Journal of Global Information Management
Volume 33 • Issue 1 • January-December 2025

Ranking Electric Utility Companies for Smart Meter Adoption:
Empirical Evidence From the United States

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ABSTRACT

The reliability of a power distribution system reflects its ability to supply uninterrupted electricity. The installation of smart meters improves reliability by minimizing outages and expediting restoration. Smart meters enhance efficient energy use, balance supply and demand, and strengthen system reliability. This study applies a simultaneous equations model and a modified Hyperlink Induced Topic Search algorithm to analyze the relationship between federal funding, smart meter adoption by electric utilities, and reliability, aiming to rank electric utility companies in the United States. Results show positive associations between federal funding and smart meter adoption rates, as well as between smart meter adoption rates and system reliability. The proposed network-based methodology ranks electric utility companies by ownership type. The research findings underscore the significance of smart meter adoption and provide valuable insights for policymakers and electric utility companies seeking to enhance power system reliability.

KEYWORDS

Reliability, Public Policy, Simultaneous Equations Model, HITS, Network Analysis, Federal Funding, Power Outage, Ranking Methodology

INTRODUCTION

As the backbone of America's economy, the electric power industry provides the energy that enables citizens and businesses to participate in global commerce. It also supports downstream sectors such as transportation, water, emergency services, telecommunications, and manufacturing. A reliable and affordable electric power supply is crucial for regular operations in today's industrialized economies (Zhu & Lin, 2022). Despite this, the United States has witnessed an increase in large outages over the past two decades (Blunt, 2022), which can trigger failures that affect banking, communications, traffic, and security. Notably, the 2003 blackout affected an estimated 45 million people across eight states (U.S.-Canada Power System Outage Task Force, 2004). In February 2021, the Texas power crisis led to shortages of water, food, and heat for over 4.5 million houses and

DOI: 10.4018/JGIM.368257

businesses, causing widespread damage and loss of life (Doan, 2021; Svitek, 2022). These incidents underscore the importance of ensuring power grid resilience and reliability, particularly in extreme weather events and other challenges.

To enhance the reliability of the power grid, numerous utility companies in the United States have modernized their grid by integrating smart meters. These advanced devices can collect and transmit detailed energy consumption data at frequent intervals, often in near-real time. This capability enables utility companies to identify and address issues promptly. According to the Edison Foundation Institute for Electric Innovation (Cooper & Shuster, 2019), smart meters notify customers of power outages, provide estimated service restoration times, and send final notifications when power is restored. Companies such as Pacific Gas and Electric (2023), Southern California Edison (2023), and San Diego Gas and Electric (2023) have reported significant improvements in outage response times and reductions in outage durations since implementing smart meters (California Public Utilities Commission, 2023). Similarly, Consolidated Edison, Inc. in New York and Oncor Electric Delivery in Texas have reported comparable successes in managing outages and restoring services by using smart meters (Sunset Advisory Commission, 2022).

Several studies have examined the relationship between smart meter adoption and factors like energy efficiency, peak load demand, dynamic pricing programs, and carbon emissions (Corbett et al., 2018; Gao et al., 2023; Zhou, 2021). However, there is a lack of consistent empirical evidence on how smart meter implementation relates to power outage frequency or duration. This study addressed the gap, recognizing the importance of providing policymakers with information to establish standards to enhance power grid reliability and performance. Empirical findings on the relationship between smart meter adoption and power reliability offer valuable insights for grid modernization efforts and help assess policy effectiveness, that is, What effects does the policy have on the targeted problem? In addition, there is a gap in the literature regarding how the ownership type of an electric utility company influences the impact of its smart meter adoption in the power grid area. Different ownership types–cooperative, investor-owned, municipal, and political subdivisions–can have varying results in taking advantage of the grid modernization policy and hence varying impacts on the power grid system. This paper examined these four types to evaluate policy equity by asking, What are the effects of this policy on different groups? Addressing this research question is essential for assessing and diagnosing these policies to gain a comprehensive understanding of their impacts.

To address these research gaps, we proposed a novel network-based methodology to rank electric utility companies across different ownership types. To begin, we formulated research hypotheses that draw on relevant theoretical references. Subsequently, we gathered real-world data from authoritative sources, specifically the U.S. Department of Energy (DOE) (2009) and the U.S. Energy Information Administration (EIA) (2022), to statistically test the formulated hypotheses using a simultaneous equations model. In addition, we constructed a network that links federal funding, smart meter adoption rates across electric utility companies with different ownership types, and reliability performance. Specifically, the federal funding refers to the American Recovery and Reinvestment Act (ARRA) funding in this study. The links and their directionality within the network are established based on the previous hypotheses, while the link weights are determined from the simultaneous equations analysis. Finally, we applied the modified Hyperlink Induced Topic Search (HITS) algorithm to the network to rank electric utility companies across various ownership types.

Our research contributes significantly to the current energy policy literature in two ways. First, by identifying and ranking electric utility companies with different ownership types, our study contributes to the energy policy field, providing significant implications for policymakers and regulators aiming to enhance the strategic allocation of federal funding and encourage smart meter adoption to improve power system reliability. Specifically, our study retrospectively diagnoses and evaluates the policy impacts on smart meter adoption and power outage metrics using U.S. data from 2014 to 2022. Second, unlike previous studies that have been qualitative and subjective in prioritizing power market programs (Ribas & da Silva Rocha, 2015; Zangeneh et al., 2009), our methodology is based on a simultaneous equations model and the HITS algorithm that offers an objective, quantitative framework for ranking utility companies by ownership type. This approach, involving estimating a set of simultaneous linear equations, actual links, and link weights in the network, allows for a precise evaluation of policy outcome. It has far-reaching implications beyond the electric power industry and can be valuable for policymakers and practitioners in various fields, such as prioritizing utility companies across different regions or sectors.

The structure of this paper is organized into five remaining sections. The second section reviews the existing literature on the relationship between ARRA funding, smart meter adoption, and reliability across different utility ownership types. Based on this literature, it then formulates statistical hypotheses. Additionally, it examines relevant literature on the evolution of ranking methodologies, focusing on the integration of regression and network analysis. The third section provides a detailed demonstration of the data set. In the fourth section, we present our network-based methodology step by step. The fifth section presents the results and discussion. Finally, in the sixth section, we draw conclusions, discuss policy implications, and highlight directions for future studies.

THEORY

Relationship Between ARRA Funding, Smart Meter Adoption, and Reliability Across Various Utility Ownership Types

In the United States, the federal government has implemented several measures to modernize the power grid by promoting the adoption of smart grids and smart meters. The 2005 Energy Policy Act was the initial federal law to advocate for using smart meters. It is recommended that utility regulators consider time-based pricing and other demand response strategies. In compliance with this legislation, utility companies have been required to provide each customer with a time-based rate schedule and a time-based meter upon request. Furthermore, the Energy Independence and Security Act of 2007 (EISA) was enacted to improve energy security in the United States, foster renewable energy production, and enhance vehicle fuel economy. The EISA mandated that the DOE, the Federal Energy Regulatory Commission, states, and utility companies must implement programs that promote the deployment of smart meters. Additionally, the EISA directed the National Institute of Standards and Technology to develop standards regarding smart grid technology and interoperability.

When a novel technology is introduced to the market, a major obstacle is the high upfront cost and the lack of seed funding for the technology. In this process, government interventions, such as information policy and subsidies, can significantly impact technology adoption (Mohiuddin et al., 2023; Qiao & Lin, 2023). The effectiveness of a subsidy policy depends on several factors. For example, the degree to which a subsidy policy for technology adoption influences the prices set by producers is a critical factor. Additionally, a significant factor is the duration of the subsidy policy. If the subsidy is available for a limited duration, it can expedite the adoption of the technology (Stoneman & Diederen, 1994). [REMOVED HYPERLINK FIELD]In 2009, the ARRA allocated $4.5 billion to hasten the development of smart grid technologies, with a focus on deploying smart grid technologies to enhance the power grid's performance. The Smart Grid Investment Grant (SGIG) program, funded by the ARRA from 2010 to 2015, utilized a competitive solicitation process based on merit to select 99 electricity providers across the United States for system upgrades. The total fund allocated for this purpose was $3.4 billion. The SGIG funding covers up to 50% of eligible project costs, encouraging investments in a range of smart grid technologies, tools, and techniques. These projects aim to improve flexibility, functionality, and operational efficiency.

Following the implementation of government funding policies, it is essential to evaluate and diagnose these policies to ensure they achieve intended outcomes. These evaluations provide insights into factors affecting success or failure (Pierson, 1993), identify the targeted beneficiaries, and highlight the specific circumstances under which policies are effective (Stéphane, 2020). Through this process, governments are expected to demonstrate evidence-based decision making, set realistic policy expectations, and ensure appropriate allocation of public resources (Head, 2016). Therefore, policy evaluation plays a pivotal role in significantly enhancing value for money, accountability, and transparency in governance (McGee & Gaventa, 2011). It legitimizes governmental decisions by assessing the use of public funds and resources and whether allocated budgets and implemented regulations meet expected goals.

Empirical evidence suggests that the allocation of $4.5 billion in matching funding for smart grid technology (The White House, 2016) under the ARRA of 2009 has facilitated the accelerated deployment of smart grid infrastructure. This has led to the widespread adoption of smart meters, commonly known as advanced metering infrastructure (AMI) meters, and the automation of distribution systems. Previous research has also shown that ARRA funding positively impacts the adoption of smart meters at the state level in the United States (Gao et al., 2022; Zhou & Matisoff, 2016) as well as within utility companies in the United States (Gao & Zhang, 2021; Strong, 2019). In addition, adoption choice is also affected by ownership types of utility companies (Kallman & Frickel, 2019; Zheng et al., 2022). Some scholars observed a decline in research and development (R&D) investment in the electric utility sector after the sector was privatized in the 1990s (Nemet & Kammen, 2007). Particularly, the decline in R&D spending is pronounced among private-owned utilities, implying a continued emphasis on innovation among publicly held utilities (Munari et al., 2002; Sterlacchini, 2012). However, some other researchers contended that larger and investor-owned firms are better positioned to rapidly adopt new technologies as they have access to robust financial, technical, and human resources. This allows them to make substantial investment and execute complex projects (Rose & Joskow, 1988). Strong (2019) provided evidence in the context of smart meter adoption to support this hypothesis. Another viewpoint posited that smaller municipal and cooperative utilities have the flexibility to make investment decisions without encountering the regulatory procedures that investor-owned utilities must deal with (Dedrick et al., 2015).[REMOVED HYPERLINK FIELD] To the best of our knowledge, no study has examined the effects of ARRA funding on the adoption rate of smart meters across electric utility companies from different ownership types. Thus, we propose the first hypothesis:

Hypothesis 1: The existence of ARRA funding leads to higher smart meter adoption rates in electric utility companies across different ownership types.

The adoption of smart meters has been recognized to enhance the reliability of power grid systems, leading to their adoption by many utility companies (He et al., 2016). Smart meter deployment has been argued to reduce both the frequency and duration of power outages by enabling utility companies to manage energy demand more effectively in several ways. First, smart meters' real-time data collection capability allows for accurate grid monitoring and early identification of potential issues (The EI Wellspring, 2022; The National Electrical Manufacturers Association, 2019). Some scholars demonstrated that frequent data collection enables smart meters to detect shorter-duration anomalies in smart grids effectively (Yen et al., 2019). Second, the adoption of smart meters allows operators to locate grid failure and areas where infrastructure upgrades could prevent future blackouts (Miller, 2022). Many SGIG projects have incorporated AMI data into outage management systems and geographic information systems. AMI data provide grid operators and repair crews with information on the locations of power outages and the number of customers impacted (DOE, 2016). These systems speed up storm responses by prioritizing repairs that restore power to most customers quickly and efficiently (DOE, 2014; The National Electrical Manufacturers Association, 2019). Third, smart meters allow for more efficient management and routing of power, reducing the strain on the grid by shifting energy consumption away from peak demand times. They can communicate with other devices, such as smart thermostats and appliances, to adjust power usage automatically during peak periods and prevent blackouts or brownouts caused by grid overload (The EI Wellspring, 2022; The National Electrical Manufacturers Association, 2019). The effects mentioned above may also vary across different ownership types. There is a lack of empirical evidence regarding the association between smart meter adoption across different ownership types and power outages, which leads us to propose to test this relationship through two hypotheses:

Hypothesis 2a: Greater smart meter adoption rates are associated with shorter power outage durations in grids operated by electric utility companies across various ownership types.

Hypothesis 2b: Greater smart meter adoption rates are associated with reduced power outage frequency in grids operated by electric utility companies across various ownership types.

Evolution of Ranking Methodologies: Integrating Regression and Network Analysis

Recently, many empirical studies have proposed various ranking methodologies within the electric power industry. The following examples illustrate the prioritization of demand response programs and investment projects. Aalami et al. (2010) developed an extended responsive load economic model based on price elasticity and customer benefit function. The authors used an analytical hierarchy process (AHP) to select the most effective demand response program, drawing on evidence from the Iranian power grid in 2007. Similarly, Kadavil et al. (2018) used the AHP for prioritizing user preferences to inform the design of home energy management systems for participating in demand response programs, using data from 1,023 survey participants. Wong (2014) suggested a framework for evaluating and ranking underground transmission cable asset renewal investment projects. This framework incorporates uncertainty modeling and assesses the significance of specific transmission line circuits in improving the overall reliability of the bulk power system. In addition, Martinez et al. (2011) applied multiple criteria analysis to prioritize an investment portfolio in capacity expansion and energy security within the Mexican electricity industry. Soares et al. (2014) presented a methodology based on AHP and the Preference Ranking Organization Method for Enrichment Evaluations for prioritizing investments in primary distribution networks. This methodology aims to assist in complex decision-making processes and optimize the implementation capacity for the capabilities of regional distribution networks. However, none of the aforementioned energy studies employed network analysis to rank or select electric utility companies.

Many research articles explored network analysis techniques, such as PageRank (Brin & Page, 1998; Zhang et al., 2019), eigenvector centrality measure (Bonacich & Lloyd, 2001), and HITS (Kleinberg, 1999) to holistically evaluate a company's importance. For example, Liu et al. (2009) and Liu and Lu (2010) suggested a network-based methodology utilizing the data envelopment analysis (DEA) and eigenvector centrality measure to rank the research and development performance of Taiwan's government-supported research institutes. Leem and Chun (2015) proposed a methodology using DEA and PageRank that ranks the port productivity in Asia. All the research mentioned above determined the link relationships and link weights in the network from reference sets and their lambda values in DEA outcomes. More recently, Fang and Partovi (2020) presented a model based on DEA and HITS to prioritize facility locations. The link weights within the network are determined based on the distance parameter between facilities. The network-based research emphasized benchmarking among companies using DEA reference sets. However, such research often neglects the effects of time and does not account for factors that may change over time. Because DEA typically analyzes a single point in time, assuming that the provided input and output data are representative of the companies' performance at that specific moment. Specifically, this paper examined factors that may change over time, such as the reliability performance metrics of the distribution system, the adoption rate of AMI within the U.S. distribution system, ARRA funding, and the size of the electric utility companies.

Therefore, we focused on methodologies that combine regression and network analysis to account for time-based changes in entity characteristics and the linking relationships among entities within the network. Some scholars have not considered time effects, even when using methodologies that integrate regression and network analysis. For example, Yang and Liu (2009) studied the automatic generation of websites' topic hierarchies. They modeled a website's link structure as a weighted directed graph and proposed various methodologies to estimate edge weights, including logistic regression. Their study did not consider time effects, as a website's sitemap does not change significantly over time. Other scholars considered time effects when using methodologies that integrate regression and network analysis. For instance, Sindhwani and Lozano (2010) identified key influencers in online social communities by constructing a directed weighted causal graph. They first addressed a variable group selection problem in multivariate regression to determine the directional relationships between nodes, with edge weights derived from regression coefficients. Then, they applied PageRank to the constructed causal graphs, obtaining an influence measure called GrangerPageRank. This paper accounted for time effects, using a collection of multivariate time series data as the input to the model. In addition, Boonpong and Pheunsane (2023) applied Granger causality analysis and the HITS algorithm to the constructed network to identify the most critical economic sectors. They also assessed these sectors' levels of influence on other sectors in countries with varying degrees of market development. Granger causality analysis, a technique within regression analysis, examines causal relationships between variables in time-series data. Consequently, this study also accounted for the effects of time. Similarly, Tu (2014) constructed a complex financial network for the Chinese stock market using the Engle-Granger cointegration test between all pairs of stocks, which involves running a cointegrating regression between the two time-series data sets. The author then applied the HITS algorithm to the directed and weighted networks. This study also considered time effects. In our study, we proposed a methodology based on the simultaneous equations model and the HITS algorithm. There are two reasons for proposing this methodology. First, as outlined in Hypothesis 2a and Hypothesis 2b, this study examined the association between smart meter adoption rates and power grid reliability rather than focusing on causal effects. That is why we employed the simultaneous equations model. Second, this methodology acknowledges that variables can interact concurrently by employing the HITS algorithm and that these interactions may evolve over time through simultaneous equation analysis. The following section presents a detailed demonstration of the data set.

DATA SET

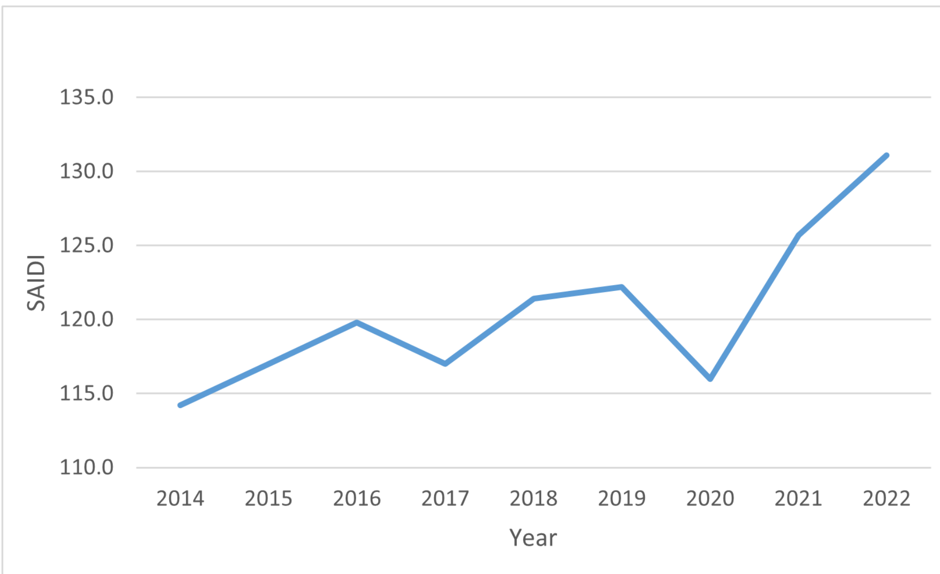
Data Description

The data utilized in this study were taken and combined from two sources between 2014 and 2022, including data on ARRA federal funding, smart meter adoption, reliability performance, and utility-level characteristics. ARRA funding data were obtained from the DOE's website (Smart Grid, 2009). Data on smart meter adoption, reliability performance, and utility-level characteristics were acquired from the EIA (2022). This section details the data sources and steps taken to create the final data set.

We collected information on electricity providers that received ARRA funding and created a binary variable, $ARRA\_Funding_{i,t-2}$, which takes a value of 1 if a utility company i received ARRA funding in year $t - 2$ and 0 otherwise. Further details on the selection process for recipients of ARRA funding can be found in the second section. Furthermore, the EIA has been conducting annual surveys via Form EIA 861 since 2007 to collect data on the electric power participants in the United States and its territories, including electric utility companies, energy service providers, and electric power producers (EIA, 2022). These surveys have included information on the reliability performance metrics of the distribution system, namely, system average interruption duration index (SAIDI) and system average interruption frequency index (SAIFI) since 2013. SAIDI represents the total duration of interruption for the average customer during a predefined period, typically one year. SAIDI is calculated by summing the number of customers affected by each outage lasting more than 5 minutes, multiplying each by the outage duration in minutes, and then dividing by the total number of customers (EIA, 2022). SAIFI measures how often the average customer experiences a sustained interruption lasting over 5 minutes during a predefined period, typically one year (EIA, 2022). It is calculated by dividing the total number of customers who experienced an interruption of more than 5 minutes by the total number of customers (EIA, 2022).

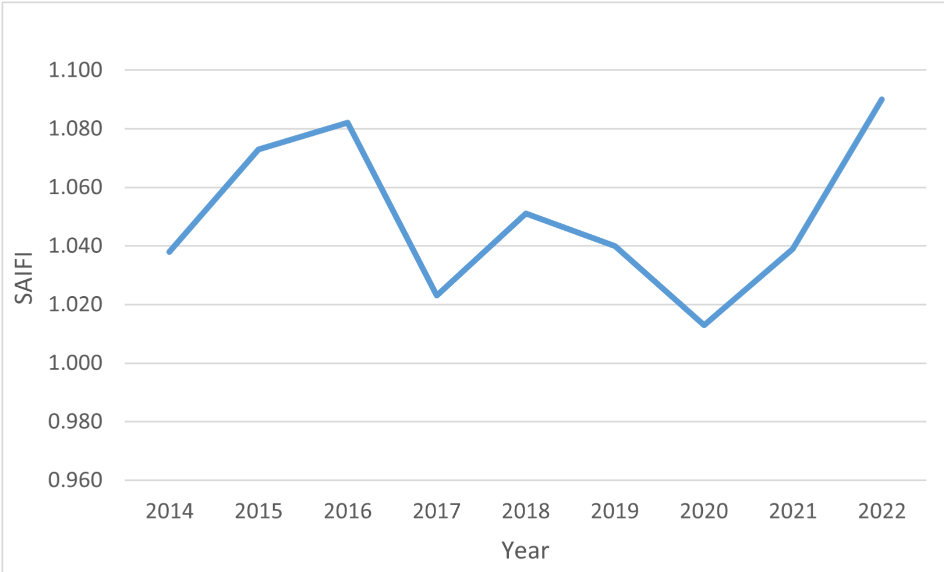
Utility companies responding to the EIA annual surveys may use Institute of Electrical and Electronics Engineers (IEEE) standards, such as IEEE 1366 - 2003, or other approaches (EIA, 2022). Those utilizing IEEE standards have the option to exclude major event days, which are defined as any day exceeding a daily SAIDI threshold. This threshold is calculated based on the daily SAIDI values from data collected over the previous five years (EIA, 2022). This study employs two reliability performance measures: SAIDI and SAIFI, using IEEE standards and excluding major event days. The use of IEEE standards, widely accepted for ensuring consistent reliability performance measures across utility companies, is crucial. Additionally, excluding major event days helps avoid bias in our results due to extreme values. Historical reliability measures from 2014 to 2022 are presented in Figures 1 and 2.

Figure 1. SAIDI of the U.S. distribution system, 2014-2022



Note. Source: U.S. Energy Information Administration (2022).

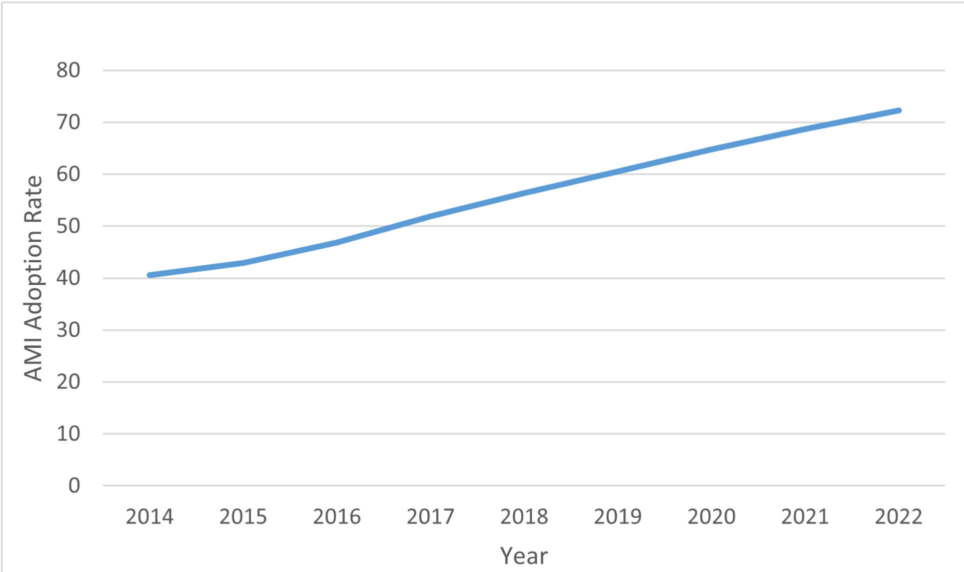
Figure 2. SAIFI of the U.S. distribution system, 2014-2022



Note. Source: U.S. Energy Information Administration (2022).

In addition, the EIA has obtained data on the quantities of meters using automated meter reading and AMI. The research specifically focused on AMI, which includes electricity meters capable of measuring and recording energy usage information on an hourly basis. These meters provide both consumers and energy companies with usage data on at least a daily basis (EIA, 2022). These meters enable two-way communication between consumers and energy companies (EIA, 2022), thereby advancing the electricity infrastructure with information and communications technology. This evolution creates a more efficient and resilient electricity network. The incorporation of AMI is often considered crucial for facilitating the transition toward a low-carbon economy. Trends related to the adoption of AMI are illustrated in Figure 3.

Figure 3. AMI adoption rates in the U.S. distribution system, 2014-2022



Note. Source: U.S. Energy Information Administration (2022).

Furthermore, characteristics of utility companies, such as ownership type, sales, number of customers, state, and other relevant factors, were incorporated into our study. Detailed descriptions of these variables are provided in Table 1. After consolidating data from all the aforementioned sources, we created a data set that covers the period from 2013 to 2022. However, since our regression equation (outlined in the fourth section) includes one-year lagged SAIDI as a control variable, our analysis data spans from 2014 to 2022. Sample records from this data set are shown in Table 2.

Table 1. Variable explanation

Variable Name	Variable Explanation
$uname_i$	Name of utility company i
uid_i	Identification of utility company i
$year_t$	Year t
$AMI\_Adoption_{it}$	Adoption rate of Advanced Metering Infrastructure by utility company i in year t
$SAIFI_{it}$	System Average Interruption Frequency Index, excluding major event days, for grids operated by utility company i in year t
$SAIDI_{it}$	System Average Interruption Duration Index, excluding major event days, for grids operated by utility company i in year t
$ARRA\_Funding_{i,t-2}$	A binary variable equals to 1 if utility company i received ARRA funding in year $t-2$
$\log\_customer_{it}$	Logarithm of the number of customers in utility company i in year t
$ownership_i$	Ownership type of utility company i, including cooperative, investor-owned, municipal, and political subdivision

Table 2. Sample data set

$uname_i$	uid_i	$year_t$	$AMI\_Adoption_{it}$	$SAIFI_{it}$	$SAIDI_{it}$	$ARRA\_Funding_{i,t-2}$	$\mathbf{log}\_customer_{it}$	$ownership_i$
City of Anaheim - (CA)	590	2014	7.99	0.80	48.50	0	11.66	Municipal
City of Anaheim - (CA)	590	2015	7.67	0.36	35.00	1	11.72	Municipal
City of Anaheim - (CA)	590	2016	7.05	0.69	27.12	1	11.77	Municipal
City of Anaheim - (CA)	590	2017	7.78	0.57	35.04	1	11.75	Municipal
City of Anaheim - (CA)	590	2018	5.93	0.50	27.40	0	11.69	Municipal
City of Anaheim - (CA)	590	2019	31.20	0.57	42.12	0	11.70	Municipal
City of Anaheim - (CA)	590	2020	53.27	0.39	26.35	0	11.70	Municipal
City of Anaheim - (CA)	590	2021	93.13	0.86	70.90	0	11.71	Municipal
City of Anaheim - (CA)	590	2022	98.80	0.44	25.49	0	11.71	Municipal
Agralite Electric Coop	155	2014	0	0.70	63.30	0	8.55	Cooperative
Agralite Electric Coop	155	2015	0	1.46	131.50	0	8.55	Cooperative
Agralite Electric Coop	155	2016	0	0.98	106.81	0	8.56	Cooperative
Agralite Electric Coop	155	2017	0	0.96	96.55	0	8.56	Cooperative
Agralite Electric Coop	155	2018	0	1.11	115.91	0	8.56	Cooperative
Agralite Electric Coop	155	2019	96.99	11.18	128.76	0	8.57	Cooperative
Agralite Electric Coop	155	2020	99.81	1.50	123.16	0	8.57	Cooperative
Agralite Electric Coop	155	2021	99.98	1.53	120.82	0	8.58	Cooperative
Agralite Electric Coop	155	2022	99.98	1.59	113.59	0	8.58	Cooperative

Data Preprocessing

To enhance the robustness of our statistical inferences and minimize the impact of outliers and extreme values, we employed a winsorizing methodology on the smart meter adoption rate. This approach involves replacing the top and bottom 1% of the adoption rate values with the 99th and 1st percentile values, respectively. This methodology aligns with the recommendations of Ghosh and Vogt (2012) and D. Kennedy et al. (1992). We employed this technique to bring observations with extreme adoption rates closer to the rest of the sample values. Additionally, we applied a logarithmic transformation to the control variable, namely the number of customers, to achieve a near-normal distribution as the original variable was skewed. This transformation also aids in interpreting our results, as suggested by Gujarati (2009) and Ives (2015).

METHODOLOGY

This paper aims to present a novel network-based methodology for ranking electric utility companies across different ownership types in the United States. The proposed methodology is built on the simultaneous equations model (P. Kennedy, 2008) and the HITS algorithm (Kleinberg, 1999). The three-step framework for implementing this methodology is described in detail in the fourth section.

Conduct Simultaneous Equations Analysis

In the first step, the two-stage least square methodology was employed to estimate the simultaneous equations models elaborated in Appendix A, since multiple interdependent relationships exist between the variables. That is, smart meter adoption and power outage duration influence each other. Higher smart meter adoption rates may lead to better utilities' performance (Gao & Zhang, 2021), such as shorter power outage duration and lower power outage frequency. Simultaneously, the utilities that experience more and longer power outages may tend to adopt more smart meters so that they can improve their power reliability. To account for the mutual dependencies and obtain consistent estimates, the regression equations are presented in Equations (1), (2), and (3).

$$AMI\_Adoption_{it} = \beta_0 + \beta_1 ARRA\_Funding_{i,t-2} + \beta_2\, SAIDI_{i,t-1} + \beta_3 \log\_\mathrm{customer}_{it} + \mu_1 + \tau_1 + \epsilon_1 \tag{1}$$

$$SAIDI_{it} = \gamma_0 + \gamma_1 AMI\_Adoption_{it} + \gamma_2 \log\_customer_{it} + \mu_2 + \tau_2 + \epsilon_2 \tag{2}$$

$$SAIFI_{it} = \alpha_0 + \alpha_1 AMI\_Adoption_{it} + \alpha_2 \log\_customer_{it} + \mu_3 + \tau_3 + \epsilon_3 \tag{3}$$

Where $AMI\_Adoption_{it}$ is the smart meter adoption rate by utility company i in year t, and $SAIDI_{it}$ and $SAIFI_{it}$ are power outage indicators of electric utility company i in year t. For detailed descriptions of $SAIDI_{it}$, $SAIFI_{it}$, and $AMI\_Adoption_{it}$, please refer to Table 1. The state-fixed effects, denoted as μ_1, μ_2, and μ_3 in Equations (1), (2) and (3), serve as controlling factors for state-level variations that may impact the outage indicator. In addition, the year-fixed effects, represented by τ_1, τ_2, and τ_3 in Equations (1), (2) and (3), control factors that remain constant across electric utility companies but vary over time. ε_1, ε_2, and ε_3 are disturbance terms. The coefficients of interest in this study are β_1 in Equation (1), γ_1 in Equation (2), and α_1 in Equation (3). We anticipate β_1 being positive, and γ_1 and α_1 being negative, respectively, based on the existing studies.

Our data comprise information on multiple electric utility companies over time, incorporating both cross-sectional and time-series dimensions. Therefore, we apply panel data models to Equations (1), (2), and (3). These equations include state-fixed effects and year-fixed effects to control for factors specific to a state and a year, respectively. These models allow fixed effects to be correlated with the regressors, focusing on within-state and within-year variations. These models help account for unobserved heterogeneity across states and years that could otherwise bias the estimation (Gujarati, 2009; P. Kennedy, 2008; Stock & Watson, 2020). In addition, we conduct random effects models, which assume that the state- and year-fixed effects are random and distributed independently of the regressors (Gujarati, 2009; P. Kennedy, 2008; Stock & Watson, 2020). In these models, state- and year-specific differences are treated as random variations, allowing for both within- and between-state and year variations in the estimation. Subsequently, we perform Hausman tests on Equations (2) and (3) to assess whether a significant difference exists between the fixed and random effects models. If the Hausman test is significant, the fixed effects model is preferred. Otherwise, the random effects model is more efficient and should be used (Wooldridge, 2010).

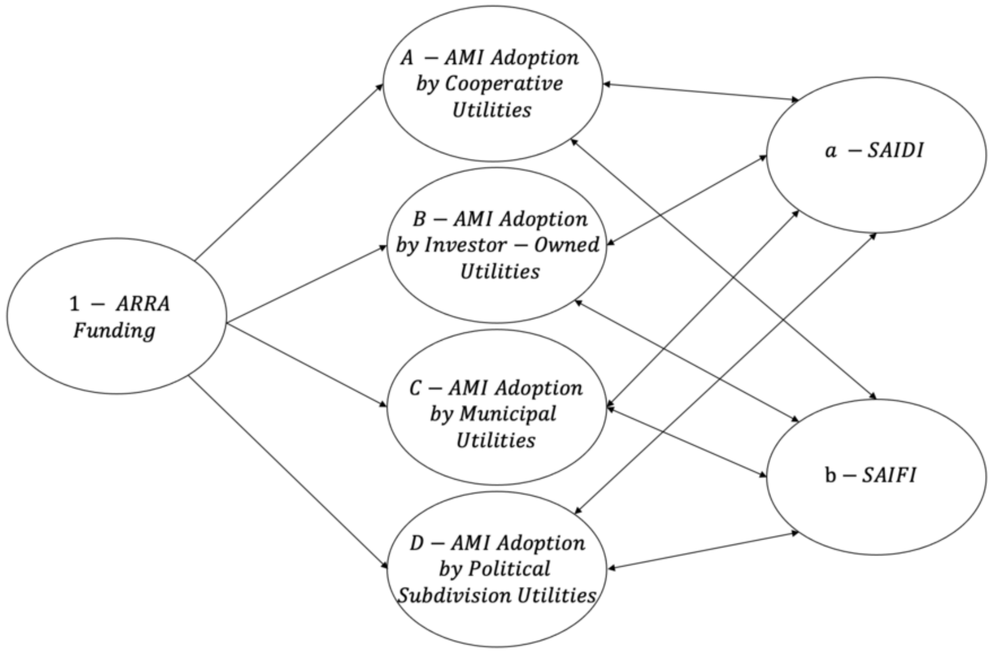
Equations (1), (2), and (3) incorporate the control variables of utility size, which is measured by the logarithm of the number of customers. For several reasons, large utility companies tend to exhibit a greater propensity for adopting new technologies, such as smart meters. First, larger firms often benefit from economies of scale, which may lower the costs of adopting smart meters. Second, large firms typically have access to multiple sources of financing, which may facilitate investment in new technologies. Finally, larger firms often prioritize their public image and commitment to sustainable development, which motivates them to adopt technologies that enhance energy efficiency and promote transparency. Also, Equation (1) controls for $SAIDI_{i,t-1}$ to account for the influence of the previous year's reliability performance on the current year's decision to adopt AMI. We do not include the $SAIFI_{i,t-1}$ in Equation (1), given the potential for multicollinearity resulting from its high correlation with the $SAIDI_{i,t-1}$.

Overall, the study contributes to the literature by providing empirical evidence of the relationship between government funding and AMI adoption, as well as between AMI adoption and power outage indicators. The findings hold significant implications for policymakers and stakeholders engaged in promoting smart energy technologies and enhancing electricity reliability.

Build Network

In the second step, we constructed a network that connects the nodes representing 'ARRA Funding,' 'AMI Adoption,' 'SAIDI,' and 'SAIFI.' This network is an essential instrument for ranking electric utility companies across different ownership types. Figure 4 illustrates an example of this network, where 'ARRA Funding' corresponds to Node 1. Nodes A, B, C, and D represent AMI Adoption rates by different ownership types of electric utility companies. Node a denotes 'SAIDI,' and Node b represents 'SAIFI.'

Figure 4. A network illustrating the relationship between ARRA funding, AMI adoption rates by various ownership types of electric utility companies, and SAIDI and SAIFI



We first examined the relationship between ARRA funding and AMI adoption in the United States. Based on Hypothesis 1, as discussed in the second section, ARRA funding influences AMI adoption in the United States. This is because government funding plays a crucial role in facilitating the adoption of smart energy technology, particularly in the early stages of adoption. To represent this, we established unidirectional links from ARRA funding to AMI adoption, specifically from Node 1 to Nodes A, B, C, and D, as shown in Figure 4.

The study also explores the association between AMI adoption and power outage indicators, specifically SAIDI and SAIFI, as per Hypothesis 2a and Hypothesis 2b discussed in the second section. We established bidirectional links between AMI adoption (Nodes A, B, C, D) and SAIDI (Node A), as well as between AMI adoption (Nodes A, B, C, D) and SAIFI (Node B). All links in Figure 4 are weighted, and their weights are calculated through simultaneous equations analysis, as discussed in the fourth section. The implementation of this step is further elaborated in the fifth section.

Apply Modified HITS Algorithm

In the third step, we utilized a modified HITS algorithm to rank electric utility companies of various ownership types based on their linking relationships. The modified HITS algorithm is applied to the network depicted in Figure 4, and its detailed implementation is provided in the fifth section. We refer readers to Appendix B for a more comprehensive understanding of the HITS algorithm (Kleinberg, 1999). Next, we outline the modified HITS algorithm utilized in our analysis.

A Modified HITS Algorithm

Each node p in the network is assigned a hub weight y_p and an authority weight x_p, all initialized to 1. We also consider the weight of link $p \rightarrow q$ in the network, denoted as w_{pq}. Here w_{pq} and w_{qp} are equal. Then $x's$ and $y's$ are iteratively updated as the formula shown in Equations (4) and (5).

Repeat:

$$x_p := \sum_{q \to p} w_{qp} y_q \tag{4}$$

$$y_p := \sum_{p \to q} w_{pq} x_q \tag{5}$$

Normalizing x and y in each iteration.

Until Convergence

To determine the final authority and hub weights for each node, the algorithm described above is iterated until it reaches convergence. As noted by Langville and Meyer (2006), convergence is typically achieved within 10 to 15 iterations. To prevent values from diverging during this iterative process, the matrix is normalized after each iteration, leading to convergent values. The convergence of x and y vectors, indicating that the algorithm terminates, has been proven by Fang and Partovi (2022). Applying the modified HITS algorithm to the network in Figure 4 yields a ranking of the electric utility companies A, B, C, and D by descending authority weights. This ranking provides valuable insights into the relative importance of these companies within the network, serving as a guide for comparing electric utility companies across various ownership types.

RESULTS AND DISCUSSION

This section presents the results and discussion of applying our proposed methodology, as outlined in the fourth section, to the data set described in the third section. It demonstrates the methodology's potential to enhance decision-making processes related to ranking electric utility companies across various ownership types.

Results of Simultaneous Equations Analysis

We conducted our analysis by utilizing the simultaneous equations model, as outlined in the fourth section, on the data set. The results obtained from estimating Equation (1) are presented in Table 3, with the dependent variable being the percentage of smart meter adoption rate. The table also highlights the subsamples used, including cooperative, investor-owned, and electric utility companies managed by municipal and political subdivisions. All regression models incorporate year- and state-fixed effects. This estimation is employed to assess the impact of ARRA federal funding from two years ago on the current year's AMI adoption rates, as discussed in Hypothesis 1. The results demonstrate that ARRA funding from two years ago is positively associated with the current year's adoption rate of smart meters by electric utility companies. These results are consistent with earlier research that highlights the effects of government funding in the same direction, albeit with varying magnitudes. Our study shows a greater impact, since we analyzed data from more recent years, during which the United States has witnessed significant growth in the smart meter market. In accordance with our regression results, Hypothesis 1 is substantiated by our findings. The adoption of smart meters by electric utility companies in the United States is encouraged through the provision of federal ARRA funding, which helps to reduce associated costs. However, the effectiveness of these federal financial incentives in driving smart meter installations varies depending on the ownership types of electric utility companies. The estimated coefficient for ARRA funding in Model 4 of Table 3 is larger in absolute value compared to the other models. This indicates that ARRA funding has a stronger effect on driving smart meter adoption in electric utility companies owned by political subdivisions. For instance, according to Model 4, electric utility companies owned by political subdivisions that received ARRA funding two years ago would experience an approximately 63% increase in smart meter adoption rate compared to those that did not receive funding. Cooperative, investor-owned, and municipally operated electric utility companies would experience increases in smart meter adoption rates of approximately 29%, 31%, and 26%, respectively, if they had received ARRA funding two years ago.

Additionally, the coefficients for electric utility company size, measured by the logarithm of the number of customers, are positive in Models 2, 3, and 4 of Table 3 and statistically significant in Models 2 and 3. However, they are negative and insignificant in Model 1. This suggests that company size is positively correlated with smart meter adoption rates across all ownership types of electric utility companies, except for cooperative electric utility companies. This finding aligns with existing studies, as larger companies generally have more capital and resources to invest in new technologies such as smart meters (Dedrick et al., 2015; Rose & Joskow, 1988). In contrast, cooperatively-owned electric utility companies are less likely to engage in research and development activities, as their primary goal is to provide affordable services to their customers rather than to maximize profit (Rose & Joskow, 1988). The coefficients for $SAIDI_{i,t-1}$ are negative across Models 1, 2, 3, and 4 in Table 3, indicating that the duration of power outages in the previous year is negatively associated with smart meter adoption rates in the current year. One possible reason is that electric utility companies that have experienced long power outages in the previous year tend to prioritize repairing and upgrading core infrastructure (Smart Electric Power Alliance, 2024). This diverts their financial and operational resources away from investing in new technologies, such as smart meters (St. John, 2020). The F statistics are statistically significant for all models in Table 3, indicating that these models provide a better fit to the data than those with no explanatory variables. Moreover, these regression results are essential to our subsequent analysis, as the coefficients serve as link weights within the network.

To test the robustness of our estimation for Equation (1), we also regress $AMI\_Adoption_{it}$ on $ARRA\_Funding_{i,t-1}$, a binary variable set to one if the electric utility company i received ARRA funding in year $t-1$. The estimations also control for $SAIDI_{i,t-1}$, the log of the number of customers, as well as state- and year-fixed effects. The results of these models, presented in Appendix C, are similar to those in Table 3, indicating that our analysis is robust.

Table 3. Effects of $ARRA\_Funding_{i,t-2}$ on $AMI\_Adoption_{it}$

Variable	Model 1 Cooperative	Model 2 Investor-owned	Model 3 Municipal	Model 4 Political Subdivision
$ARRA\_Funding_{i,t-2}$	28.63*** (6.480)	31.04*** (5.340)	25.83*** (8.959)	62.61*** (23.69)
$\log\_customer_{it}$	-1.017 (0.909)	5.756*** (0.792)	5.113*** (1.100)	0.150 (3.024)
$SAIDI_{i,t-1}$	- 0.0228*** (0.00549)	- 0.0220 (0.0134)	- 0.0221 (0.0174)	- 0.0473 (0.0328)
Constant	73.91*** (10.33)	-85.04*** (18.27)	-18.43 (15.01)	30.94 (40.91)
N	3,072	1,194	1,434	168
Adjusted R^2	0.15	0.40	0.35	0.26
Overall F-stats	10.88***	14.49***	16.14***	4.50***

Note. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Tables 4 and 5 present the results of estimating regression Equations (2) for SAIDI and (3) for SAIFI, respectively. Different ownership types, including cooperative, investor-owned, municipal-owned, and political subdivisions are examined in Models 5, 6, 7, and 8 and Models 9, 10, 11, and 12, respectively. The coefficients for AMI adoption are negative and statistically significant in Models 5, 6, 7, and 8 of Table 4 and Models 9, 10, 11, and 12 of Table 5. These findings indicate a significant negative association between AMI adoption rate and power outage indicators, with stronger results observed for SAIDI than SAIFI regarding the magnitude and significance level. For instance, as shown in Model 5 of Table 4, a 1% increase in the AMI adoption rate is associated with an average reduction of approximately 15 minutes in power outage duration for grids operated by cooperative electric utility companies. Investor-owned, municipal-owned, and political subdivision-owned utility companies would experience a reduction of around 2.4, 3.5, and 3 minutes in power outage duration in their grids, respectively, if they increase their AMI adoption rate by 1%. In contrast, as displayed in Model 9 of Table 5, a 1% increase in AMI adoption rate is associated with a 0.06 decrease in the number of power outages experienced by the average customer in a year for cooperative electric utility company. Thus, the results support our Hypothesis 2a and 2b by demonstrating a negative association between AMI adoption and two power outage indicators.

Additionally, the results for the relationship between company size and power outage indicators are mixed. For investor-owned and municipal-owned electric utility companies, the coefficients for $\log\_customer_{it}$ are positive and statistically significant at the 1% level in Models 6 and 7 of Table 4, as well as Models 10 and 11 of Table 5. This suggests that the number of customers positively impacts both the duration and frequency of power outages in grids managed by investor-owned and municipal-owned electric utility companies. In contrast, the coefficients for $\log\_customer_{it}$ are negative and statistically significant in Models 5 and 8 of Table 4, and Model 9 of Table 5, although this negative effect loses significance in Model 12 of Table 5. This suggests that the number of customers is negatively associated with both power outage indicators in grids managed by cooperative and political subdivision-owned electric utility companies. Furthermore, the F-statistics presented in Tables 3, 4, and 5 provide compelling evidence that the regression models offer a better fit for the data than the model without any independent variables. The results from Hausman tests in Tables 4 and 5 are statistically significant, indicating that fixed effects models are preferred, with the exception of Model 12 in Table 5. To maintain consistency, we have chosen to use fixed effects models across all analyses rather than random effects models.

These results have important implications for electric utility company managers and consumers. First, smart meters allow electric utility companies to monitor and detect power outages more quickly and accurately. With real-time information about the location and extent of outages, electric utility companies can respond faster and more efficiently, reducing outage durations and frequencies. This can lead to improved customer satisfaction and reduced costs for both electric utility companies and consumers. Second, adopting smart meters can improve the reliability and resiliency of the electrical grid. By reducing the impact of outages, smart meters can help ensure that critical infrastructure, such as hospitals and emergency services, remain operational during power disruptions. Third, the adoption of smart meters also benefits the environment. Power outages often result in the loss of perishable food items, which can lead to increased waste and greenhouse gas emissions. By reducing outage durations and frequencies, smart meters can help mitigate these environmental impacts. Overall, smart meter adoption has significant potential to improve the reliability, resiliency, and environmental sustainability of the electric grid.

Table 4. Effects of $AMI\_Adoption_{it}$ on $SAIDI_{it}$

Variable	Model 5 Cooperative	Model 6 Investor-owned	Model 7 Municipal	Model 8 Political Subdivision
$AMI\_Adoption_{it}$	- 14.60*** (0.522)	- 2.400*** (0.372)	- 3.520*** (0.415)	- 3.035*** (0.783)
$\log\_customer_{it}$	- 28.87*** (2.784)	11.79*** (2.800)	31.25*** (2.528)	- 40.55*** (6.716)

continued on following page

Table 4. Continued

Variable	Model 5 Cooperative	Model 6 Investor-owned	Model 7 Municipal	Model 8 Political Subdivision
Constant	1,344*** (45.62)	- 23.79*** (51.16)	- 142.0*** (20.71)	768.7*** (84.67)
N	3,072	1,194	1,434	168
Adjusted R^2	0.33	0.45	0.31	0.44
Overall F-stats	29.88***	18.33***	14.40***	9.2***
Hausman Tests	1,018.6***	56.6***	116.93***	25.48***

Note. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5. Effects of $AMI\_Adoption_{it}$ on $SAIFI_{it}$

Variable	Model 9 Cooperative	Model 10 Investor-owned	Model 11 Municipal	Model 12 Political Subdivision
$AMI\_Adoption_{it}$	- 0.0584*** (0.00375)	- 0.0120* (0.00223)	- 0.0315*** (0.00468)	- 0.0132*** (0.00445)
$\log\_customer_{it}$	- 0.0794*** (0.0200)	0.0313*** (0.0168)	0.280*** (0.0285)	- 0.0187 (0.0382)
Constant	5.771*** (0.328)	2.810*** (0.306)	- 0.870*** (0.233)	1.452*** (0.481)
N	3,072	1,194	1,434	168
Adjusted R^2	0.25	0.35	0.31	0.29
Overall F-stats	21.08***	12.09***	13.94***	5.32***
Hausman Tests	267.48***	26.76***	74.98***	8.91

Note. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Rankings of Electric Utility Companies

This subsection aims to illustrate utilizing a modified HITS algorithm for ranking electric utility companies across varying ownership types. First, we obtain the values of w_{qp} or w_{pq} from Tables 3, 4, and 5. As an illustration, w_{1A} denotes the weight value assigned to the link that connects Node 1 to Node A. Node 1 corresponds to ARRA funding, and Node A represents the adoption of AMI by cooperative electric utility companies. This link is situated within the network depicted in Figure 4. w_{1A} is 28.63 and is located in the second row and second column of Table 3. In instances where the coefficient is negative in Tables 3, 4, and 5, we take the absolute value of the coefficient. Subsequently, we apply Equations (4) and (5) to the network depicted in Figure 4, which yields the following equations:

$$x_1 = 0$$

$$y_1 = \sum_{1\rightarrow q} w_{1q} x_q = w_{1A}x_A + w_{1B}x_B + w_{1C}x_C + w_{1D}x_D = 28.63x_A + 31.04x_B + 25.83x_C + 62.61x_D$$

$$x_A = \sum_{q\rightarrow A} w_{qA} y_q = w_{1A}y_1 + w_{aA}y_a + w_{bA}y_b = 28.63y_1 + 14.6y_a + 0.0584y_b$$

$$y_A = \sum_{A \to q} w_{Aq} x_q = w_{Aa} x_a + w_{Ab} x_b = 14.6 x_a + 0.0584 x_b$$

$$x_B = \sum_{q \to B} w_{qB} y_q = w_{1B} y_1 + w_{aB} y_a + w_{bB} y_b = 31.04 y_1 + 2.4 y_a + 0.012 y_b$$

$$y_B = \sum_{B \to q} w_{Bq} x_q = w_{Ba} x_a + w_{Bb} x_b = 2.4 x_a + 0.012 x_b$$

$$x_C = \sum_{q \to C} w_{qC} y_q = w_{1C} y_1 + w_{aC} y_a + w_{bC} y_b = 25.83 y_1 + 3.52 y_a + 0.0315 y_b$$

$$y_C = \sum_{C \to q} w_{Cq} x_q = w_{Ca} x_a + w_{Cb} x_b = 3.52 x_a + 0.0315 x_b$$

$$x_D = \sum_{q \to D} w_{qD} y_q = w_{1D} y_1 + w_{aD} y_a + w_{bD} y_b = 62.61 y_1 + 3.035 y_a + 0.0132 y_b$$

$$y_D = \sum_{D \to q} w_{Dq} x_q = w_{Da} x_a + w_{Db} x_b = 3.035 x_a + 0.0132 x_b$$

$$x_a = \sum_{q \to a} w_{qa} y_q = w_{Aa} y_A + w_{Ba} y_B + w_{Ca} y_C + w_{Da} y_D = 14.6 y_A + 2.4 y_B + 3.52 y_C + 3.035 y_D$$

$$y_a = \sum_{a \to q} w_{aq} x_q = w_{aA} x_A + w_{aB} x_B + w_{aC} x_C + w_{aD} x_D = 14.6 x_A + 2.4 x_B + 3.52 x_C + 3.035 x_D$$

$$x_b = \sum_{q \to b} w_{qb} y_q = w_{Ab} y_A + w_{Bb} y_B + w_{Cb} y_C + w_{Db} y_D = 0.0584 y_A + 0.012 y_B + 0.0315 y_C + 0.0132 y_D$$

$$y_b = \sum_{b \to q} w_{bq} x_q = w_{bA} x_A + w_{bB} x_B + w_{bC} x_C + w_{bD} x_D = 0.0584 x_A + 0.012 x_B + 0.0315 x_C + 0.0132 x_D$$

Columns 3 and 4 of Table 6 display the authority and hub weights obtained using the modified HITS algorithm. According to Kleinberg (1999), the authority weight of a node refers to its value as an information source, representing the node's credibility or trustworthiness. The ranking results of authority weights indicate that AMI adoption by political subdivision-owned electric utility companies has achieved the highest rank, followed by AMI adoption by investor-owned electric utility companies. Therefore, electric utility companies managed by political subdivisions that adopt AMI are the most credible or valuable information sources from which other companies can learn. The last two rankings of authority weights are occupied by AMI adoption by cooperative and municipal electric utility companies.

Hub weight refers to how well a node serves as a directory or collection of links pointing to authoritative nodes, representing its ability to identify good information sources. According to Column 4 of Table 6, the ranking results of hub weights indicate that SAIDI achieves the highest rank, followed by SAIFI and ARRA Funding. Therefore, SAIDI has the greatest ability to identify good information sources.

Column 5 of Table 6, which shows the HITS ranking, is based on the descending order of the authority weights in Column 3. Our findings suggest that AMI adoption by political subdivision-owned electric utility companies is deemed to be the most significant and pertinent for improving the reliability of the power grid system. Specifically, electric utility companies owned by political subdivisions appear more committed to prioritizing community needs and upholding social responsibility compared to other ownership types. This greater commitment may be due to several factors (American Public

Power Association, 2023; Darling & Hoff, 2019). First, electric utility companies operated by a political subdivision, functioning as a branch of a local government, are publicly owned and thus are accountable to the public. Second, such electric utility companies typically possess a more reliable grid, leading to fewer power outages for their customers. These electric utility companies can exert more direct control and oversight within the local community and utilize their revenue to invest in infrastructure after covering operating costs. Finally, these companies may prioritize the needs of their customers over profit-driven ownership types by promoting energy efficiency and sustainability.

Table 6. Rankings by modified HITS

1	2	3	4	5
No.	**Representation**	**Authority weight**	**Hub weight**	**HITS ranking**
1	$ARRA\_Funding_{t-2}$	0	0.0013	
A	AMI adoption by cooperative utility companies	0.3604	0	3
B	AMI adoption by investor-owned utility companies	0.3887	0	2
C	AMI adoption by municipal utility companies	0.3237	0	4
D	AMI adoption by political subdivision utility companies	0.7837	0	1
a	SAIDI	0	1.0000	
b	SAIFI	0	0.0048	

CONCLUSION AND POLICY IMPLICATIONS

The electric power industry is fundamental in sustaining the U.S. economy, with interdependent linkages downstream spanning diverse sectors. However, there have been rising occurrences of significant power outages over the last two decades, underscoring the need for enhanced power grid resilience and reliability. Many utility companies across the U.S. have extensively integrated smart meter technology to bolster outage response times and curtail the duration of power outages. Nonetheless, a dearth of empirical studies exploring the association between smart meter adoption and power grid reliability underscores an evident research gap in the existing literature. In addition, there is a gap in the systematic ranking of utility companies based on their distinguishing features.

This paper evaluates the impact of funding policies on power grid reliability, leading to the following conclusions. First, the empirical evidence strongly supports that federal funding positively promotes AMI adoption in the United States. Second, greater AMI adoption leads to higher reliability of electricity, with lower power outage duration and frequency. Third, AMI adoption in electric utility companies run by political subdivision-owned electric utility companies is the most influential ownership in our study, followed by investor-owned electric utility companies. Our empirical results provide compelling evidence for the positive impact of AMI adoption in the utility industry's grid modernization. Federal ARRA funding encourages electric utility companies in the United States to adopt smart meters. This funding has a greater impact on investor-owned electric utility companies and those owned by political subdivisions than on other types of electric utility companies. Smart meters can improve the reliability of the electrical grid, reducing outage durations and frequencies, and potentially benefit the environment. These advantages can lead to improved customer satisfaction, reduced costs for electric utility companies and consumers, and mitigated environmental impacts.

Our findings have several policy implications. First of all, our results highlight the importance of considering ownership types of utility companies when creating financial incentives for new technology adoption. Specifically, political subdivision-owned electric utility companies are deemed to be most impactful within the smart meter adoption network, as publicly owned utility companies prioritize community needs, possess more dependable grids, and may likely prioritize energy efficiency and sustainability over profit-making. Second, since the passage of the Recovery Act of 2009, there has been a noticeable absence of federal-level policies aimed at promoting the adoption of smart meters. However, with the passage of a $1 trillion infrastructure bill signed by the Biden administration in 2021 (DOE, 2022), policymakers and stakeholders are presented with an opportunity to consider the benefits of integrating smart meter infrastructure when making investment decisions in the utility industry. This law includes over $65 billion to modernize and enhance the resilience of the U.S. power grid, with a focus on improving reliability, reducing outages, and advancing clean energy integration (The White House, 2021). To capitalize on these advancements, policymakers should consider a range of policy instruments, such as grants and subsidies, to encourage political subdivision-owned utility companies to adopt AMI technology and enhance the reliability of the power grid. Third, other market-based public policies, such as carbon pricing or emissions trading, can further promote the adoption of AMI technology by motivating utility companies to reduce their carbon footprint and improve their energy efficiency. Finally, our findings provide valuable insights for advancing global information management. Our study is based on data from one country, the Unites States. Nonetheless, the findings have important implications on a global level. Smart meters, a key innovation in intelligent infrastructure, enable real-time data collection and analytics. Our study provides empirical evidence for the positive impact of AMI adoption in the grid resilience. This conclusion is applicable in a different country or geo-political region. Globally, the integration of smart technologies facilitates more efficient electric power distribution, enhances early fault detection, and accelerates restoration during outages. By aggregating, processing, and visualizing data from smart meters, information management systems empower utility companies to optimize operations and make data-driven decisions in different countries. Additionally, these systems engage consumers by offering actionable insights into their power usage. This study poses new directions for global information management research. It will be interesting to observe the reactions of consumers with different levels of information literacy and from different cultural backgrounds. We encourage that future studies should compare the effectiveness of smart meter adoption in triggering behavior changes for sustainable electricity consumption based on data from different countries or regions. The results will shed light on the interactions between technology, behavior, and culture.

In addition, this paper proposes a prescriptive methodology to rank electric utility companies. This approach is based on a simultaneous equations model and the HITS algorithm. The methodology involved four steps. In the first step, we developed hypotheses about the relationships among ARRA funding, smart meter adoption, and power outage indicators, such as power outage duration and frequency. In the second step, we applied a simultaneous equations model to utility-level data from the United States to statistically test these hypotheses. In the third step, we established a network consisting of nodes representing ARRA funding, AMI adoption, SAIDI, and SAIFI. The directions and weights of the links between these nodes were determined from the results in the second step. Finally, in the fourth step, we ranked electric utility companies based on their ownership type, using the modified HITS algorithm on the network.

This study contributes to the literature by identifying several gaps in existing research. First, our study proposes a novel methodology to rank electric utility companies of various ownership types, based on a simultaneous equations model and HITS. These are quantitative and objective methodologies. In contrast, traditional methodologies previously used for prioritizing promising projects or programs in the power market are qualitative and subjective (Aalami et al., 2010; Wong, 2014). Specifically, our study is the first to propose a network-based methodology for prioritizing electric utility companies. Second, our proposed methodology is prescriptive and can be extended to various scenarios, such as ranking utility companies of different sizes, or those based on their participation in formal wholesale markets or demand-side management activities. Third, our study is the first to statistically evaluate the relationship between federal funding, smart meter adoption rates of electric utility companies across different ownership types, and their reliability. Our analysis provides quantifiable measurements of how receiving federal ARRA funding affects the smart meter adoption by utility companies, which, in turn, affects the power outage duration and frequency in grids operated by utility companies. This provides valuable insights that enhance the federal government's decision-making process in promoting social benefits of a stronger electric grid. Finally, our study's conclusions can assist policymakers and practitioners in identifying the most critical electric utility companies across different ownership types and their levels of influence within the power grid industry.

We wish to acknowledge the limitations of our study and emphasize potential directions for future research. Our study is context-specific, and the relationships we have identified between federal funding, smart meter adoption, and power grid reliability, as well as the ranking of electric utility companies, are established within the U.S. context. Nevertheless, we believe our study provides valuable insights into the U.S. public energy policy, particularly regarding financial incentives, given that these policies have been in place for over a decade. Our findings may inspire and inform policymakers and practitioners worldwide as they seek to improve energy policy in their own countries. Furthermore, we recommend that future research should explore the ranking of utility companies across additional factors, such as company size and involvement in the wholesale market, which can enhance understanding of factors shaping public energy policy and complement our study's findings.

AUTHOR NOTE

Yue Gao and Jin Fang contributed equally to this work and should be considered co-first authors.

COMPETING INTERESTS STATEMENT

The authors of this publication declare there are no competing interests.

FUNDING STATEMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. Funding for this research was covered by the authors of the article.

PROCESS DATES

Received: February 10, 2024, Revision: December 24, 2024, Accepted: December 31, 2024

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APPENDIX

Appendix A: The Simultaneous Equations Model

A simultaneous equations model is a statistical approach that involves a system of linear equations to estimate all the structural relationships among variables simultaneously. This differentiates from estimating each regression parameter separately, as stated by P. Kennedy (2008). This model is commonly used when explanatory variables determine the response variable, and some of the explanatory variables are also affected by the response variable, creating a simultaneous dependence between the response variable and explanatory variables (Gujarati, 2009; Stock & Watson, 2020). The following two equations demonstrate a possible model for the variables P_1 and P_2.

$$P_1 = \beta_0 + \beta_1 P_2 + \beta_2 Q_1 + \mu_1 \tag{6}$$

$$P_2 = \gamma_0 + \gamma_1 P_1 + \gamma_2 Q_2 + \mu_2 \tag{7}$$

Specifically, P_1 and P_2 are mutually dependent variables, while Q_1 and Q_2 are exogenous variables. Moreover, the equations incorporate stochastic disturbance terms μ_1 and μ_2. Equations (6) and (7) jointly represent a simultaneous set of structural equations. Equation (6) specifies P_1 as a function of P_2 and Q_1, where β_1 denotes the effect of a change in P_2 on P_1. Meanwhile, equation (7) represents the reverse causal effect of P_1 on P_2. By solving for P_1 and P_2 separately, a set of reduced-form equations corresponding to equations (6) and (7) can be derived.

Solving for P_1

$$P_1 = \beta_0 + \beta_1(\gamma_0 + \gamma_1 P_1 + \gamma_2 Q_2 + \mu_2) + \beta_2 Q_1 + \mu_1 \tag{8}$$

Solving for P_2

$$P_2 = \gamma_0 + \gamma_1(\beta_0 + \beta_1 P_2 + \beta_2 Q_1 + \mu_1) + \gamma_2 Q_2 + \mu_2 \tag{9}$$

Rearranging (8)

$$P_1 = \beta_0 + \beta_1\gamma_0 + \beta_1\gamma_1 P_1 + \beta_1\gamma_2 Q_2 + \beta_1\mu_2 + \beta_2 Q_1 + \mu_1 \tag{10}$$

$$P_1 - \beta_1\gamma_1 P_1 = \beta_0 + \beta_1\gamma_0 + \beta_1\gamma_2 Q_2 + \beta_1\mu_2 + \beta_2 Q_1 + \mu_1 \tag{11}$$

$$(1 - \beta_1\gamma_1)P_1 = \beta_0 + \beta_1\gamma_0 + \beta_1\gamma_2 Q_2 + \beta_1\mu_2 + \beta_2 Q_1 + \mu_1 \tag{12}$$

$$P_1 = \frac{\beta_0}{1-\beta_1\gamma_1} + \frac{\beta_1\gamma_0}{1-\beta_1\gamma_1} + \frac{\beta_1\gamma_2 Q_2}{1-\beta_1\gamma_1} + \frac{\beta_1\mu_2}{1-\beta_1\gamma_1} + \frac{\beta_2 Q_1}{1-\beta_1\gamma_1} + \frac{\mu_1}{1-\beta_1\gamma_1} \tag{13}$$

Rearranging (9)

$$P_2 = \gamma_0 + \gamma_1\beta_0 + \gamma_1\beta_1 P_2 + \gamma_1\beta_2 Q_1 + \gamma_1\mu_1 + \gamma_2 Q_2 + \mu_2 \tag{14}$$

$$P_2 - \gamma_1\beta_1 P_2 = \gamma_0 + \gamma_1\beta_0 + \gamma_1\beta_2 Q_1 + \gamma_1\mu_1 + \gamma_2 Q_2 + \mu_2 \tag{15}$$

$$(1 - \gamma_1\beta_1)P_2 = \gamma_0 + \gamma_1\beta_0 + \gamma_1\beta_2 Q_1 + \gamma_1\mu_1 + \gamma_2 Q_2 + \mu_2 \tag{16}$$

$$P_2 = \frac{\gamma_0}{1-\gamma_1\beta_1} + \frac{\gamma_1\beta_0}{1-\gamma_1\beta_1} + \frac{\gamma_1\beta_2 Q_1}{1-\gamma_1\beta_1} + \frac{\gamma_1\mu_1}{1-\gamma_1\beta_1} + \frac{\gamma_2 Q_2}{1-\gamma_1\beta_1} + \frac{\mu_2}{1-\gamma_1\beta_1} \tag{17}$$

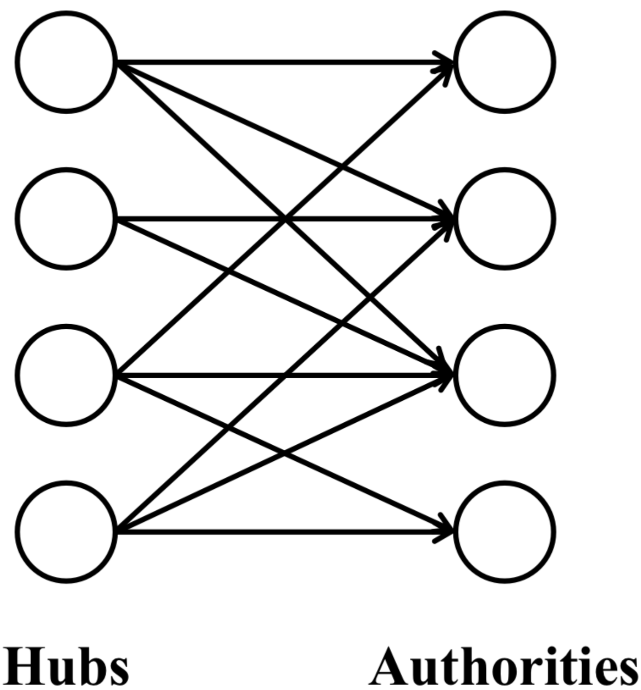
Equations (13) and (17) are derived by solving the simultaneous structural equations (6) and (7) for P_1 and P_2, respectively. These reduced-form equations only incorporate exogenous variables, Q_1 and Q_2, on the right-hand side of the equations.

Simultaneous equations models are widely employed in the empirical analysis of various economic models, such as the wage-price model (Lee, 1978), the demand and supply model (Agthe et al., 1986; Hausman, 1983), and the Keynesian model of Income Determination (Kriesler & Nevile, 2013). One of the primary advantages of these models is their ability to produce a smaller asymptotic variance-covariance matrix compared to single equation models, as they incorporate all available information in the estimation process (P. Kennedy, 2008).

Appendix B: HITS Algorithm

The HITS algorithm (Kleinberg, 1999) is a web page ranking algorithm that utilizes the link structure among web pages. In this algorithm, a web page is considered a good hub if it points to many good authorities, while a good authority is a web page that is pointed to by many good hubs. The mutually reinforcing relationship between authorities and hubs is visually represented in Figure 5, where the nodes represent web pages and the directed edges between two nodes represent the link relationships between the corresponding two web pages.

Figure 5. Hubs and authorities in HITS



A non-negative authority weight x_p and a non-negative hub weight y_p are assigned to each web page p. As per Shen et al. (2009), an authority weight indicates a page's quality of content, while a hub weight reflects the quality of the webpage's links. Based on Kleinberg (1999), authority weights and hub weights are calculated as follows:

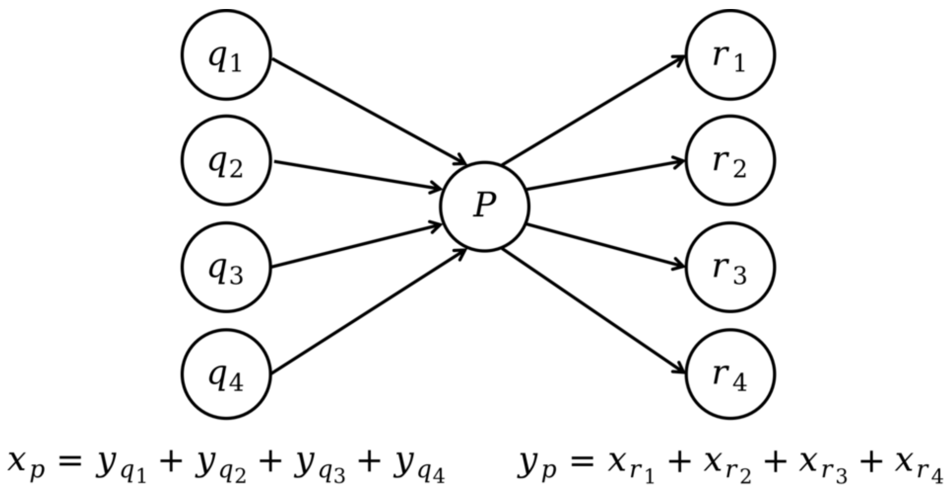
$$x_p := \sum_{q \to p} y_q \tag{18}$$

$$y_p := \sum_{p \to q} x_q \tag{19}$$

Normalizing x_p and y_p so that $\sum_p x_p^2 = \sum_p y_p^2 = 1$.

Kleinberg (1999) shows that the algorithm will terminate, proving that the algorithm will be convergent. It usually takes about ten iterations for the algorithm to converge. The calculation of hub weights and authority weights can be seen in Figure 6.

Figure 6. An example of HITS operation



The HITS algorithm is modified in practical application to account for the influence of multiple web pages from the same host (Bharat & Henzinger, 1998). Further discussion regarding various applications and developments of HITS can be found in several studies, including those by Bharat and Henzinger (1998); Borodin et al. (2001); Chakrabarti et al. (1999); Cohn and Chang (2000); Kleinberg (1999); Kumar et al. (1999); Lempel and Moran (2001); Ng et al. (2001).

Appendix C

Table 7. Effects of $ARRA\_Funding_{i,t-1}$ on $AMI\_Adoption_{it}$

Variable	Model 13 Cooperative	Model 14 Investor-owned	Model 15 Municipal	Model 16 Political Subdivision
$ARRA\_Funding_{i,t-1}$	31.69*** (8.436)	28.11*** (6.770)	15.20 (10.18)	63.74* (32.95)
$\log\_customer_{it}$	-0.917 (0.909)	5.778*** (0.797)	5.255*** (1.101)	0.713 (3.039)

continued on following page

Table 7. Continued

Variable	Model 13 Cooperative	Model 14 Investor-owned	Model 15 Municipal	Model 16 Political Subdivision
$SAIDI_{i,t-1}$	-0.0218*** (0.00549)	-0.0230* (0.0135)	-0.0213 (0.0174)	-0.0473 (0.0332)
Constant	72.38*** (10.33)	-84.30*** (18.41)	-19.42 (15.04)	27.49 (41.48)
N	3,072	1,194	1,434	168
Adjusted R^2	0.14	0.39	0.34	0.25
Overall F-stats	10.76***	14.01***	15.95***	4.22***

Note. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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