of Corruption Estimate. The Human Development Index and the CPIA index both have negligible results. Therefore, it can be concluded the best formula for this model is:

$$\%PowerLosses = \alpha_0 \times CPI + \alpha_1 \times CPI^2 + Inercept \tag{4.3}$$

Table 4.9. Correlation analysis of electric power consumption, development, and corruption.

Item	Electric power transmission and distribution losses (% of output)	CPIA transparency, accountability, and corruption in the public sector rating (1=low to 6=high)	Control of Corruption: Estimate	Human development index (HDI)	Corruption Perception Index
Electric power transmission and distribution losses (% of output)	1.00	-0.02	-0.46	-0.02	-0.47
CPIA transparency, accountability, and corruption in the public sector rating (1=low to 6=high)	-0.02	1.00	0.82	0.23	0.87
Control of Corruption: Estimate	-0.46	0.82	1.00	0.41	0.99
Human development index (HDI)	-0.02	0.23	0.41	1.00	NaN
Corruption Perception Index	-0.47	0.87	0.99	NaN	1.00

Table 4.10. Summary of the regression analysis.

Parameter	Number of Observations	Adjusted R^2	R^2
Corruption Perception Index	381	0.24	0.236
Control of Corruption Estimate	2038	0.216	0.215
Human development index HDI	236	0.018	0.01
CPIA transparency accountability and corruption	371	0.007	0.001

Table 4.11 shows the statistical parameters of the best formula found, shown in Equation (4.3). From the numbers shown in Table 4.11, it can be seen that the p-values are all low and acceptable, which shows that the CPI has a high significance in the model. Figure 4.11 shows the scatter plot of the actual vs the fitted values using the chosen regression model. Overall, the model shows a good fit. It can therefore be concluded that corruption is strongly linked to electrical power losses in distribution.

Table 4.11. Parameters of the polynomial regression model found.

	Coefficient	*Standard Error*	*P-Value*	*Confidence (95%)*	
				Lower	*Higher*
Intercept	32.1482	2.764	0	26.714	37.583
Corruption Perception Index	-0.5879	0.121	0	-0.826	-0.35
(Corruption Perception Index)^2	0.0032	0.001	0.006	0.001	0.005

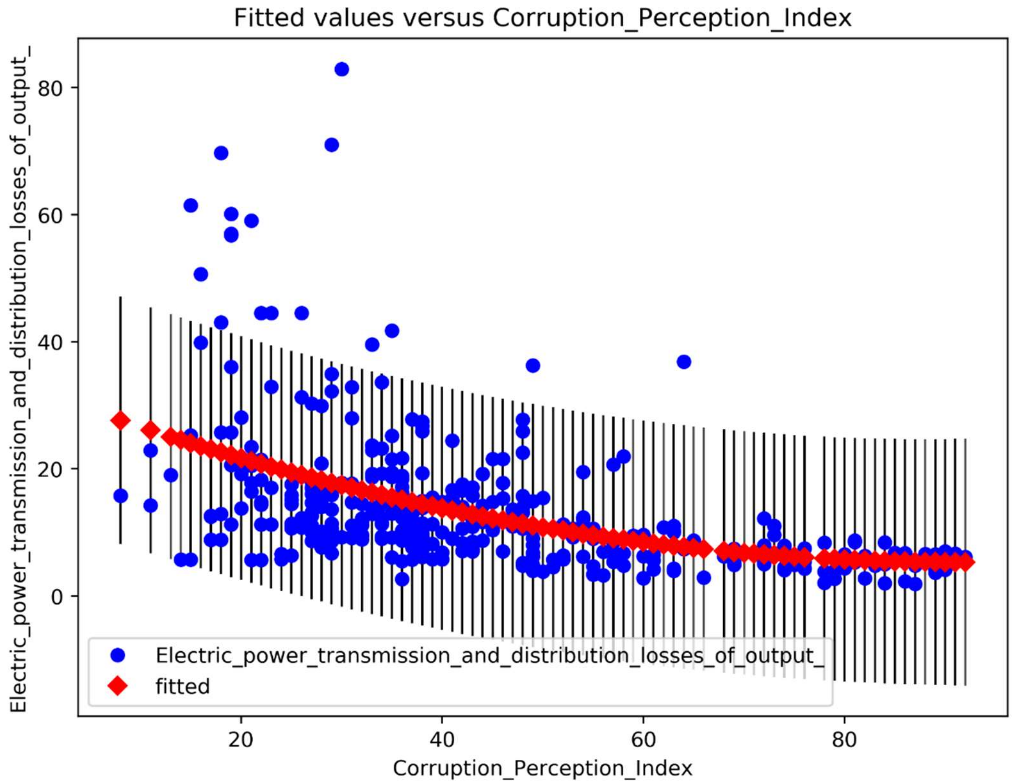


Figure 4.11. Fitted and actual values for electric power losses calculated using the corruption perception index.

4.1.4.1. Panel analysis. Results of Panel Analysis are shown in Table 4.12. Results of the Pooled OLS for Control of Corruption Estimate and Corruption Perception Index are in line with the previously shown linear regression analysis. It was also found that the FEM with Time effect for the same two factors, the Control of Corruption Estimate and Corruption Perception Index, are also somewhat significant. This means that those factors have a relationship with Electric Power Losses when taking into consideration unobserved time-dependent effects. Results of the REM show good results for the CIA Rating, Human Development Index, and the Corruption Perception Index. Overall, the results of the panel analysis for the relationship between corruption indices and electric power losses are mixed and hard to interpret considering unobserved effects. However, the results show that there is a connection between corruption and electric power losses.

Table 4.12. Results of panel analysis for electrical power losses as dependent variable.

Variable	*No. Obs.*	*Method*	*R-squared*	*P-value (F-stat)*	*Coef. Of Variable*	*T-Stat of Coef.*
CPIA transparency, accountability, and corruption in the public sector rating (1=low to 6=high)	371	[Pooled]	0.00	0.73	-0.43	(-0.35)
		[FE (Time Effect)]	0.00	0.73	-0.42	(-0.34)
		[FE (Entity Effect)]	0.01	0.15	1.88	1.43
		[FE (Time and Entity Effect)]	0.01	0.16	1.89	1.42
		[RE]	0.17	0.00	5.96	8.56
Control of Corruption: Estimate	2054	[Pooled]	0.21	0.00	-4.61	(-23.44)
		[FE (Time Effect)]	0.21	0.00	-4.62	(-23.40)
		[FE (Entity Effect)]	0.00	0.05	-1.32	(-1.94)
		[FE (Time and Entity Effect)]	0.00	0.05	-1.36	(-1.99)
		[RE]	0.00	0.00	-1.97	(-3.20)
Human development index (HDI)	236	[Pooled]	0.00	0.71	-2.79	(-0.37)
		[FE (Time Effect)]	0.00	0.29	-8.06	(-1.05)
		[FE (Entity Effect)]	0.03	0.01	34.07	2.57
		[FE (Time and Entity Effect)]	0.02	0.03	-50.17	(-2.24)
		[RE]	0.17	0.00	40.01	6.99
Corruption Perception Index	381	[Pooled]	0.22	0.00	-0.26	(-10.484)
		[FE (Time Effect)]	0.23	0.00	-0.26	(-10.468)
		[FE (Entity Effect)]	0.00	0.45	0.08	-0.76
		[FE (Time and Entity Effect)]	0.00	0.48	0.07	-0.70
		[RE]	0.14	0.00	0.21	-7.96

4.2. DEVELOPMENT OF THE ABM

The results in this part show the results of the baseline case using the developed ABM, which is further developed in the following parts. The baseline case is mostly used as the initial building block for comparison of the results in the following parts. As shown in Figure 4.12, there is a slight decrease in the number of active customers, which totals 2,249,741 at the end of the 5 years duration of the simulation. In other words, 6.2% of the initial 2,400,000 customers decided to install DSG and detach from the grid from their LSEs from an. The highest number of customers detaching is at LSE 6, which is an expected outcome because it is located at Node 6 which does not have any generators and consequently has the highest LMP. On the other hand, the lowest adoption of DSG is at LSE 3, which is also expected because it is located at Node 3 which has a nuclear generator supplying cheap power, is at the center of the network, and is connected to four adjacent nodes resulting in an abundance of low-cost power. The commitment percentage of the generators is shown in Figure 4.13. Most generators have slowly decreased commitment. The rate of decrease in the commitment is associated with the generation costs of each generator type. The nuclear generator at node 3 is the least affected because it produces the least expensive power, followed by the coal generators, and then the natural gas generators. The commitment of the generators is also affected by their location on the grid. For example, generator 1 is a natural gas generator and is located at the same node as generator 2, which is a coal generator and less expensive. Therefore, generator 1 is affected by the competition with generator 2. The resulting total gross profit of the generators in the baseline case was found to be $\$\ 1.077 \times e^{10}$ and the final number of customers connected to the LSEs was $2{,}249{,}741$ customers. Overall, the baseline case shows how that the developed model can simulate the complexity of the interaction between the adoption of DSG and economics of the wholesale power market. Figure 4.14 shows the average monthly LMP for each LSE. It should be noted that the LMPs represent the marginal cost of one additional unit of power. The values of the LMPs are location based and depend on the complex interaction between the demand at each node on one side and the generation parameters and congestion in the grid on the other side. For example, it can be seen that the LMPs at node 6 are the highest. It can also be seen by comparing Figure 4.12 and Figure 4.14 that the high cost of electricity at LSE 6 is related to the high adoption rate. The opposite is noted for LSE 3. In other words, customers at LSEs where the cost of Power is high are more inclined to install DSG systems as it is the more economical source of power. The following parts buildup on the base ABM and baseline case to add RL, incentives, and optimization for reducing system vulnerability.

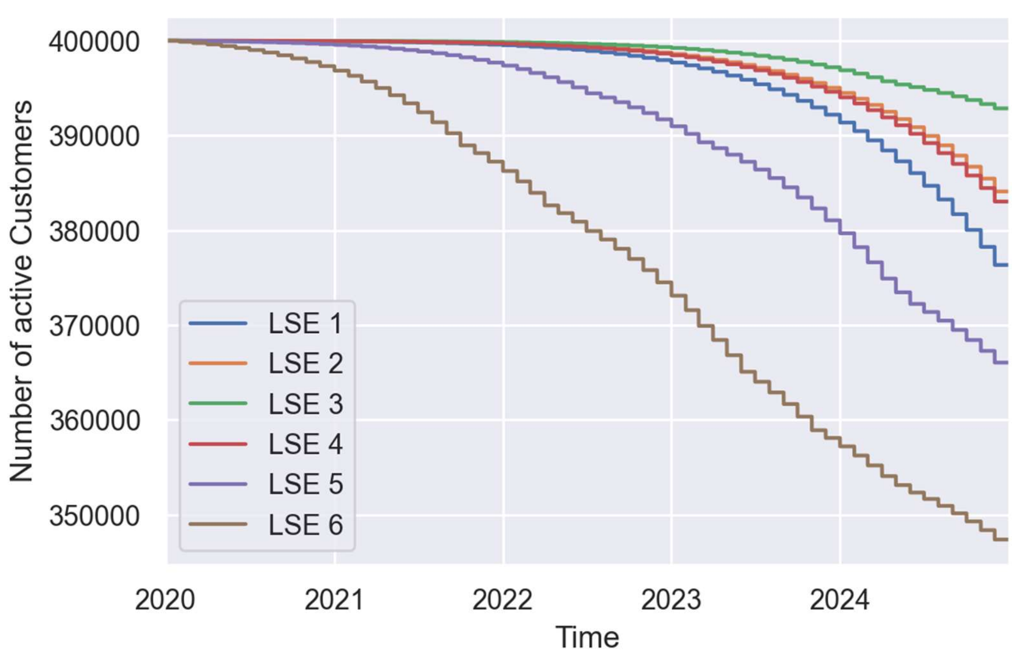


Figure 4.12. Number of active customers in the baseline case.

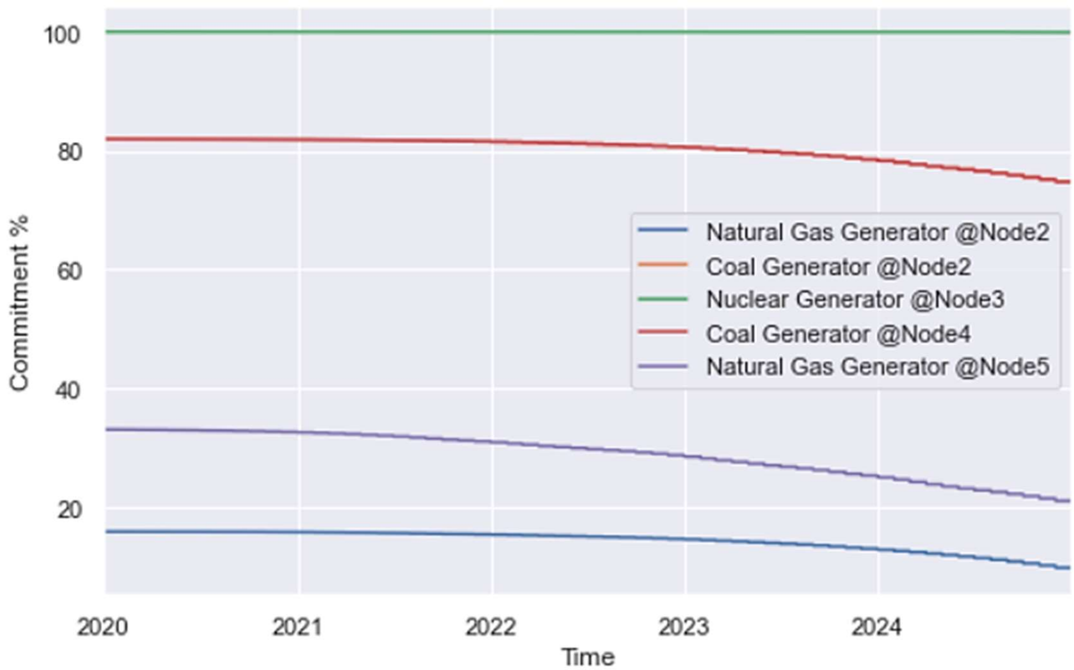


Figure 4.13. Commitment % of the generators in the baseline case.

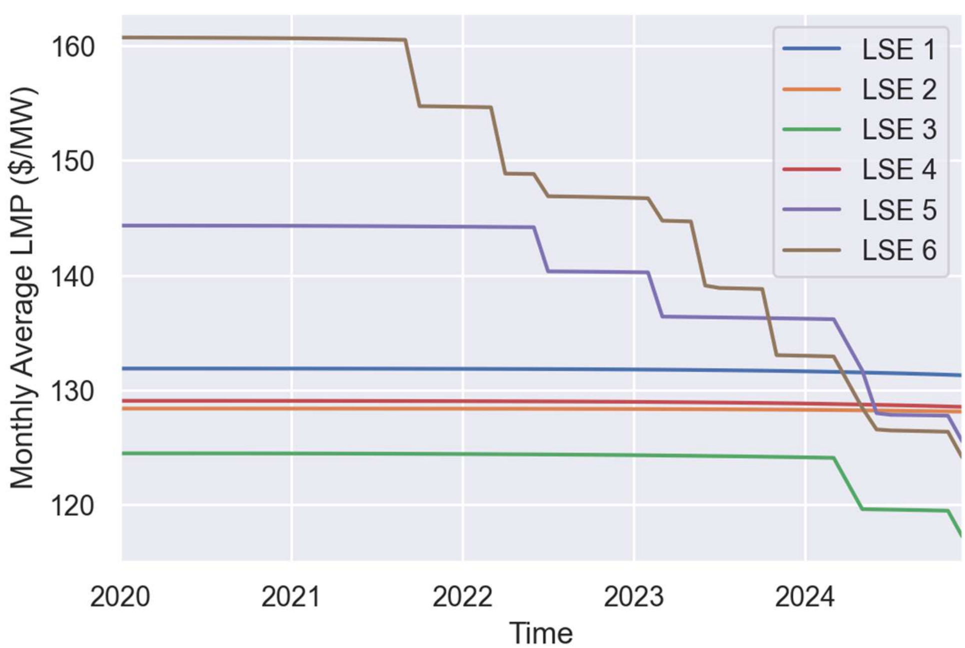


Figure 4.14. Monthly average LMPs for each LSE.

4.3. DYNAMIC PRICING USING REINFORCEMENT LEARNING (RL)

The following sections show the results for the ABM with three RL algorithms as discussed in the methodology: (1) Baric RL; (2) Multiplicative RL; and (3) Roth-Erev RL.

4.3.1. Basic RL. Figure 4.15 shows the number of customers using the basic probability formulation in Equation (3.20) and the Gibbs-Boltzmann colling factor method in Equation (3.25). Figure 4.16 shows the weekly average LMPs for each LSE. Figure 4.17 shows the weekly average markups for the generators, while Figure 4.18 shows their commitment percentages. In comparison with the results of the baseline case, the results using a basic RL show that is not able to fully grasp the complexity of the problem and create an intelligent and steady learning behavior. To simplify the analysis of the results, it is assumed that the markup of a generator is calculated using the new $a_{g,RL}$ parameter from the RL and the original $a_{g,original}$ parameter such that $markup_g = \frac{a_{g,RL}}{a_{g,original}}$. Figure 4.17 shows that the markups of the generators are highly unstable where the generators keep testing new markups without converging to a noticeable trend. The results of the RL using Gibbs-Boltzmann are more acceptable in comparison with the basic probability formulation, as shown in Figure 4.17 (bottom). A generally observed behavior is that coal generators decrease their supply offer. The contrary applies to natural gas generators. This behavior shows how different generator types can have different strategies to compete and improve their gross profit. Overall, the total gross profit was $9.952 \times e^9$ and the final number of customers was $1{,}797{,}242$ using the basic probability method, and $1.330 \times e^{10}$ and $1{,}909{,}465$ using Gibbs-Boltzmann Cooling factor. Basic RL using basic probability calculation is unstable and unsatisfactory. By implanting the Gibbs-Boltzmann cooling factor, the basic RL results in a total gross profit that is higher than the baseline case although DSG adoption is higher.

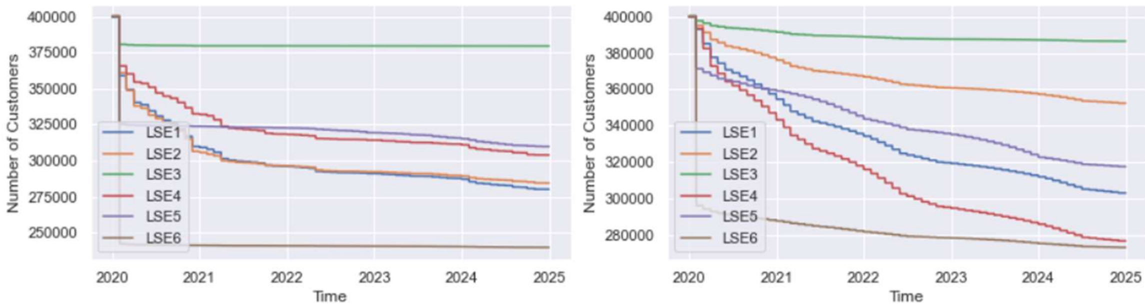


Figure 4.15. Number of customers using basic probability (left) and Gibbs-Boltzmann (right).

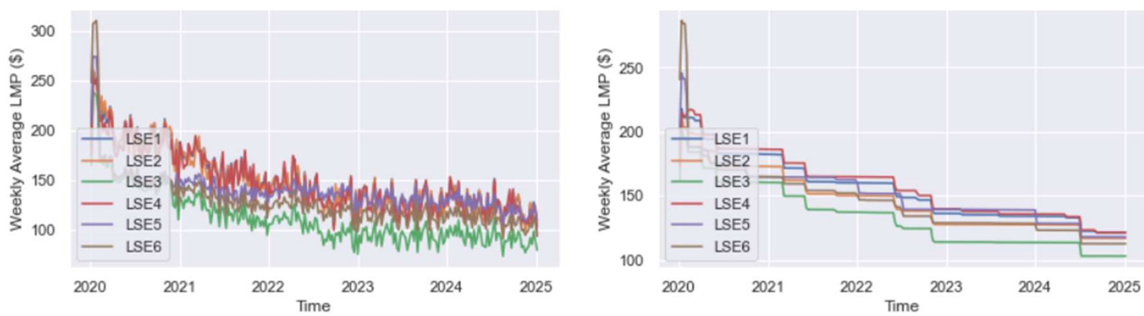


Figure 4.16. Weekly average LMPs using basic probability (left) and Gibbs-Boltzmann (right).

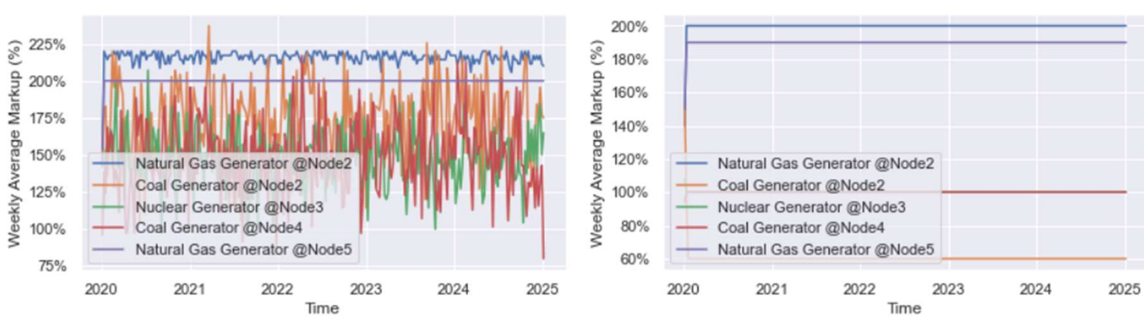


Figure 4.17. Weekly average markups using basic probability (left) and Gibbs-Boltzmann (right).

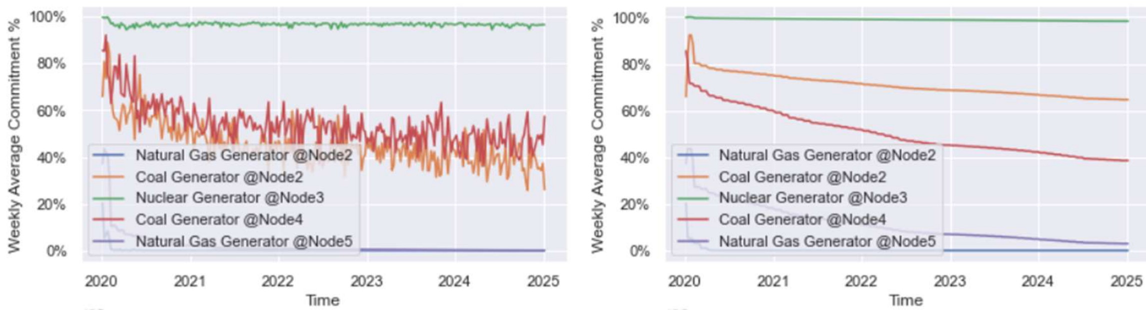


Figure 4.18. Generator commitment percentages using basic probability (left) and Gibbs-Boltzmann (right).

4.3.2. Multiplicative RL. The multiplicative RL algorithm is an improvement upon the basic RL because it includes an LR that controls the learning behavior. A range of LR between 0.1 and 0.9 is tested to find the best value. Figure 4.19, Figure 4.20, Figure 4.21, Figure 4.22, and Figure 4.23 show the markups chosen by generators 1, 2, 3, 4, and 5, respectively. An LR of 0.1 results in distinctively steady learning behavior, specifically for generators 2, 3, and 4. It should be noted that natural gas generators are the most expensive, and therefore they are severely affected by the adoption of DSG in combination with the competition from the coal power plants. For example, generator 1 (natural gas) and generator 2 (coal) are on the same node. Generator 2 is less expensive than generator 1 and strategically chooses the best markup to compete. Due to those reasons, generator 1 reaches a commitment of 0% by the first year, while generator 2 maintains superior commitment. On the other hand, generator 3 has the lowest power overall, which allows it to choose the highest markups while also generating the highest amounts of power, reaching a minimum of 96%. Overall, the results of the multiplicative RL using Gibbs-Boltzmann for probability calculation resulted in more stable learning behavior, as shown in Figure 4.20 (right), than the behavior of the basic RL. A low LR of 0.1 was found to results in a steady learning behavior because it can regulate the magnitude of the reward calculated using the gross profits of the generators better. However, its results are worse than the baseline and the basic RL with a total gross profit of $1.119 \times e^{10}$ and 1,781,148 final number of customers.

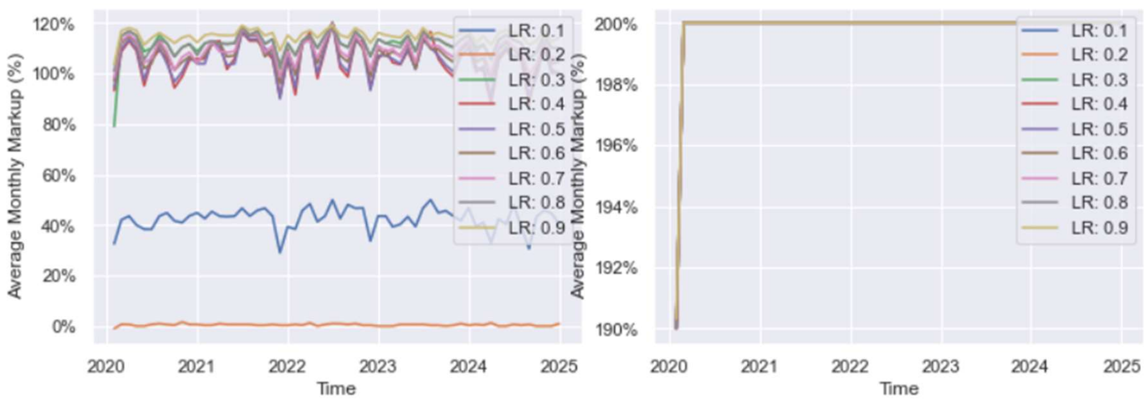


Figure 4.19. Markups of generator 1 (natural gas) using multiplicate RL with basic probability (left) and Gibbs-Boltzmann (right).

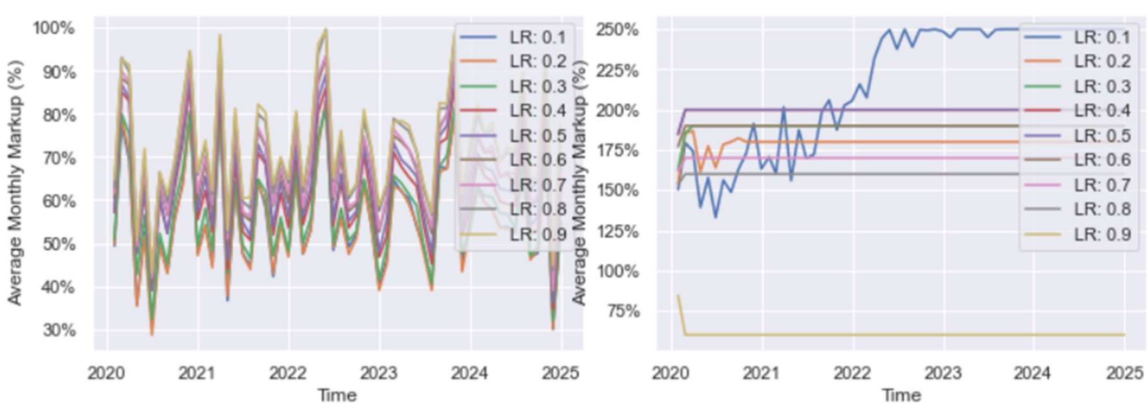


Figure 4.20. Markups of generator 2 (coal) using multiplicate RL with basic probability (top) and Gibbs-Boltzmann (bottom).

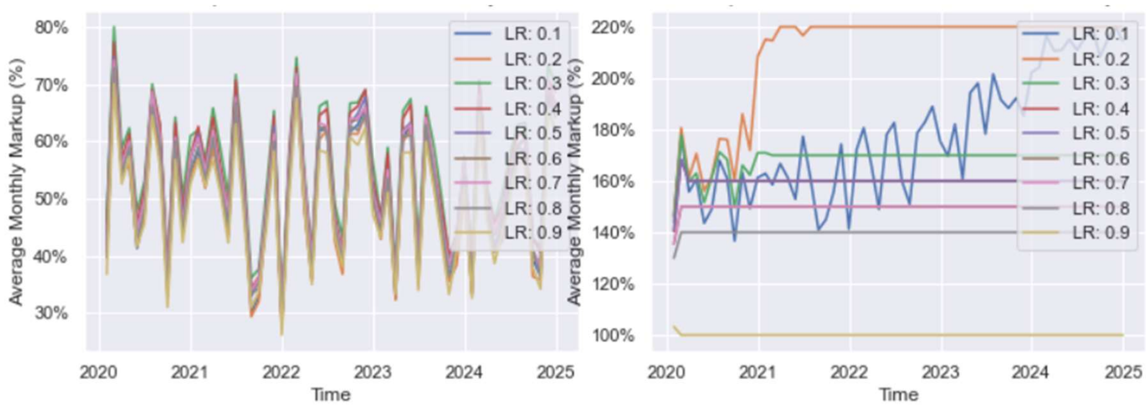


Figure 4.21. Markups of generator 3 (nuclear) using multiplicate RL with basic probability (left) and Gibbs-Boltzmann (right).

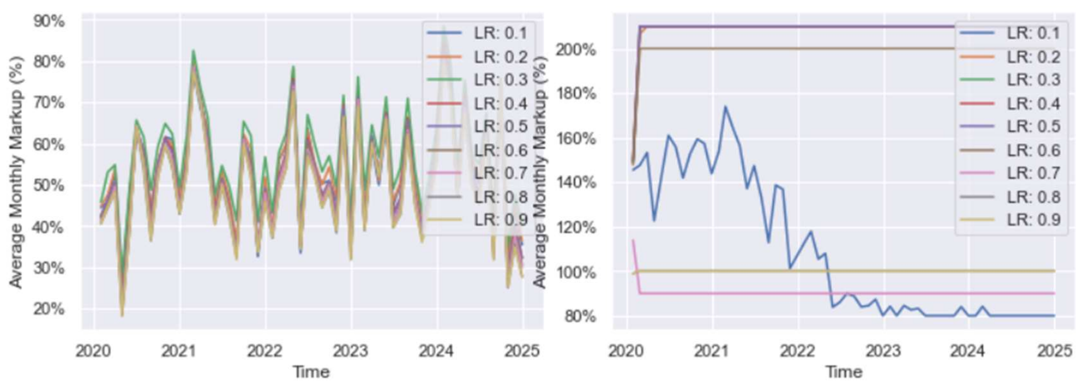


Figure 4.22. Markups of generator 4 (coal) using multiplicate RL with basic probability (left) and Gibbs-Boltzmann (right).

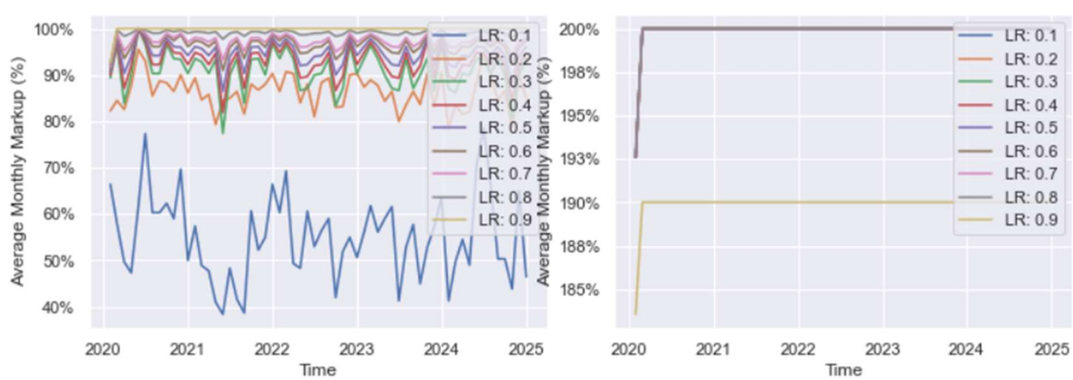


Figure 4.23. Markups of generator 5 (natural gas) using multiplicate RL with basic probability (left) and Gibbs-Boltzmann (right).

4.3.3. Roth-Erev RL. The Roth-Erev algorithm and its modified version have a more realistic replication of learning behavior because they replicate forgetfulness and experimentation using a forgetting factor (ϕ) and an experimentation factor (ϵ). To perform hyper-parameter optimization, the combinations from the following options were exhaustively tested: (1) forgetting factor between 0.1 to 0.9; (2) experimentation factor between 0.1 to 0.9; (3) original Roth-Erev vs. modified Roth-Erev; and (4) basic probability calculation vs. Gibbs-Boltzmann cooling factor probability. Figure 25 shows heatmaps that visualize the results from all the combinations. The heatmaps show that increasing or decreasing the forgetting and experimentation factors can decrease the gross profits. The modified Roth-Erev using a forgetting parameter of 0.2, experimentation parameter of 0.5 in combination with the Gibbs-Boltzmann probability method resulted in the highest total gross profit for the generators, as shown in Figure 4.24 (b). The resulting total gross profit and final number of customers were found to be $1.415 \times e^{10}$ and $1{,}910{,}627$, respectively. The adoption of DSG is higher than the baseline case but lower than the other RL algorithms tested in the previous sections. However, the total gross profit was found to be the best among the other RL cases and the baseline case.

To further understand the performance of the selected RL, Figure 4.25, Figure 4.26, and Figure 4.27 show the markups decided by the generators, the gross profits of the generators, and the total number of customers for each LSE, respectively. The results show that the generators reached convergence their optimum markups during the first 10 days of the simulation. The choice of markups remained unchanged during the remaining duration of the simulation. It can be seen from Figure 4.26 that generator 3 (nuclear) has the highest gross profit, followed by generator 4 (coal). Figure 4.27 shows a rate of adoption of DSG that is higher than the baseline case due to the addition of generator markups. There is a sharp increase in the rate of adoption of DSG at LSE 6, which is located at a node with no generators, resulting in high LMPs at that location and in turn high electricity rates to be paid by customers. The rate of adoption of DSG is therefore high until the LMPs are reasonably close to the cost of installing a DSG system.

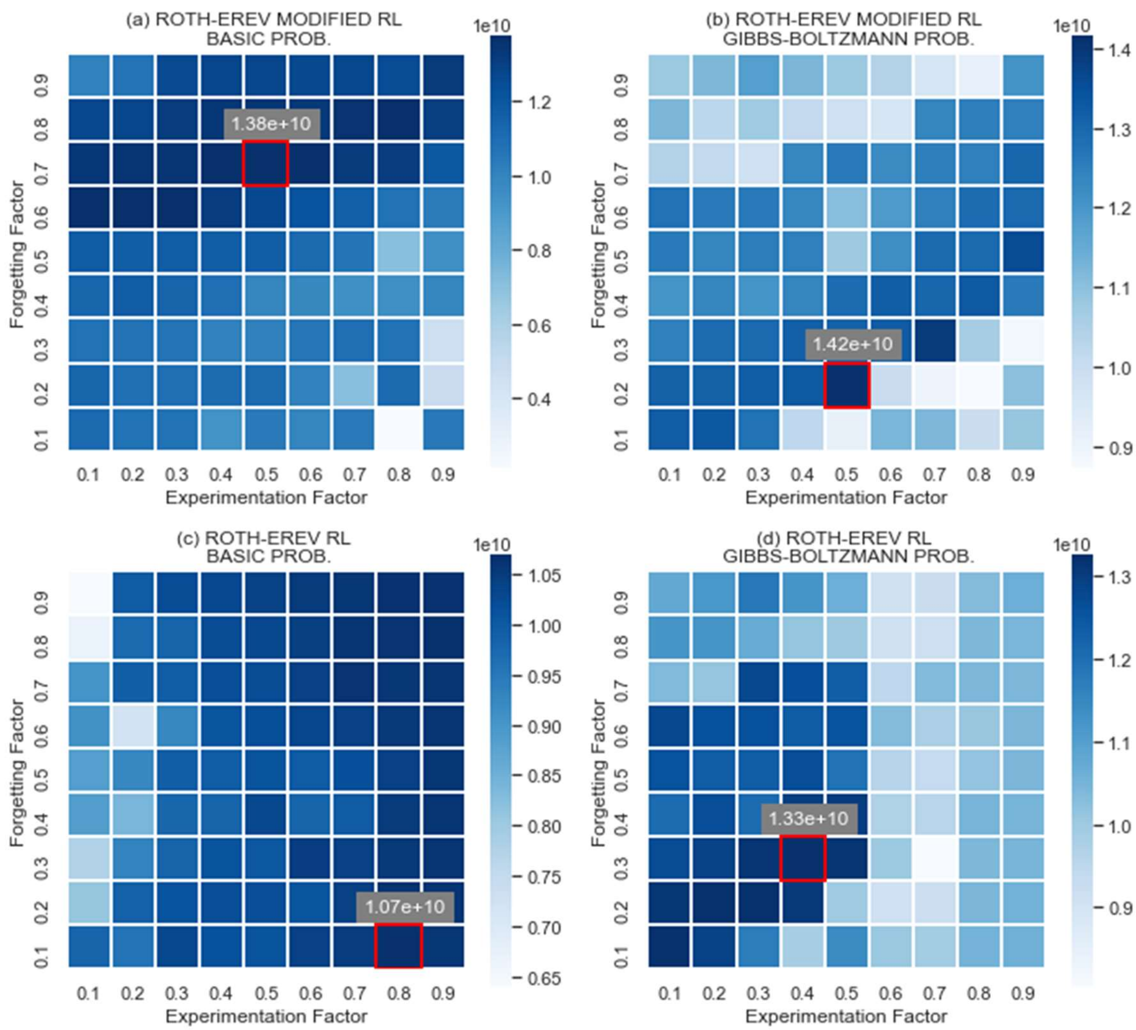


Figure 4.24. Total gross profit results using: (a) modified Roth-Erev with basic probability and (b) Gibbs-Boltzmann probability; and (c) original Roth-Erev with basic probability and (d) Gibbs-Boltzmann probability.

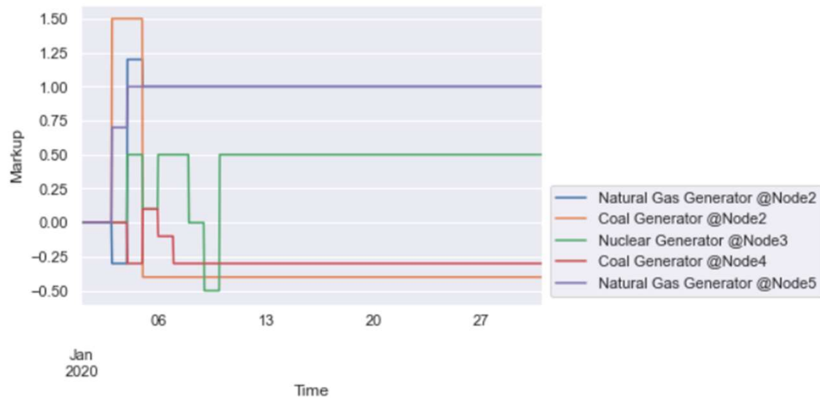


Figure 4.25. Markups during the first 30 days.

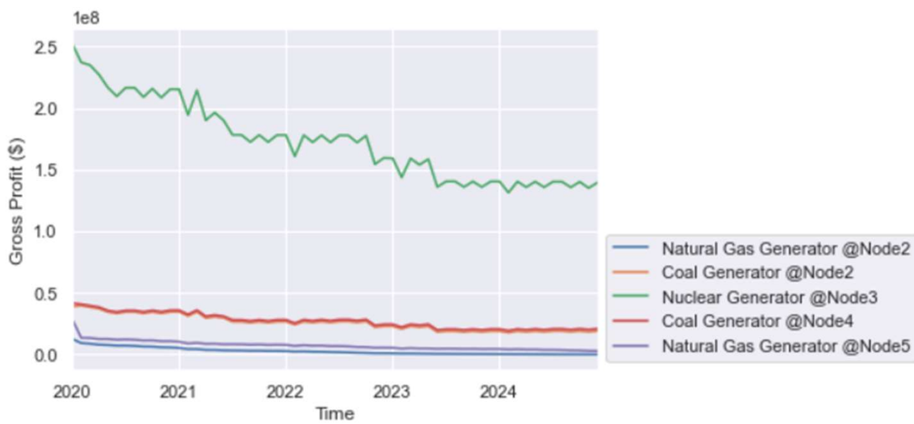


Figure 4.26. Generator gross profits.

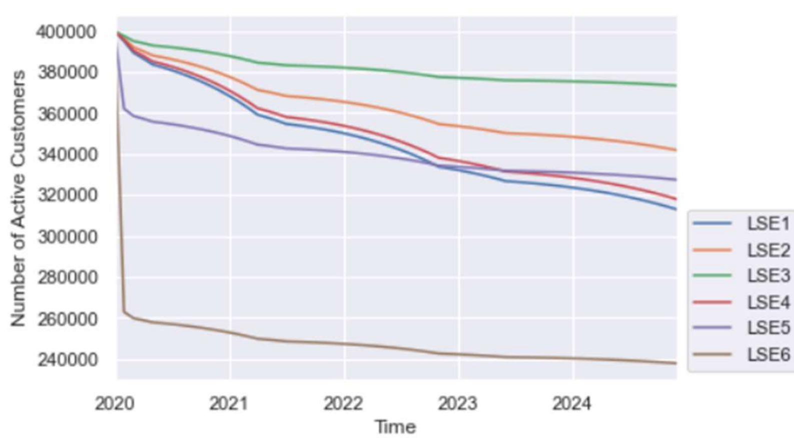


Figure 4.27. Number of customers.

To further verify the results of the Roth-Erev algorithm, it is necessary to take into consideration the effect of the pseudo-random number generation seed on the convergence of the RL. To do that, the simulation was re-run for $1{,}000$ iterations using randomized seeds. Figure 4.28 shows a histogram of the results. It can be seen that the pseudorandom generator seeds have a crucial effect on the results. The median profit was found to be $1.14e^{10}$. The highest profit was found to be $1.43e^{10}$ and the lower profit was found to be $9.57e^{8}$. The markups for the generators for the simulations with the highest and lowest runs are shown in Figure 4.29 and Figure 4.30, respectively. The generators are more likely to have the highest profit if they converge to a near-optimum markup early in the simulation and maintain it. Erratic changes in the markups may result in significant DSG adoption rates and loss of profit. Further elaboration on this finding is explained in the following discussion section.

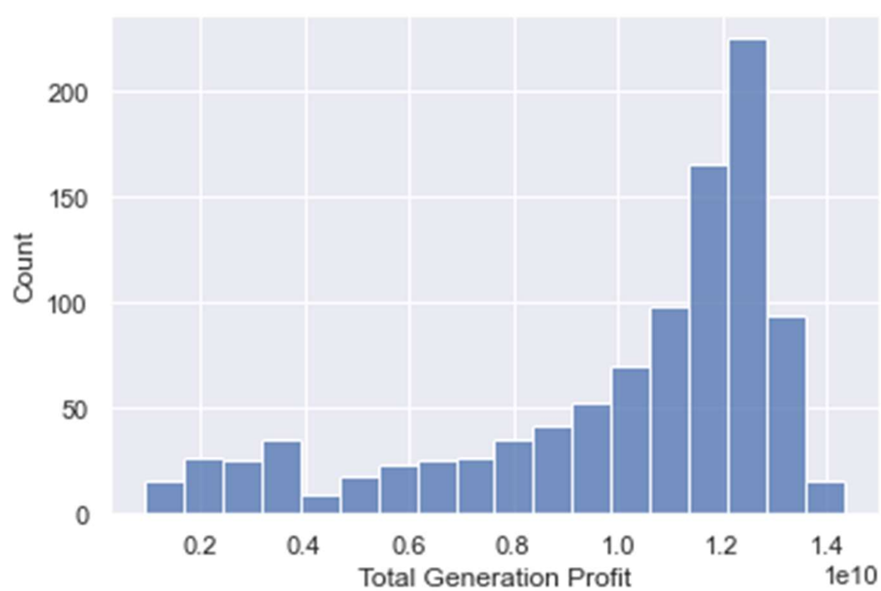


Figure 4.28. Histogram for total generation profits from simulation re-runs.

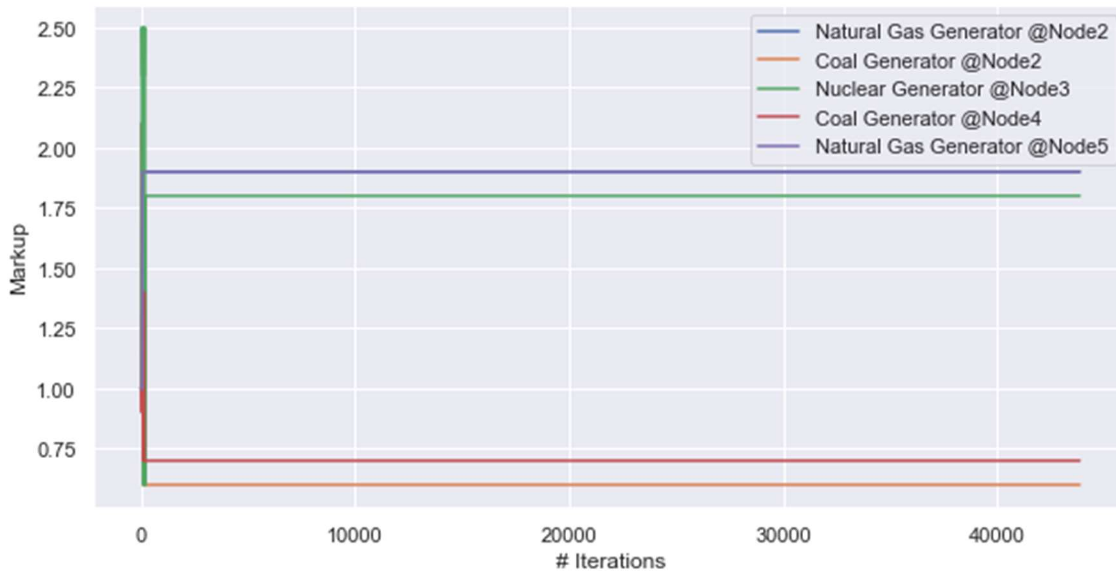


Figure 4.29. Convergence in the simulation with the highest profit.

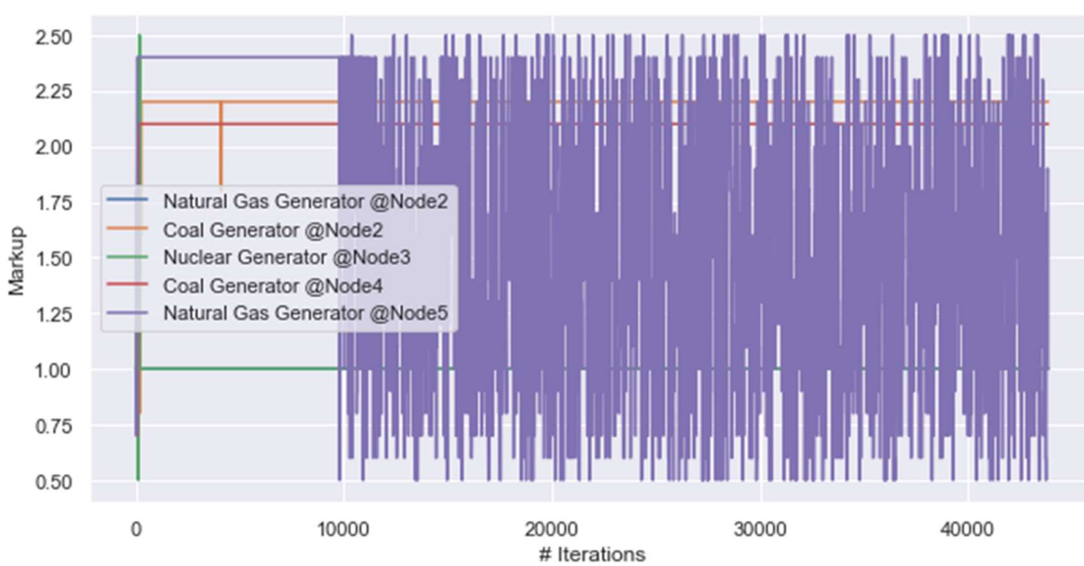


Figure 4.30. Convergence in the simulation with the lowest profit**.**

4.4. DSG POLICY INCENTIVES

The following sections show the results and analysis for (1) the baseline case; (2) the effect of incentives introduced at one LSE; and (3) the effect of incentives on the electric power network.

4.4.1. Baseline Case Results. The baseline case was executed with no incentives, i.e., there are no rebates on the initial cost of DSG, and loans are given with a 6% interest rate. The results show a smooth adoption rate as shown in Figure 4.31. The overall adoption rate for the entire network was 6.2% over the entire duration of the simulation, which is 5 years. The highest adoption rate was found at LSE3, while the lowest adoption rate was found at LSE 6. Figure 4.32 shows the LMPs for each LSE. By comparing Figure 4.31 and Figure 4.32, it is found that the higher adoption rates of DSG are associated with high LMPs and vice-versa. For example, LSE 6 has the highest LMP overall in Figure 4.32 and the highest adoption rate in Figure 4.31. This is an expected behavior considering that customers at locations where the electric power rates are higher would be more inclined to make the switch to DSG. The opposite effect applies to LSE 3. Another observation based on Figure 4.32 shows that the LMPs at LSEs 1, 2, and 4 are constant throughout the simulation and are the highest three at the end of the simulation. LSE 1 has the highest LMP at the end of the simulation. The changes in the number of customers and LMPs manifest from the emergent behavior of the SoS. A main property of complex systems is that they can create emergent behaviors that are not controlled by a single component and may not be easily derivable from single entities (Siegfried, 2014). Accordingly, the following section will focus on introducing incentives at LSE1 and studying the effect on LSE1 for two reasons: (1) LSE 1 has an average adoption rate which makes it a good representation for the effect of the network; and (2) LSE 1 is disadvantaged compared to the other LSEs due to having the highest LMP at the end of the simulation.

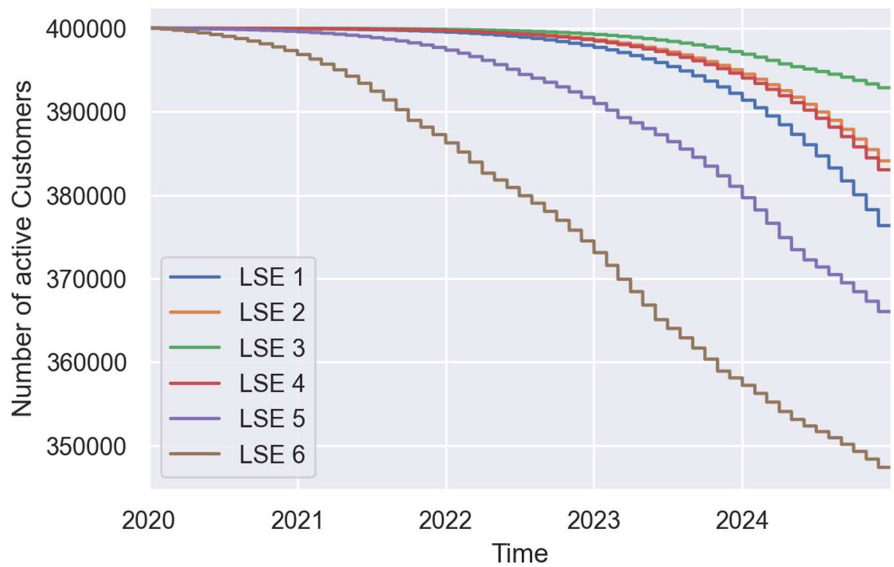


Figure 4.31. Number of active customers for each LSE.

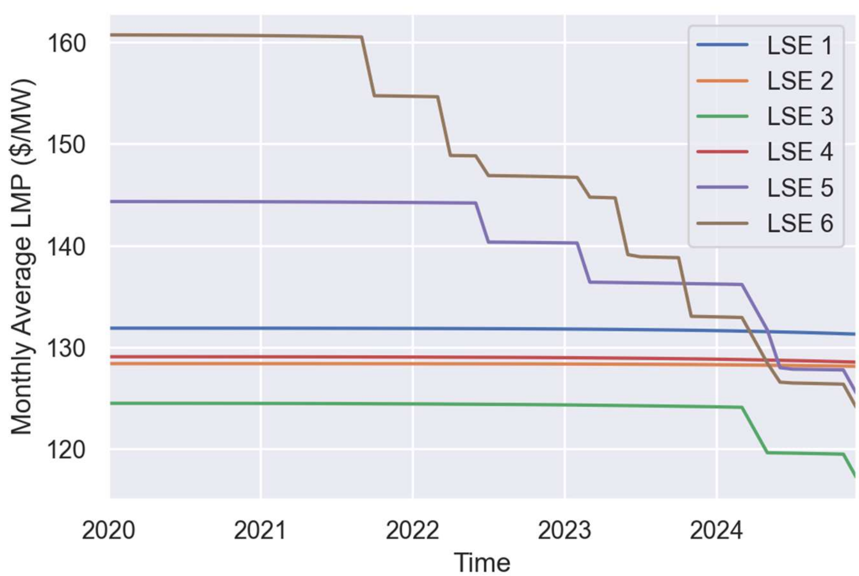


Figure 4.32. Monthly average LMPs for each LSE.

A sensitivity analysis was performed to investigate modeling assumptions by isolating and observing the effect of selected variables on the final number of customers at each LSE. Specifically, two variables were investigated. The first variable is the variance parameter of the lognormal distribution used to compare the cost of electric power bills and the cost of installing a DSG system as part of the consumer decision process. The results of this sensitivity analysis are shown in Figure 4.33. As expected, increasing the variance would result in increased consumer adoption consistently with a lognormal distribution. The second variable is the daily sun hours as shown in Figure 4.34. The results of this sensitivity analysis are also expected because higher sun-hour values would allow DSG systems to generate more energy per day making them more feasible and motivating higher DSG adoption rates.

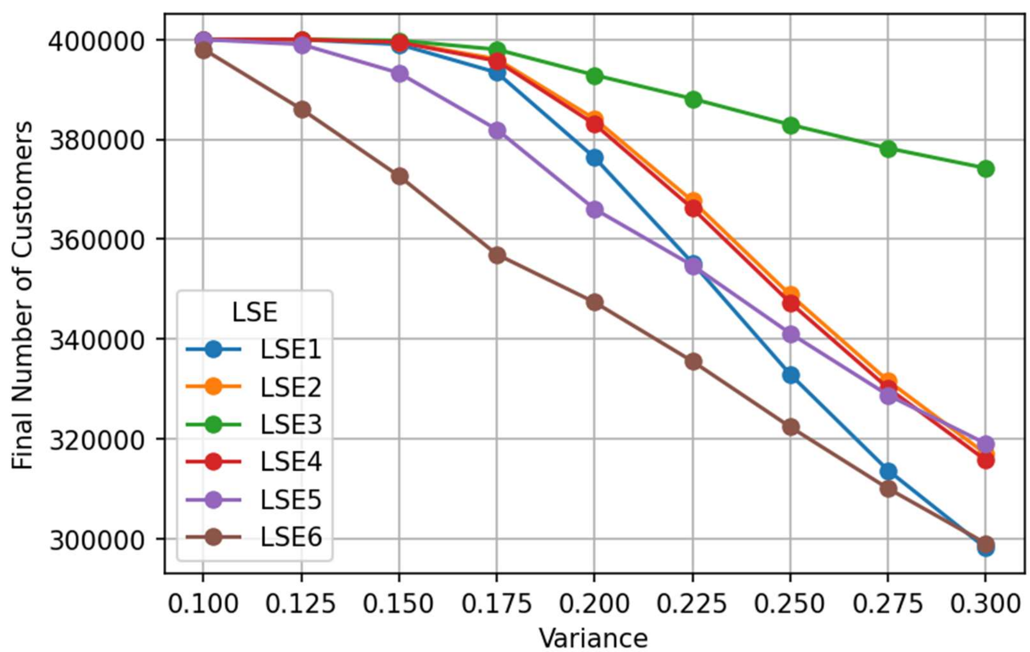


Figure 4.33. Sensitivity analysis for the variance parameter.

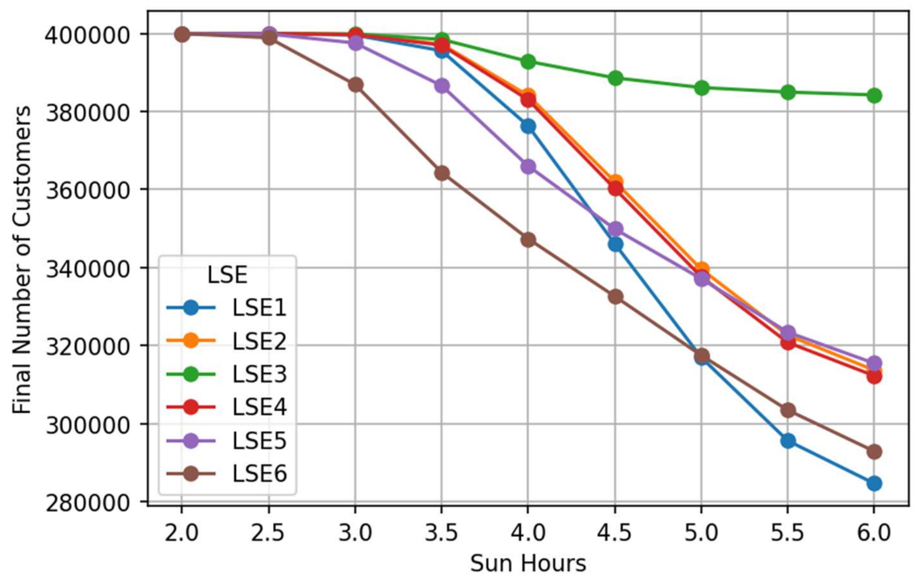
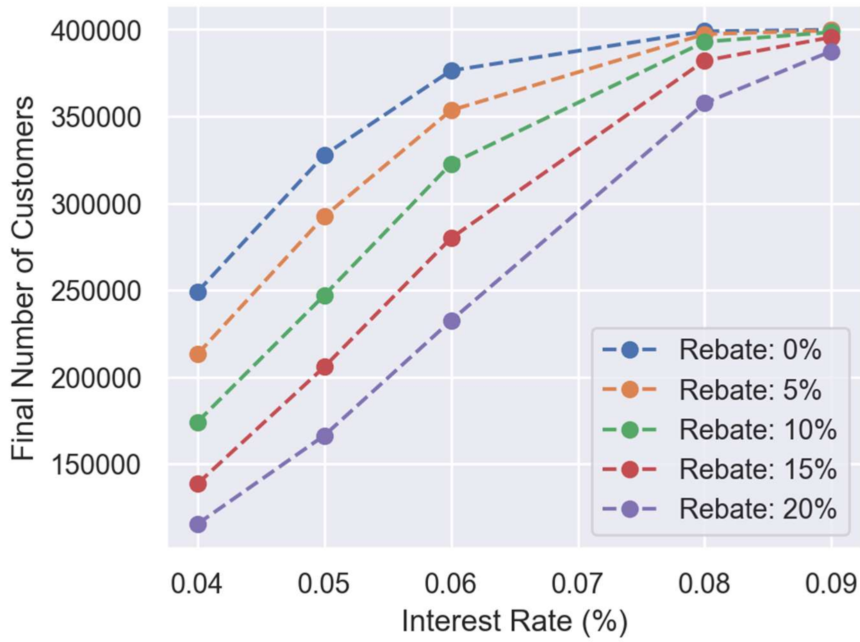


Figure 4.34. Sensitivity analysis of the daily sun-hours.

4.4.2. Isolated Effect of Incentives at LSE 1. A range of incentives was introduced at LSE1. This section discusses their isolated effect on LSE 1, and the following section discusses their rippling effect on the rest of the network. The range of incentives tested includes the interest rate for loans such that $(i) \in [4\%, 5\%, 6\%, 8\%, 9\%]$ and the effect of tax credits or rebates on the price of DSG systems $\in [0\%, 5\%, 10\%, 15\%, 20\%]$. Figure 4.35 shows the results in two scatter plots for (1) the effect of interest rates and rebates on the final number of active customers at LSE 1 and (2) the final daily average LMP. Figure 4.36 shows the same results visualized as heatmaps. The results show that decreasing the interest rate of loans and/or introducing rebates on the price of DSG both have a significant effect on the adoption rate at LSE 1. The results also show that interest rates have a large effect on the adoption rate. This is an expected observation because the loans are long-term (25 years) and, as such, the interest rates have a substantial effect.



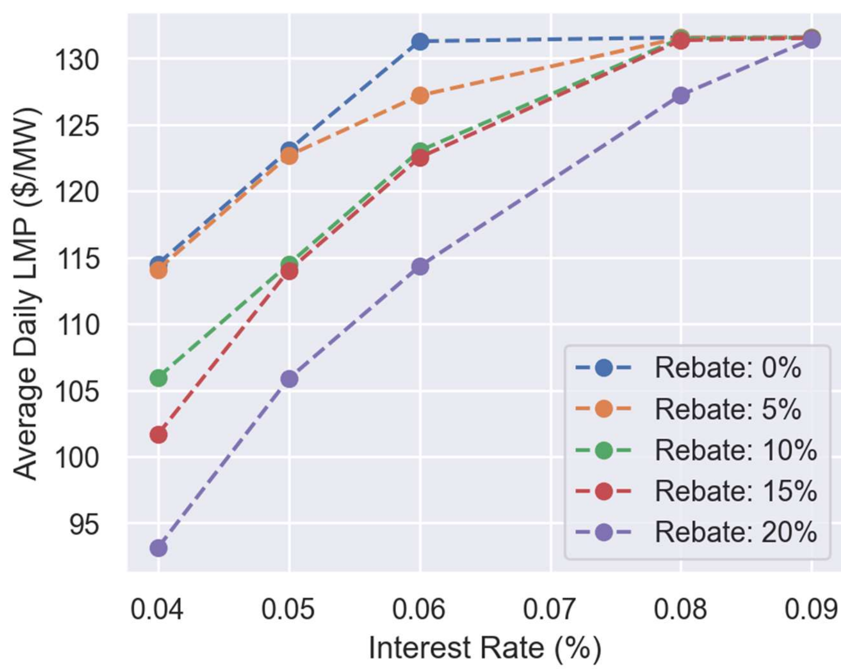


Figure 4.35. Scatterplots for number of active customers (top) and LMPs (bottom).

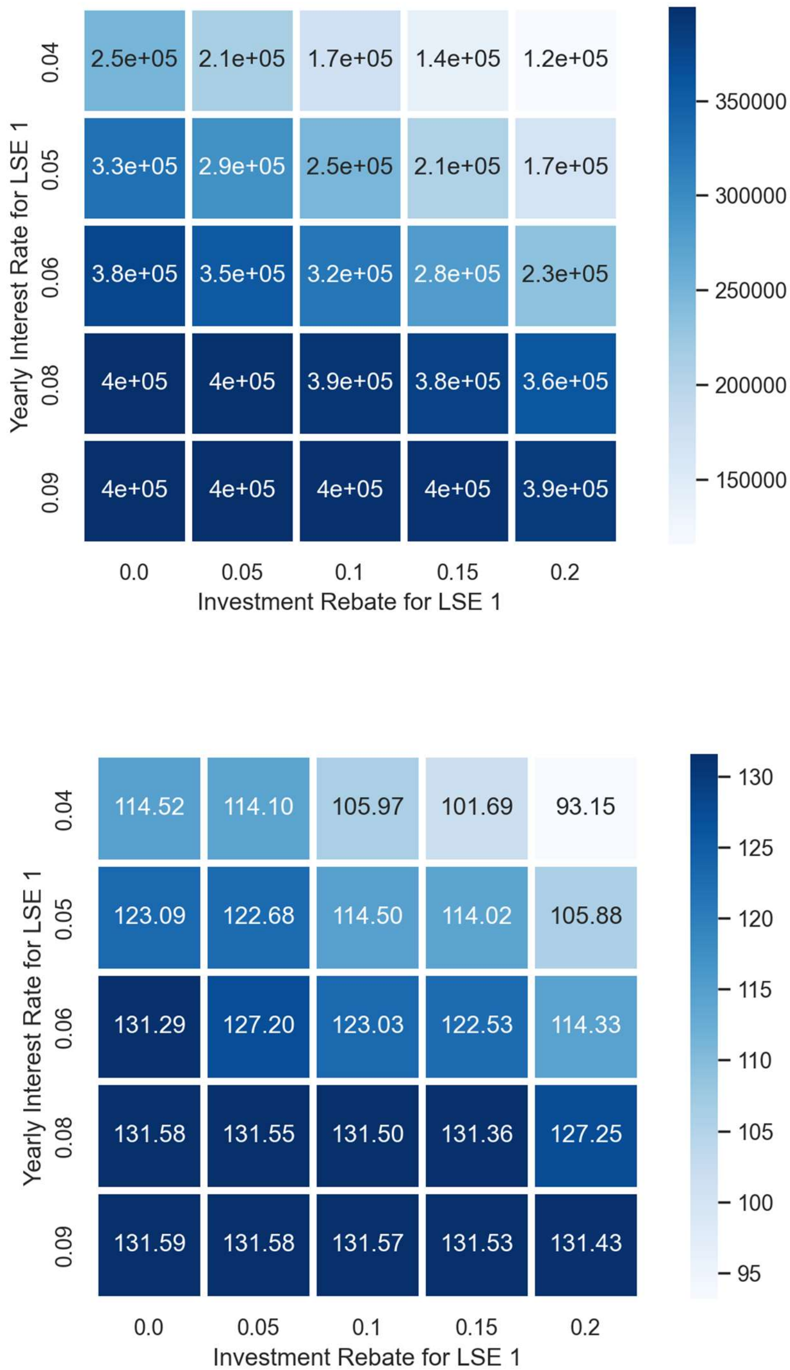


Figure 4.36. Heatmaps for number of active customers (top) and LMPs (bottom).

4.4.3. Effect of Incentives at LSE 1 on Entire Network. The isolated effect of incentives introduced at an LSE on the adoption rate at the same LSE is rather direct and intuitive. However, the effect of incentives on the rest of the network as a SoS is more dynamic. Table 4.13 shows the effect of incentives described in the previous section on all LSEs in the network. Table 4.14 shows the effect on the final daily LMPs. The results show that the incentives at LSE 1 have widely varying effects on the other LSEs. For example, an observation can be that the number of customers in LSEs 2 through 5 is higher when the interest rate for LSE1 is lowered with the same rebate value at 0%. In other words, the adoption rate at LSEs 2 to 5 is lower when the interest rate for loans at LSE 1 is lower. Table 4.14 shows that the LMPs at the same LSEs are lower with higher interest at LSE1. This observation can be explained by the following series of effects: (1) The lowered interest rates at LSE1 increase the adoption rate at LSE1; (2) There is lower demand for power at LSE1 which results in lower LMPs at LSE1 and LSEs 2 to 5; and (3) the lower LMPs at LSEs 2 to 5 make adoption less feasible for the customers. However, this effect is reversed for LSE6 where the lower interest rate at LSE 1 results in higher adoption rates. It should be noted that there are no generators at LSE 6 which forces it to rely on power transmitted from other LSEs. The lower adoption rates at the nodes connected to LSE 6 result in higher LMPs at LSE 6 and accordingly higher adoption rates. To conclude, this case shows that the effect of incentives on electric grids and power markets requires a thorough consideration of the rippling effects.

Table 4.13. Final number of customers for each LSEs vs. incentive percentages at LSE 1.

Interest	***Rebate***	***LSE 1***	***LSE 2***	***LSE 3***	***LSE 4***	***LSE 5***	***LSE 6***
4%	0%	249,020	393,902	397,564	393,589	369,396	335,888
	5%	213,152	396,506	398,620	396,344	371,140	331,279
	10%	174,152	398,127	399,340	398,057	373,396	324,717
	15%	138,581	399,139	399,725	399,113	376,017	318,610
	20%	115,432	399,698	399,910	399,690	378,986	312,421
5%	0%	327,717	388,048	394,424	387,307	366,422	342,104
	5%	292,439	391,398	396,225	390,891	367,902	338,539
	10%	247,020	394,127	397,651	393,827	369,407	335,581
	15%	205,805	396,817	398,771	396,669	371,173	330,144
	20%	166,312	398,525	399,496	398,472	374,413	321,456
6%	0%	376,341	384,098	392,861	383,032	366,039	347,370
	5%	353,470	385,143	393,272	384,197	366,073	346,358
	10%	322,712	388,626	394,701	387,922	366,434	340,895
	15%	279,924	391,994	396,578	391,541	368,297	338,159
	20%	232,495	395,246	398,113	395,009	370,058	333,705
8%	0%	398,971	384,026	392,829	382,895	366,017	347,321
	5%	397,276	384,030	392,833	382,901	366,018	347,324
	10%	392,906	384,046	392,838	382,928	366,019	347,334
	15%	382,024	384,076	392,853	382,996	366,033	347,358
	20%	357,659	384,660	393,083	383,684	366,066	346,863
9%	0%	399,817	384,025	392,828	382,890	366,016	347,320
	5%	399,460	384,026	392,828	382,893	366,017	347,320
	10%	398,437	384,027	392,829	382,897	366,018	347,321
	15%	395,528	384,039	392,836	382,913	366,018	347,327
	20%	387,516	384,063	392,846	382,962	366,027	347,344

Table 4.14. LMPs ($) for each LSEs vs. incentive percentages at LSE 1.

Interest	***Rebate***	***LSE 1***	***LSE 2***	***LSE 3***	***LSE 4***	***LSE 5***	***LSE 6***
4%	0%	114.52	112.49	101.66	112.64	121.59	125.74
	5%	114.10	112.39	101.57	112.47	121.56	125.62
	10%	105.97	104.59	93.79	104.62	121.50	133.11
	15%	101.69	100.60	87.64	100.60	119.25	123.15
	20%	93.15	92.24	83.71	92.24	119.22	126.82
5%	0%	123.09	120.37	109.50	120.66	121.66	123.99
	5%	122.68	120.27	109.42	120.50	121.63	123.90
	10%	114.50	112.49	101.66	112.63	121.59	125.73
	15%	114.02	112.36	101.54	112.43	121.54	125.59
	20%	105.88	104.56	91.56	104.58	119.28	125.13

Table 4.14. LMPs ($) for each LSEs vs. incentive percentages at LSE 1 (cont.).

Interest	***Rebate***	***LSE 1***	***LSE 2***	***LSE 3***	***LSE 4***	***LSE 5***	***LSE 6***
6%	0%	131.29	128.13	117.27	128.54	125.54	124.13
	5%	127.20	124.25	113.39	124.60	125.52	127.90
	10%	123.03	120.35	109.49	120.64	121.65	123.97
	15%	122.53	120.23	109.39	120.43	121.62	123.88
	20%	114.33	112.45	101.62	112.56	121.58	125.68
8%	0%	131.58	128.20	117.34	128.68	125.56	124.18
	5%	131.55	128.20	117.33	128.67	125.56	124.18
	10%	131.50	128.18	117.32	128.64	125.56	124.17
	15%	131.36	128.15	117.28	128.57	125.55	124.15
	20%	127.25	124.26	113.40	124.62	125.52	127.91
9%	0%	131.59	128.20	117.34	128.68	125.56	124.18
	5%	131.58	128.20	117.34	128.68	125.56	124.18
	10%	131.57	128.20	117.33	128.68	125.56	124.18
	15%	131.53	128.19	117.33	128.66	125.56	124.17
	20%	131.43	128.16	117.30	128.61	125.55	124.16

4.4.4. Sensitivity Analysis of the Effect of Incentives Using Regression. As shown in the previous section, the introduction of incentives at an LSE has a rippling effect on all the LSE connected to the same electric power grid. Therefore, there is a need to test a broad spectrum of incentives at different locations of the grid to study their effect. To achieve that, the same ranges of inputs for the interest rates $(i) \in [4\%, 5\%, 6\%, 8\%, 9\%]$ and rebates $\in [0\%, 5\%, 10\%, 15\%, 20\%]$ were tested at each LSEs and the results were recorded. This resulted in a database of 150 cases ($5 \times 5 \times 6\ LSEs$). Multiple regression analysis was performed on this database considering two exogenous variables separately for each LSE: (1) the final number of active customers and (2) the final daily average LMPs. As such, the full analysis includes 12 separate regression models. The R^2 values for each equation are shown in Table 4.15. All the R^2 values are higher than 0.8, which shows a good fit for the models in general.

Table 4.16 shows the coefficients of each regression model. The endogenous variable for each model is the final number of customers at the LSEs marked in each column. The rows represent the percentage of incentives (rebate or interest) at each LSE. The significance of the coefficients is represented by the symbol (*) where each additional symbol marks a p-value less than 0.05, 0.02, and 0.01, respectively. Table 4.17 shows the results for the final daily LMPs in a similar representation to Table 6. In other words, the numbers represent LMPs (USD) per percentage of incentives (rebate or interest). This is further represented in Figure 4.37, which shows a heatmap of the significant coefficients (p-value < 0.05) from Table 4.16 and Table 4.17.

Table 4.15. $\boldsymbol{R^2}$ results for the regression models.

Endogenous	***LSE***	$\boldsymbol{R^2}$
Final Number of Customers	LSE 1	0.898
	LSE 2	0.888
	LSE 3	0.869
	LSE 4	0.890
	LSE 5	0.918
	LSE 6	0.936
Final Average Daily LMP	LSE 1	0.833
	LSE 2	0.827
	LSE 3	0.843
	LSE 4	0.831
	LSE 5	0.946
	LSE 6	0.902

Table 4.16. Coefficient results for regression models with the final number of active customers as the endogenous variable ($\boldsymbol{Customers}/\%$).

Incentive	***LSE***	***LSE1***	***LSE2***	***LSE3***	***LSE4***	***LSE5***	***LSE6***
Rebate	*LSE1*	-7.31e+05***	8.12e+04***	3.62e+04*	8.4e+04***	4.9e+04*	-6.25e+04***
	LSE2	9.99e+04***	-6.5e+05***	3.46E+04	7.88e+04***	5.22e+04*	-4.07e+04*
	LSE3	8.04e+04***	6.54e+04*	-3.88e+05***	6.53e+04*	8.56e+04***	2.55E+04
	LSE4	1.01e+05***	7.74e+04***	3.50E+04	-6.48e+05***	5.25e+04*	-4.06e+04*
	LSE5	5.50E+04	4.78E+04	3.63e+04*	4.77E+04	-6.25e+05***	2e+05***
	LSE6	5.61E+04	4.83E+04	3.65e+04*	4.89E+04	1.4e+05***	-5.67e+05***
Interest	*LSE1*	4.21e+06***	-2.47E+05	-1.14E+05	-2.67E+05	-1.27E+05	4.4e+05***
	LSE2	-3.43e+05*	3.66e+06***	-1.07E+05	-2.42E+05	-1.42E+05	3.4e+05***
	LSE3	-2.49E+05	-1.71E+05	2.11e+06***	-1.77E+05	-3.21e+05**	5.20E+03
	LSE4	-3.5e+05*	-2.27E+05	-1.09E+05	3.66e+06***	-1.43E+05	3.37e+05***
	LSE5	-1.23E+05	-8.44E+04	-1.59E+05	-9.02E+04	3.85e+06***	-1.04e+06***
	LSE6	-5.10E+04	-2.92E+04	-1.20E+05	-3.68E+04	-9.5e+05***	3.62e+06***

* $\rightarrow$ *p-value* < 0.05
** $\rightarrow$ *p-value* < 0.02
*** $\rightarrow$ *p-value* < 0.01

Table 4.17. Coefficient results for regression models with LMPs as the endogenous variable ($/%).

Incentive	***LSE***	***LSE1***	***LSE2***	***LSE3***	***LSE4***	***LSE5***	***LSE6***
Rebate	*LSE1*	-68.5***	-62.2***	-60.3***	-63.3***	-10.3***	-1.74
	LSE2	-53.7***	-66.2***	-50.5***	-42.8***	-8.15**	-3.7
	LSE3	-15.1**	-15.7**	-42.7***	-15.7**	-3.16	7.37
	LSE4	-52.9***	-40.8***	-49.0***	-66.5***	-8.39**	-6.37
	LSE5	1.56	0.856	-33.6***	1.4	-68.2***	-76.4***
	LSE6	-1.05	-1.49	-37.4***	-1.49	-68.9***	-81.7***
Interest	*LSE1*	4.88e+02***	4.51e+02***	4.55e+02***	4.59e+02***	1.1e+02***	-42.1
	LSE2	4.07e+02***	4.65e+02***	4.07e+02***	3.54e+02***	99.1***	-36.3
	LSE3	2.28e+02***	2.29e+02***	4.43e+02***	2.31e+02***	1.41e+02***	-28.4
	LSE4	4.07e+02***	3.46e+02***	4.04e+02***	4.74e+02***	1.04e+02***	-25.1
	LSE5	1.52e+02***	1.53e+02***	4.41e+02***	1.52e+02***	5.99e+02***	4.75e+02***
	LSE6	43.7	42.6	3.23e+02***	45.6	5.3e+02***	7.93e+02***

* $\rightarrow$ *p-value* < 0.05
** $\rightarrow$ *p-value* < 0.02
*** $\rightarrow$ *p-value* < 0.01

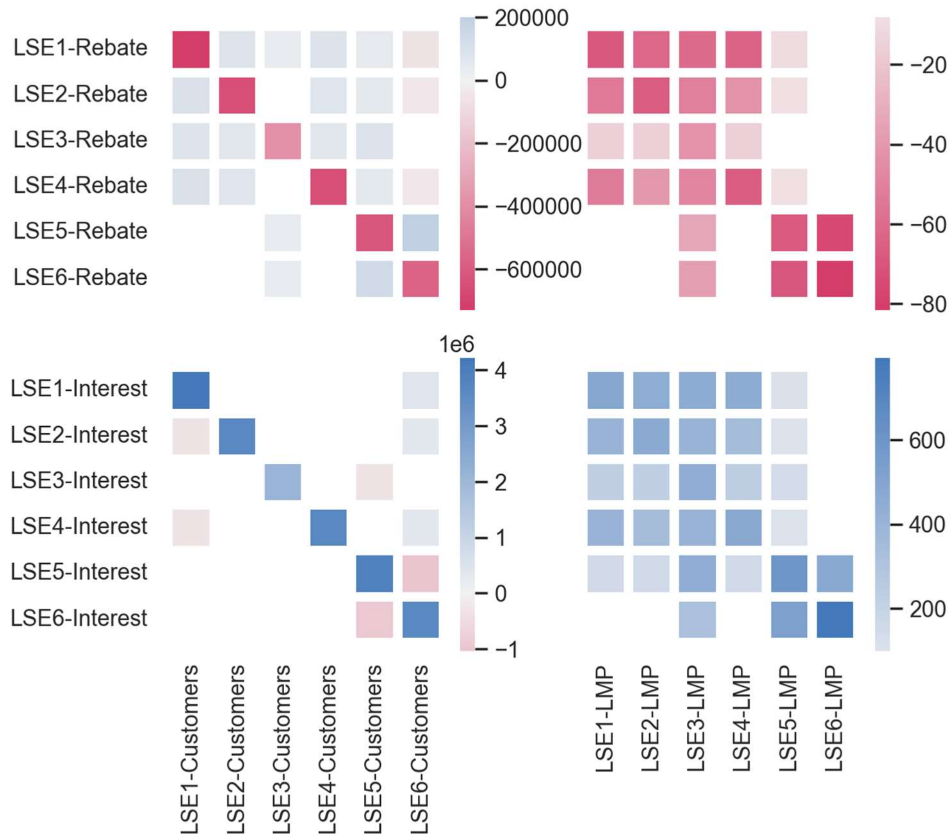


Figure 4.37. Heatmap of the significant regression parameters.

As expected, introducing incentives at an LSE has a significant effect on the same LSE, which is supported by the p-values and the magnitude of the coefficients. In addition, the effect of incentives introduced at an LSE on other LSEs is significant in many cases. For example, introducing rebates at LSE 1 has a significant effect on the number of customers at LSEs 2, 3, and 4, as shown in Table 4.16. It should be noted LSEs 2 and 4 are connected to LSE 1 while LSE 3 is connected to LSEs 2 and 4, therefore they are the most affected. The effect on the LMPs is also significant in many cases as shown in Table 4.17. The results also support the fact that incentives at an LSE can affect the adoption rates and

LMPs at other nodes depending on the configuration of the grid. This is supported by the fact that the coefficients which are shown in Table 4.16 and Table 4.17 can vary between positive and negative values. For example, higher interest rates at LSE 4 have a significant negative effect on the number of customers at LSE 1 and a significant positive effect on the number of customers at LSE 4. In other words, when interest rates are higher at LSE 4, fewer consumers would adopt DSG at LSEs 4 and 6 while more customers would adopt DSG at LSE 1. It should be noted that LSE 1 is connected to LSE 4 through transmission line 3, while LSE 6 is in the furthest node away from LSE 1. As such, based on the results shown in Table 4.16 and Table 4.17, all of the proposed hypotheses are acceptable after rejecting the null hypotheses. It is concluded that (1) Rebates for DSG systems can positively or negatively influence the adoption of DSG; (2) Rebates for DSG systems can positively or negatively influence LMPs; (3) Interest rates for DSG loans can positively or negatively influence DSG adoption of DSG; and (4) Interest rates for DSG loans can positively or negatively influence LMPs.

4.5. REDUCING VULNERABILITY AGAINST NATURAL DISASTERS

The following sub-sections show the results and analysis related to reducing the vulnerability against natural disasters by capitalizing on DSG. The results and analysis are divided into two main subsections: (1) Single-Node Optimization; and (2) Network Optimization using GA.

4.5.1. Single-Node Optimization. The results of the proof of concept for the percentage allocation of DSG, demands, and generator commitments are shown in Table 4.18, Table 4.19, and Table 4.20, respectively. As shown in Table 4.18, the results show that scenario 2 did not affect the stability of the grid. However, the remaining scenarios affected the grid, and the DSG was needed to mitigate against the failure of transmission lines. Each scenario was found to have singular solutions, whereas two scenarios were found to have two possible solutions each: Scenario 4 can be solved by allocating 62% DSG at LSE 1 or LSE 4, and Scenario 5 can be solved by allocating 22% at LSE 5 or LSE 6. In total, the entire grid may be optimized against the failure of any line by allocating a total of 640,000 units. It is assumed in Table 4.19 and Table 4.20 that DSG is allocated at LSE 4 and LSE 6 to mitigate scenarios 4 and 5. By referring again to the configuration of the grid, the allocation DSG at the determined LSEs is expected. For example, it is expected that a failure in the transmission lines of scenarios 1 and 3 would affect LSE 1, which was found to limit the maximum demand at 62% and 36% respectively. Similarly, LSE 6 was affected in scenarios 6 and 7, where the maximum demand needed to be reduced to 36% for each. By allocating the cumulative maximum over all scenarios, the entire grid can survive the impact of natural disasters on any line. Table 4.19 shows the results for the demands at the LSEs. The resulting changes in demands are consistent with the allocation of DSG shown in Table 4.18, such as LSE 1 in Scenarios 1 and 3, and LSE 6 in Scenarios 6 and 7. The generators were affected by the disruptions as shown by their commitments in Table 4.20. The results show a change in the commitment of each generator according to the flow of power when a line is affected. A notable example is the commitment of Generator 1 is highest when Line 2 is disconnected. This may be due to the fact that Node 2 is no longer receiving power from Node 3 when Line 2 is disconnected. This may also be confirmed by the reduced commitment of Generator 3. Several similar observations can be made by observing the results, which show the complex dynamics of the power infrastructure and market. Also, it shows that relieving the demand using DSG, combined with the dynamics of the wholesale power market, can reduce vulnerability to natural disasters.

Table 4.18. DSG allocation.

Scenario	***LSE 1***	***LSE 2***	***LSE 3***	***LSE 4***	***LSE 5***	***LSE 6***
Line 1	62%	0%	0%	0%	0%	0%
Line 2 *	0%	0%	0%	0%	0%	0%
Line 3	36%	0%	0%	0%	0%	0%
Line 4 **	62%	0%	0%	62%	0%	0%
Line 5 **	0%	0%	0%	0%	22%	22%
Line 6	0%	0%	0%	0%	0%	36%
Line 7	0%	0%	0%	0%	0%	36%
Maximum	***62%***	***0%***	***0%***	***62%***	***0%***	***36%***

*Scenario does not require DSG.
** Scenario has two possible solutions.

Table 4.19. Total demand at LSEs in MW.

Scenario	*LSE 1*	*LSE 2*	*LSE 3*	*LSE 4*	*LSE 5*	*LSE 6*
Line 1	234.02	615.84	615.84	615.84	615.84	615.84
Line 2	615.84	615.84	615.84	615.84	615.84	615.84
Line 3	394.14	615.84	615.84	615.84	615.84	615.84
Line 4	615.84	615.84	615.84	234.02	615.84	615.84
Line 5	615.84	615.84	615.84	615.84	615.84	480.36
Line 6	615.84	615.84	615.84	615.84	615.84	394.14
Line 7	615.84	615.84	615.84	615.84	615.84	394.14

Table 4.20. Generator commitments.

Scenario	*Generator 1*	*Generator 2*	*Generator 3*	*Generator 4*	*Generator 5*
Line 1	0	215.84	2000	449.86	647.52
Line 2	547.52	450	1600	450	647.52
Line 3	159.98	450	2000	215.84	647.52
Line 4	165.7	450	1600	450	647.52
Line 5	295.04	450	1668.32	450	696.2
Line 6	295.04	450	1668.32	450	609.98
Line 7	295.04	450	2000	450	278.3

4.5.2. Network Optimization Using GA. The optimization approach using a GA enabled the optimization of the entire network to determine the minimum DSG allocation over all LSEs that would mitigate the loss of any transmission line. Compared to the previous method, the GA algorithm was designed to find feasible solutions that mitigate the failure of any transmission by optimizing over all the nodes. The population size was set to 100 and the stopping criteria for the GA was set to 50 Epochs. This configuration was found to be suitable to achieve a near-optimum solution is achieved. The convergence of the optimization is shown in Figure 4.38. The evolutionary behavior of the GA can be seen in the convergence of the population as the best solutions are kept and the non-suitable solutions are removed in every epoch. The best solution was achieved quickly at Epoch 22 with a total DSG requirement of 395,873 units.

Table 4.21 shows the optimized DSG allocation size and percentage for each LSE. The optimization algorithm found an allocation of DSG that is better distributed and lower than the allocation resulting from the one-node-at-a-time optimization in the previous method. By strategically allocating DSG across the grid, the effect of natural disasters on transmission lines was mitigated with fewer resources: The total number was 395,873 using the Genetic Optimization vs. 640,000 using the previous method of optimizing single nodes. Further, as shown in Table 4.22, the distribution of the generator commitment is close to the average results from the previous method. Also, the average total generation in the previous method was 3,499 MW and in the GA method it was found to be 3,085 MW. Although the total demands from both methods are therefore close, the GA achieved a better distribution of DSG. It can be seen the optimized solution allocated most DSG at LSE 1, LSE 4, and LSE 6, which are the same LSEs identified in the single-node optimization approach. Overall, the results show that optimizing the entire network, combined with the capabilities of ABM, has resulted in less DSG needed to mitigate the effect of natural disasters on transmission lines.

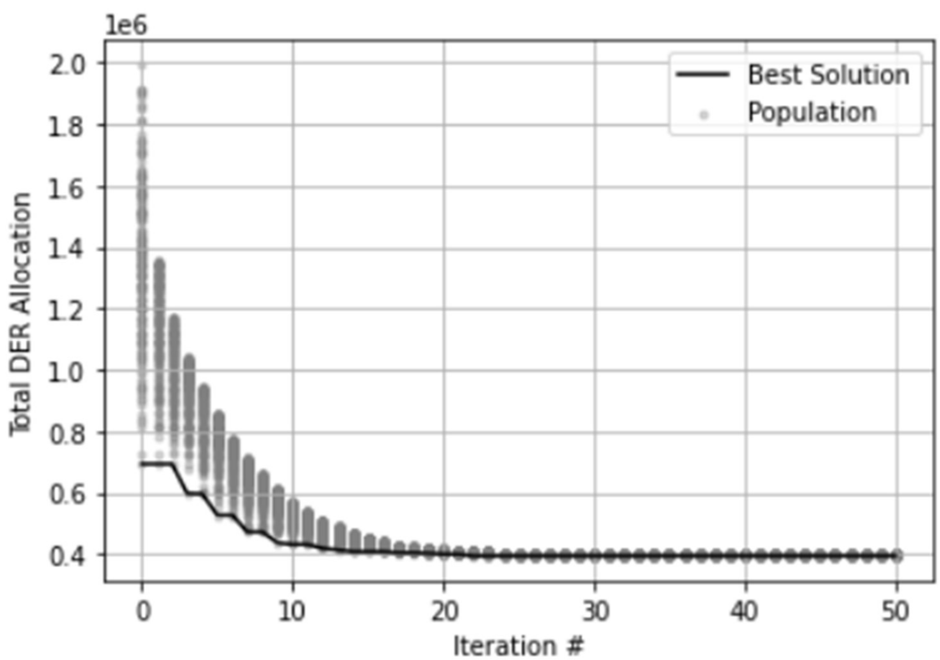


Figure 4.38. Convergence of the GA.

Table 4.21. Optimized allocation of DSG.

LSE #	***Allocation Percentage***
LSE 1	42.43%
LSE 2	0.11%
LSE 3	0.45%
LSE 4	19.60%
LSE 5	1.11%
LSE 6	35.27%

Table 4.22. Generator commitments.

Scenario	***Generator 1***	***Generator 2***	***Generator 3***	***Generator 4***	***Generator 5***
Line 1	0	427.24	2000	450	208.31
Line 3	119.72	450	2000	307.52	208.31
Line 4	164.84	450	1812.41	450	208.31
Line 5	0	392.44	1813.09	272.39	607.63
Line 6	0	392.44	1813.09	272.39	607.63
Line 7	0	450	2000	426.56	208.99

Although the GA reached a minimum allocation of DSG, the issue of the LMPs requires a deeper analysis. Figure 4.39 shows separate plots for the average LMP and variation in the LMP as the difference between the highest and lower LMPs, for each of the critical transmission lines. It can be seen that although the GA achieved a near-optimum DSG allocation minima, the best solution is associated with the highest LMP, and in some cases high variations in LMPs between the nodes in the network. In some cases, such as line 3 for example, a lower average LMP may be achieved with minimal addition of DSG beyond the optimum solution. The effect of LMPs should be taken into consideration to mitigate against natural disasters while avoiding exuberant electricity rates for customers. The results of the GA show that this can be achieved by strategically motivating the best allocation of DSG that results in reasonable real-time electricity rates for customers.

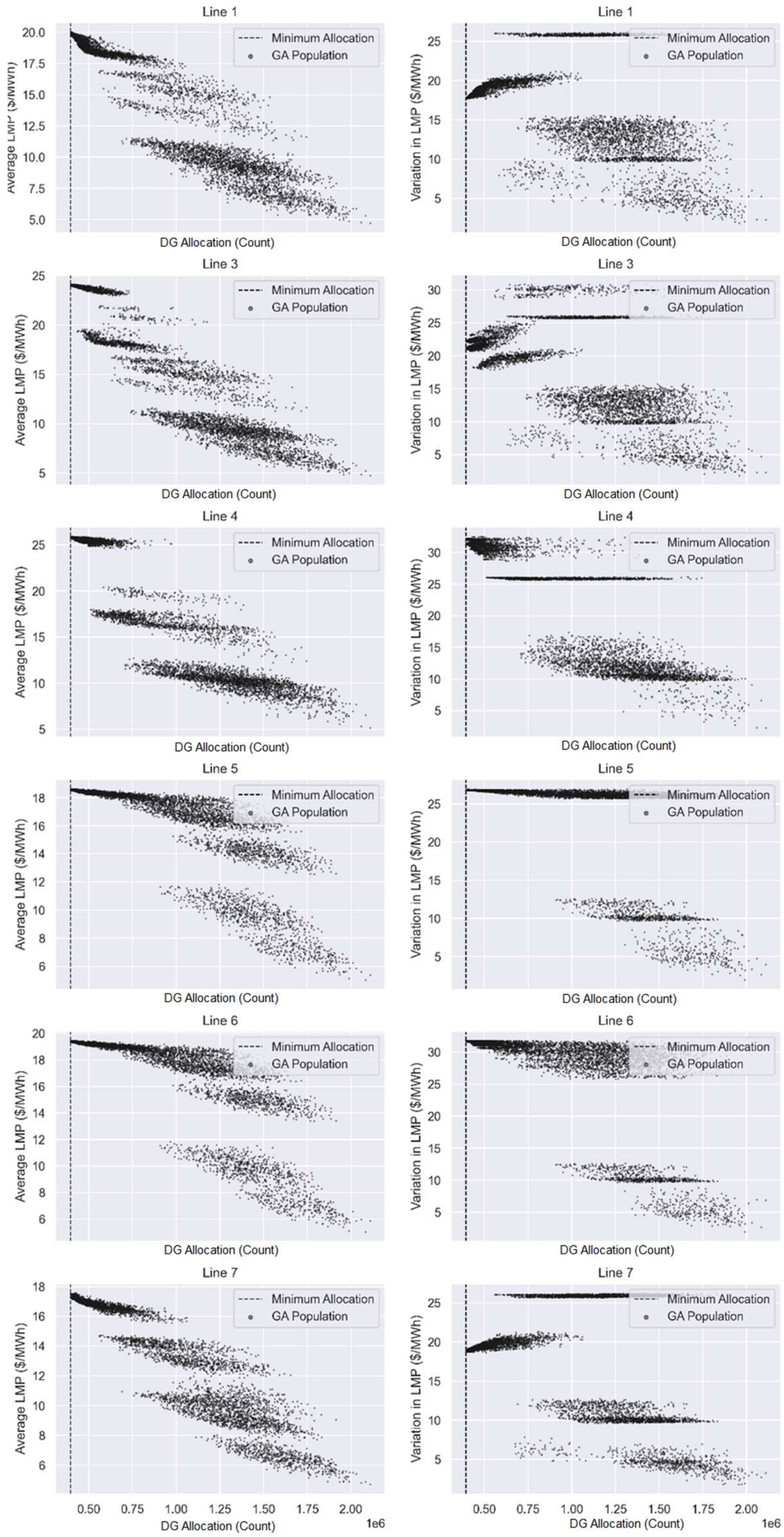


Figure 4.39. GA population by transmission line failure: average LMP vs. DSG allocation (left); variation in LMP vs. DSG allocation (right).

5. DISCUSSION

5.1. RELATIONSHIP BETWEEN THE ELECTRIC POWER SECTOR AND SOCIOECONOMIC INDICATORS

Electric demand increased significantly in the past decades, and it is expected to keep increasing in the future. Aside from the fact that the world population is growing, the increase in demand can be attributed to economic growth, and human development, among other factors. This research investigates the relationship between electrical power consumption per capita and three types of socio-economic indicators: economic growth, human development, and corruption. In addition, the relationship between electrical losses in distribution and both human development and corruption was studied.

The results show that there is a positive correlation between electrical power consumption per capita, on one side, and economic growth, human development, and corruption on the other side. This relationship, however, does not necessarily hold for every country separately; in some countries, this relationship is stronger than others. Overall, in all countries, there is a good relationship between electric consumption per capita, and both economic growth and human development. These findings are expected, because, naturally, countries that have healthier economies and more improved human development are expected to have higher electric power consumption per capita. However, the results of causality on electrical power consumption per capita are mixed. Results of Granger-causality testing showed that there is no causality effect, at least in the short term, between electrical power consumption and any of the studies indicators. Overall, the findings show that there is a generally positive relationship between electrical power consumption on one side, and socioeconomic indicators of economic growth, human development, and corruption, on the other side.

The relationship between electrical losses in distribution and both corruption and human development was tested. The results are mixed and hard to interpret. However, as an overall conclusion, it was found that there is an apparent relationship between lower corruption and lower electrical losses. In other words, countries that have a highly corrupt environment and low enforcement of the law are more prone to electrical losses in distribution. This is not surprising because corruption results in increased power theft through illegal connections or corrupt consumers who do not pay bills. These results show that corruption, politics, ineffective law enforcement, and theft affect electrical losses in distribution. These losses are generated but are not billed, and cause unjustified strain on the electrical grid and infrastructure. Therefore, it is necessary to understand that strict law enforcement regarding electrical power theft and corruption is critical to reducing the unjustified strain on the power grid.

To sum up, there is a direct relationship between economic growth, human development, and lower corruption, on one side, and electrical power consumption on the other. In general, countries that have stronger economies and improved human development have higher electrical power consumption than countries that are not. There is also a relationship between corruption and electrical power losses. Countries that have less corruption and stricter law enforcement have lower electrical power losses than countries that are more corrupt.

5.2. DYNAMIC PRICING USING REINFORCEMENT LEARNING (RL)

5.2.1. Learning and Convergence Process of RL. RL, using a modified Roth-Erev, was found to be an effective approach for generating companies to maximize their gross profits considering the effect of electricity on accelerating DSG adoption. In this research, the chosen parameters for the modified Roth-Erev, which was found to result in the highest total generation profits, resulted in an early convergence after ten iterations, as shown in Figure 26. It should be noted that the purpose of this research is not to determine the optimum results but rather to identify the best pricing strategy for generating companies to maximize their profits considering the effect of the adoption of DSG which can be accelerated by high electricity rates. The highly dynamic nature of the complex problem in this research results in an emergent behavior where generating companies are more likely to make the highest profit if they converge earlier. The results where other algorithms and parameters are tested show that the generators will test other markup actions at the cost of higher adoption rates and ultimately profits. Therefore, it is recommended that generating companies maintain their price rates. Increasing prices to increase profits and/or recover from reduced demand may exacerbate the problem.

5.2.2. Occurrence of a Death Spiral. The results show that the early convergence of the RL algorithm may be the best course of action for generating companies as opposed to changing the prices in response to the adoption of DSG. Any increase in prices may exacerbate the problem and any decrease may lower profits. As generating companies are rational profit-seeking entities, it is expected that they would follow the same behavior. A feedback loop consistent with a death spiral was not identified in the results. Therefore, the effect of a death spiral is not expected to be catastrophic, which is in line with findings from literature (Muaafa et al. 2017; Castaneda et al. 2017). Still, as the results suggest, the penetration of DSG may be noticeable in isolated areas on the electric grid where local generation is not available, and the transmission and congestion costs are high.

5.2.3. Effect of DSG Adtopion on Generators. The results show that low-cost generators are the least affected by the adoption of DSG and may increase their prices given that: (1) there is enough demand for low-cost generators to fill; (2) there are no other lower-priced generators that may compete with them and low-bid their offers; and, (3) their production costs are lower than the cost of the alternative opportunity to install a DSG system. On the other hand, high-cost generators are the most affected, specifically when their generation costs result in electricity rates that are at a financial disadvantage compared to the cost of installing a DSG system and lower-priced generators that are competing with them. One consideration that is not included in this research is that high-cost generators may have the advantage of being able to fulfill short-term or sudden demand peaks if their ramp rate requirements are adequate. However, this consideration is beyond the scope of this research due to the excessive complexity of implementing it in a long-term simulation and combining it with RL. Still, this effect may be less critical in the future with the emerging advances in large-scale power storage using innovative battery systems and distributed power storage such as electric cars.

5.2.4. Emergent Behavior of ABM. The multiple interactions between the agents in an ABM create an emergent behavior that is not controlled by a single component. This behavior may not be obviously derivable from the behavior of the individual components of the ABM (Siegfried 2014). In this research, the behavior of the ABM model is affected by the following multiple elements including the complex feedback loops between them:

(1) the decrease in the cost of PV systems and batteries, (2) the dynamic pricing decided by the RL, (3) the power flow in the grid which affects wholesale pricing, and (4) consumer behavior to adopt DSG. The emergent behavior from those elements allows for studying the adoption of DSG as a complex emergent behavior of an SoS.

5.3. DSG POLICY INCENTIVES

Many incentives are offered to encourage DSG adoption, such as tax credits and loans with low interest. The goal of this research part is to investigate the effect of such incentives on the electric power infrastructure and market. This was achieved by developing a SoS framework to simulate electric power networks affected by incentivized adoption of DSG. The effects of tax credits and loans were simulated to study the effect of incentives at one LSE on other locations on the grid. The model was applied to a case study using a modified IEEE 6-bus grid and real electric power market data. The case study is intended to verify that the model achieved the required functionalities and to show an example of the complexity of the effect of incentives on electric power infrastructure and markets. The results show that incentives can have widely varying effects on other locations across electric grids. In some cases, introducing incentives at an LSE may locally encourage DSG adoption while discouraging DSG adoption in other locations due to decreasing prices in response to the decreasing demand from the electric power grid. In some other cases, incentives may have the opposite effect where they might increase prices at other locations and hence encourage DSG adoption. The results support the notion that incentives have a rippling effect on other locations across the electric power grid. Significant effects of incentives were identified by running multiple scenarios and performing statistical testing of the results using multiple regression analysis. As such, the framework suggested in this research can benefit ISOs and policymakers to simulate electric power grids and markets to investigate the effect of incentives on electric power grids and strategically capitalize on their benefits. Careful management of incentives if needed to achieve the intended objectives considering that consumer behavior to adopt DSG. For example, if two different LSEs have DSG incentives, their interaction may result in unexpected market conditions in those two LSEs or even other locations on the grid. The developed model can be modified to represent electric grids at specific geographic locations, electric grids, and supply and demand parameters.

5.4. REDUCING VULNERABILITY AGAINST NATURAL DISASTERS

The framework developed in this model combined ABM, economics of supply and demand in wholesale power markets, OPF optimization, and reliability assessment to create a complex SoS and investigate the requirements for DSG to mitigate the impact of natural disasters. The results show that the developed approach can capitalize on the benefits of DSG to reduce the vulnerability of the electric power grid. Two optimization methods were used in this research to optimize the use of DSG and mitigate the impact of natural disasters on transmission lines. The first method involved the allocation of a minimum number of DSG at one location on the grid such as to avoid a targeted blackout following the failure of a transmission line. In practical application, the calculated number of DSG may be deployed post-disaster to the determined location on the grid to meet demand and recover the stability of the electric grid. The results of this method also show that a few selected locations can be assigned an optimized number of DSG pre-disaster to mitigate the loss of any transmission line to natural disasters. The second method improves on the first method by optimizing the entire grid for any transmission line failure using a GA. The optimization resulted in a lower number of DSG that can be strategically distributed across the electric power grid pre-disaster to mitigate against the failure of any transmission line. Further analysis of the results shows that, although there are many feasible allocations of DSG that can mitigate against the failure of transmission lines, the shifts in demand and electricity rates should be taken into consideration. If left unchecked, the locational prices at some locations on the grid may reach unreasonably high electrical power prices, which is a known problem that may occur due to electric power congestion when the electric grid is disrupted.

6. CONCLUSION

This research explored several aspects related to the electric power infrastructure and markets with a focus on the increasing adoption of DSG. The outcomes of this research can be separated into four distinct outcomes. First, the relationship between the electric power sector and socio-economic indicators was studied using statistical time-series analysis. Second, this research explored the dynamic pricing in power market utilities considering the effect of the adoption of DSG and the emergence of a *Death Spiral*. Third, the effect of policy incentives on the adoption of DSG was explored to show and optimize their complex relationships. Fourth, the benefits of DSG to improve system reliability against natural disasters were examined. To achieve the outcomes of this research, a novel ABM framework was developed to simulate the complex relationship between DSG adoption and the wholesale power market and used as the founding block to achieve each objective separately. A detailed conclusion for each part follows.

6.1. RELATIONSHIP BETWEEN THE ELECTRIC POWER SECTOR AND SOCIOECONOMIC INDICATORS

6.1.1. Research Summary. This research objective investigates (1) the relationship between electrical power consumption per capita and three types of socio-economic indicators: economic growth, human development, and corruption; and (2) the relationship between electrical losses in distribution and both human development and corruption was studied. The results show a positive correlation between electrical power consumption per capita, on one side, and economic growth, human development, and corruption on the other side. Countries with healthier economies and human development have higher electric power consumption per capita. There is also a relationship between corruption and electrical power losses. Countries that have less corruption and stricter law enforcement have lower electrical power losses than countries that are more corrupt. Overall, the results show that there is an apparent connection between the electric power sector and various socio-economic indicators.

6.1.2. Research Contribution. This research presents a holistic and worldwide perspective on the relationship between the electric sector, on one side, and economic growth, human development, and corruption, on the other side. It also emphasizes that the dynamics of the electrical power sector should be examined from the economic and social perspectives, and not only the engineering technical perspective. In addition, this research highlights the notion that electrical power production and consumption are linked to national well-being and development, giving additional reason to fund and improve electrical power infrastructure.

6.1.3. Limitations and Future Work. The limitations of this research arise in principle from inconsistencies and missing values in the data. There are missing values for certain countries and years such that the variables cannot be concatenated into a single dataset. This prevents performing multivariate regression or panel analysis using all variables at once. In order to overcome this obstacle, the methodology was designed to test each variable in an exhaustive manner to study the sole respective relationships for each variable. Though it is not doable using the mentioned dataset, a multivariate panel analysis is however recommended for future work using a refined selection of variables. Also, future work is suggested to use Instrument Value (IV) Regression and Two-Stage Least Squares (2SLS) Regression. These methods were not performed in this research, again due to limitations in the data. Concerns of endogeneity in this research were checked through scatter plots of the residuals, causality testing, and panel analysis using random effects and fixed effects. However, the suggested methods for future work should be able to resolve concerns of endogeneity further, if any.

6.2. DYNAMIC PRICING USING REINFORCEMENT LEARNING (RL)

6.2.1. Research Summary. The effect of the penetration of DSG on the power infrastructure and wholesale power markets considering dynamic pricing was investigated using ABM and RL. In particular, the occurrence of a utility death spiral, which may emerge from the feedback loop between the adoption rate of DSG and electricity prices, was investigated. This was achieved by developing a complex SoS framework using ABM, DC-OPF, and several RL algorithms. Low-cost generators were found to be the least affected by the adoption of DSG, while high-cost generators are the most affected. It was proven that a modified Roth-Erev algorithm can maximize the gross profits of generating companies impacted by increasing DSG adoption. The results also showed that a utility death spiral is unlikely. The feedback between increasing DSG adoption and electricity rates will span many years and will most likely not result in a sudden devastating effect.

6.2.2. Research Contribution. This research part investigated the impact of DSG on the electrical power market considering the dynamic pricing of electrical power by generating companies. This research adds to the body of knowledge by introducing a complex simulation framework that can assist different associated stakeholders in understanding and simulating the interaction between dynamic pricing in wholesale power markets and the adoption of DSG. By simulating the long-term effect of DSG on the electric power infrastructure and market, policymakers can introduce regulations and pricing mechanisms that can strategically influence the rate of adoption of DSG.

6.2.3. Limitations and Future Work. The RL module in this research tested multiple RL algorithms and compares them. However, there may be other RL, game-theory-related, or broader machine learning algorithms that may be worth testing in future work. In addition, the behavior of the generating companies is assumed to follow wholesale power market mechanisms and financial structures. However, future work can investigate regulated markets, monopolies, and specific financial conditions of generating companies and utilities that may have unique interplay with DSG diffusion and the occurrence of a utility death spiral. Future research can also consider the ramp rates of generators to fulfill electric demand peaks that are not served by DSG, the effect of carbon taxes, and recent advances in power storage that can enhance DSG integration.

6.3. DSG POLICY INCENTIVES

6.3.1. Research Summary. This part explored the effect of DSG policy incentives on the wholesale power market. Specifically, this part focused on rebates that affect the cost of DSG systems, and reduced interest rates for loans. This was achieved using the developed ABM model with enhancement to add the effect of policy incentives. An exhaustive array of scenarios were executed and their results were thoroughly investigated using multiple regression analysis. The findings show that incentives at a location on the grid can have unexpected effects on other locations, which supports the need to carefully consider wholesale power markets and infrastructures as complex systems.

6.3.2. Research Contribution. This research part contributes to the body of knowledge with a novel framework to simulate the effect of incentives on electrical power grids and wholesale power markets considering the power system constraints and power market economics. The framework and findings from this research support the notion that policies and incentives should be carefully studied regarding their complex effect on the market and the electric grid. The interplay between policies, power rates, and DSG adoption may result in unexpected behavior that is not necessarily intuitive.

6.3.3. Limitations and Future Work. This research is limited to studying the effect of rebates and interest for loans to install DSG. Future research may study additional types of incentives and market structures that are relevant to grid-tied DSG system owners, such as feed-in-tariff and net metering, as they can allow for "selling" power back to the grid and consuming power from the grid when needed.

6.4. REDUCING VULNERABILITY AGAINST NATURAL DISASTERS

6.4.1. Research Summary. Every year, natural disasters, such as storms, hurricanes, or earthquakes, cause significant damage to the electrical power infrastructure and result in significant losses and necessary repair costs. Accordingly, the goal of this research was to investigate reducing the vulnerability of the electric power infrastructure against natural disasters by leveraging DSG. This was achieved by extending the ABM with reliability analysis and planning. DSG optimization was performed using two different approaches: (1) single-node optimization, and (2) entire network optimization using GA. The results show that GA combined with ABM is an effective approach to test strategic allocations of DSG that mitigate the effect of natural disasters. Further analysis of the results shows that LMPs should be taken into consideration to further mitigate unreasonable electricity rates, which is a problem that can occur in wholesale power markets impacted by natural disasters.

6.4.2. Research Contribution. This research can benefit future researchers to optimize electric power infrastructure and markets by reducing their vulnerability against natural disasters as complex systems. The parameters and layout of the simulated network tested in the model developed in this research can be easily modified to various grids and locations. The developed framework integrates ABM, OPF, and GA in a multilayer DSG optimization approach that fulfills the need for simulating and optimizing dynamic electrical networks as opposed to a conventional static grid model. Overall, the framework and methods presented in this research are intended to support the understanding of the benefits of DSG in reducing the vulnerability of the electric power grid against natural disasters, which can be achieved pre-or-post-disaster. The vulnerability of the grid may be improved by adjusting market regulations and policy incentives such as tax incentives to strategically promote the adoption of DSG at targeted locations on the electric grid. DSG can also be strategically allocated for emergency post-disaster relief.

6.4.3. Limitations and Future Work. The limitations of this research, which are also suggested for future work, are (1) to account for the cost of installing DSG systems at different locations on the grid, which can lead to the development of a multi-objective optimization problem that investigates the trade-off between vulnerability and the cost of expansion; (2) design a multi-objective optimization that also considers the LMPs; (3) test and compare other optimization algorithms in addition to GA such as simulated annealing, particle swarm optimization, and others; (4) perform a probabilistic analysis considering a daily variation in demand for each LSE; (5) consider the effect of natural disasters such as earthquakes on power generation plants of different parameters such as their types, scales, and seismic zones; and (6) verify the model using a large-scale case study with a realistic natural hazard scale of impact, geographic system footprint, and market conditions.

6.5. OVERALL LIMITATIONS AND FUTURE WORK

The overall limitations and future work of this research as related to the ABM framework include: (1) the consumer behavior to adopt DSG is assumed to compare the monthly electric cost from the grid and the cost to install a DSG system in a stochastic process as discussed in the methodology. Future work may include the social and economic factors, such as income, education, concerns of environmental impact, and/or home type to improve this process. (2) The generator parameters were calibrated to match historical electricity prices. Future research may enhance this process by calibrating additional parameters to better describe the financial elements related to generation and/or utilities. (3) DSG systems are assumed to include PV and batteries such that they supply the needed electrical energy for a full day under average efficiency parameters. Further research may consider increasing power storage, considering efficiencies of different PV and battery technologies, and other relevant effects such as weather.

6.6. CONCLUDING REMARKS

This research provides distinct contributions to the body of knowledge. The findings in this research support sustainable DSG diffusion and prove the potential benefits to consumers and the electric power system. This research introduced, implemented, and tested a novel ABM-based framework that can simulate electric power markets and infrastructure impacted by DSG adoption. The framework combined ABM, OPF, RL, and GA in a data-driven complex optimization. The novelty of this research is that is presents a holistic framework to many aspects of DSG adoption that is highly multidisciplinary as it combines infrastructure engineering, electric power engineering, economics, social science, and computer modeling. Overall, the findings of this research can assist researchers, system operators, and decision-makers to plan and/or promote DSG adoption, capitalize on their many benefits, and improve the efficiency, reliability, and sustainability of the electric power infrastructure.

APPENDIX

The code created in this research is part of an ongoing collaborative research. Accordingly, it cannot be shared for confidentiality and proprietary reasons. For those interested in specific parts of the code, they can provide their request to the author and the advisor who will reasonably evaluate it at that point in time.

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