frontiers | Frontiers in Sustainable Energy Policy

TYPE Mini Review
PUBLISHED 24 May 2023
DOI 10.3389/fsuep.2023.1171093

Review of application of high frequency smart meter data in energy economics and policy research

Xiaofeng Ye†, Zheyu Zhang† and Yueming (Lucy) Qiu*

School of Public Policy, University of Maryland, College Park, MD, United States

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Devaraj D.,
Kalasalingam University, India

*CORRESPONDENCE
Yueming (Lucy) Qiu
✉ yqiu16@umd.edu

†These authors share first authorship

RECEIVED 21 February 2023
ACCEPTED 08 May 2023
PUBLISHED 24 May 2023

CITATION
Ye X, Zhang Z and Qiu YL (2023) Review of application of high frequency smart meter data in energy economics and policy research. *Front. Sustain. Energy Policy* 2:1171093.
doi: 10.3389/fsuep.2023.1171093

The rapid popularization of advanced metering infrastructure (AMI) smart meters produces customer high-frequency energy consumption data. These data provide diverse options for energy economics and policy research. In this review, we examine studies applying high frequency smart meter data to explore the overall impact of household new technology adoption and COVID-19 on energy consumption patterns. We find that high frequency smart meter data boosts the accuracy of forecasting models with various data-driven algorithms. In addition, there is a lack of precise assessment and inclusive understanding of energy poverty in advanced economics. Smart meter data help expand and deepen the energy poverty research. Research on how vulnerable groups exhibit energy poverty can improve society's understanding of energy poverty and help implement related policy assistance programs.

KEYWORDS

smart meter, energy poverty, household technology adoption, high frequency data, energy economic, energy consumption patterns, review

1. Smart meter

Smart meters are used to accurately record the amount of electricity consumption at a very high frequency, dramatically changing the collection of electricity data and driving the household energy transition (Ribeiro Serrenh and Bertoldi, 2019). High frequency interval meter data, typically hourly and 15 min, provides important and rich information about household consumption patterns. Smart meter data can be used to cluster, classify, predict, and optimize electricity consumption patterns through a series of analytical methods and techniques (Yildiz et al., 2017). The popularity of smart meters has grown rapidly over the past decade, from <2.5 million smart meters deployed globally in 2007 to ~729.1 million in 2019, an increase of 294 times, with the United States and China accounting for the highest percentage, 85.4% (Sovacool et al., 2021). Smart meters provide utilities with detailed information and enable effective demand side management. Two-way AMI meters, which allow communication capability between electric utilities and customers, have been more prevalent after 2013 [U.S. Energy Information Administration (EIA), 2023]. By providing real-time or near real-time electricity data, it supports smart consumption applications based on customer preferences and demand.

The use of smart meters has increased the accuracy and breadth of research in the energy sector in three main dimensions. Firstly, high frequency electricity consumption data can inform hourly electricity usage in homes, the peak hours, and detailed outage information in the event of system disruption. It helps to understand in detail the patterns of electricity consumption as well as electric load. Secondly, high frequency data improves the accuracy of electricity power and energy demand forecasting, providing support for future energy supply management and energy transition. Thirdly, combining household smart meter data with household characteristics, and natural and socio-economic factors could further explore the relationship between energy consumption and socio-economic characteristics, promoting policies to address energy poverty, improve residents' electricity consumption habits, and advance overall social development.

2. Electricity consumption patterns and forecast

High-frequency electricity data helps understand the electricity consumption patterns in different consumer groups at various time periods, and the changes in behaviors after the adoption of new technologies and demand-side management measures. Further, high-frequency data increases the accuracy of energy consumption forecasts due to the larger variation provided by the data.

Applying high frequency electricity data during pandemic times, studies have analyzed and examined the overall impact of COVID-19 on energy consumption and transition in pre- and post-pandemic. The world has seen a shift in people's habits and daily activities due to the pandemic. Therefore, electricity consumption patterns in both residential and commercial buildings have changed. Ku et al. (2022) used individual hourly power consumption data within a machine learning framework to examine changes in electricity use patterns due to COVID-19 mandates in Arizona. Chinthavali et al. (2022) examined changes in energy use patterns on weekdays and weekends before and after the COVID-19 pandemic. Raman and Peng (2021) used residential electricity consumption data to reveal a strong positive correlation between pandemic progress and residential electricity consumption in Singapore. Li et al. (2021) analyzed data from apartments in New York to examine the impact of the number of COVID-19 cases and the outdoor temperature on residential electricity usage. Lou et al. (2021) found that the COVID-19 measures increased residential electricity consumption by 4–5% and exacerbated energy insecurity using individual smart meter data from Arizona and Illinois. Sánchez-López et al. (2022) explored the evolution of energy demands with hourly data among residential, commercial, and industrial demand during the first wave of COVID-19. Understanding how household hourly electricity demand changes after the pandemic, especially due to working from home, provides electricity system operators with valuable information in operation and management. Also, based on the changes in the spatial and temporal distributions of energy consumption, policymakers could make better decisions to increase the ratio of power supply from renewable energy sources.

The application of high frequency electricity data could help understand the electricity consumption patterns of specific consumer groups, especially families that have adopted new technologies [e.g., Photovoltaics (PV), batteries, and electric Vehicles (EV)]. Qiu et al. (2022a) applied a difference-in-differences approach to 1600 EV households' high frequency smart meter data and found that people increased EV charging in lower-priced off-peak hours. Another study (Oliva and MacGill, 2014) found that households who installed solar panels could consume more electricity than before. Similarly, Qiu et al. (2019) estimated an 18% solar rebound effect using hourly electricity consumption data and hourly solar panel data from 2013 to 2017 in Phoenix Arizona. Al Khafaf et al. (2022) compared the electricity consumption of consumers with PV and energy storage systems (ESS) against consumers without ESS using over 5,000 energy consumers' 30-min window smart meters recording. They found that on extremely hot days, installing batteries, to some extent, reduces peak power usage in the afternoon. Using household hourly electricity data in Arizona, Qiu et al. (2022b) found a high degree of heterogeneity in consumption patterns of PV consumers after adding battery storage. As to heat pump adoption, Liang et al. (2022a) provided empirical evidence from Arizona which suggested that heat pumps do not necessarily save energy. Besides, combining electric vehicle charging profiles with residential electricity data helps study the impact of EVs on electricity distribution networks (Hill et al., 2010; Neaimeh et al., 2015; Liang et al., 2022b). These patterns not only help residents explore the economic benefits of new technologies adoptions, but also answer whether and how those new technologies adoption has an impact on existing electric grid's capacity.

Forecast analysis relies on the data they're trained on, and high frequency smart meter data boosts the accuracy of the prediction model. High-resolution forecasting models with various data-driven algorithms need to be validated from high frequency data. Popularization of smart meters in recent years has created opportunities for improving household load forecasting. Accurate electricity load forecasting provides scientific theoretical support for the smart grid, like demand response, energy management, and infrastructure planning and investment. Sousa and Bernardo (2022) compared the accuracy of multivariate adaptive regression splines, random forests, and artificial neural networks to predict the load of the next day with 5,567 households' half-hourly readings. Shaukat et al. (2021) carried out short-term load forecasting by different models, such as artificial neural networks. Lin et al. (2022) combined smart meters, telephone surveys, demographic information, and physical attributes of 83 houses in Oshawa; and identified that the backpropagation neural network model is the best in predicting the annual electricity and gas consumption among eight data-driven algorithms. Fekri et al. (2021) proposed a load forecasting method that can continuously learn from new data and adapt to new patterns to test for load forecasting. Singh and Yassine (2018) proposed unsupervised data clustering and frequent pattern mining analysis on three datasets, then did forecasting with Bayesian network and achieved energy consumption forecast accuracies of 81.89%. The data resolution of the high-frequency smart meter reached 6 s and 1 min, respectively.

3. Further applications of smart meter data

Beyond tracking consumption patterns and forecasting, further applications of smart meter data include studying household energy consumption behavior from the socio-economic perspective and assessing the impact of energy management strategies. Studying consumers' demand choices helps optimize electricity operations and balance electricity supply and demand in a timely fashion.

Besides, smart meter data can be used to support utility companies to do revenue protection.

Many papers use smart meter data to study household energy consumption behavior from the socio-economic perspective (Kang and Reiner, 2022a). Kaur and Gabrijelčič (2022) divided the electricity consumption dataset of 5,038 consumers in Slovenia into clusters and conducted a cluster analysis to identify the primary consumption profiles. Wang et al. (2022) investigated the impact of relationships among household members, community, and identity on electricity use. Lu et al. (2022) studied electricity use and household characteristics in a dynamic pricing experiment in a collective housing area in a Japanese community. Al Khafaf et al. (2022) studied how residential battery installation leads to behavioral changes in energy consumption patterns. Tang et al. (2022) used machine learning to identify the influencing factors of residential energy consumption patterns from a socio-economic angle. Tran et al. (2021) studied the end-use of electricity in 12 households in a purely electric apartment in Japan and found a significant relationship between household characteristics and electricity end-use. Andersen et al. (2021) linked smart meter data from Denmark in 2017 with detailed household characteristics derived from an administrative register to analyze the relationship between hourly electricity consumption levels and these characteristics.

Research also assesses the impact of energy management strategies [e.g., Time-of-use (TOU) pricing] and economic incentives on the demand side using smart meter data. Qiu et al. (2018) evaluated a voluntary business TOU pricing plan in the Phoenix metropolitan area and found a significant reduction in energy demand during peak hours. Applying hourly electricity data, Liang et al. (2021) estimated the electricity savings and social benefits of energy-efficient AC replacements under different pricing plans. Liang et al. (2020) also found that TOU consumers are more likely to have solar panels and estimated that TOU correlates to the similar impact of incentives provided by tax credits or solar adoption rebates of $2,070 to10,472. Oliva and MacGill (2014) examined the financial implications of two net-metering feed-in-tariffs (net-FiT) policies for residential photovoltaics and the returns for households. In another study, Oliva et al. (2016) also investigated the financial advantages of PV in a home, using actual half-hourly PV generation and electricity data in Australia. Considering the cost of battery energy storage systems, researchers study the decision-making of energy storage with smart meter data (Ratnam et al., 2015; Li et al., 2019; Raillard-Cazanove and Barbour, 2022). For example, Li et al. (2019) concluded that energy storage with a battery cost of $0.2/kWh or more was not economically feasible based on smart meter data and real-time PV generation in the studied region. Kantor et al. (2015) studied hourly household data from Ontario, Canada, to analyse the potential for households to have storage systems by manipulating two financial policy triggers. A deeper analysis of smart meter data ensures making evidence-based policy decisions. For example, Liang et al. (2020) suggested that policymakers could combine TOU and solar panels when implementing educational programs or providing financial incentives to consumers. Smart meter data can be also used to support utility needs, such as load profiling, asset loading, and revenue protection (e.g., the detection of tampering, theft or leakage). Canizes et al. (2022) presented a new approach to enhance consumer demand response participation and flexibility of renewable energy as an ancillary service are proposed to alleviate congestion in the low voltage distribution network. Munoz et al. (2022) presented the design, construction, and validation of a smart meter as load control that will become part of a household energy management system. From smart meter data and computer science, energy theft can be detected and addressed with precision. Gerasopoulos et al. (2022) reviewed and classified the energy theft problem in European Union using smart meter data. By imitating normal consumption patterns and compromising neighborhood smart meters simultaneously, Cui et al. (2022) presented an advanced, covert energy theft strategy from machine learning. Then, they designed a feature extraction scheme that will capture the relationship between attacks and customers, and developed a detection model based on deep learning. Tanwar et al. (2022) proposed an energy theft detection strategy, GrAb, using DL-based long short-term memory (LSTM) model, which will categorize the energy losses into technical, energy theft, and normal consumption.

4. Energy poverty

Research in energy poverty has also evolved because of high frequency smart meter data. Before, energy poverty, the inability of a household to meet its energy needs, is characterized by univariate or multivariate approaches (Alkire and Foster, 2011; Deller et al., 2021; Sy and Mokaddem, 2022; Wang and Lin, 2022), including four index (Apergis et al., 2022). Rao et al. (2022) evaluated energy poverty from three aspects: energy availability, energy affordability, and energy cleanability. Energy availability mainly refers to the proportion of the population supplied with electricity. Energy affordability includes per capita GDP, per capita development index, etc. Energy cleanability includes energy intensity, clean fuel accessibility and technologies for cooking, fossil fuel energy consumption, etc. These indicators' data are mostly obtained by questionnaires, but the lack of household consumption data hinders in-depth research on energy poverty.

The use of high frequency data recorded by smart meter extends the methodology for describing energy poverty, helping promote more targeted and effective energy poverty policies. Fine-grained data on electrical consumption allows us to study the impact of economic and social activities on electricity consumption and energy poverty (Fezzi and Fanghella, 2020), and also can be translated into relevant parameters describing electricity consumption, such as electricity Gini, to study energy inequality. Matching the hourly smart meter data of each household with socio-economic data could reshape the understanding of energy poverty and the implementation of energy poverty assistance. Lou et al. (2021) used smart meter data from Arizona and Illinois to show the differential influence of COVID-19 on different demographic groups. Chen et al. (2022) used electricity Gini calculated by smart meter data to study the inequality of electricity consumption and the vulnerability of adaptation. Other studies utilize smart meter data to detect household disconnections to portray energy poverty and to study its relationship with natural factors and household characteristics (Kang and Reiner, 2022b).

For example, Longden et al. (2022) studied the length and number of disconnections in remote indigenous communities in Australia and analyzed its relation to temperature extremes. Barreca et al. (2022) used disconnection dates from the smart meter of 300,000 low-income households in California from 2012 to 2017 to study the relationship between temperature and the risk of disconnection. However, most of the current electricity disconnection calculated by smart meters focus on the duration and number of disconnections, without distinguishing the causes of disconnection in detail. Some of the disconnections that are not related to energy poverty, such as self-disconnection due to traveling, are still counted, which interferes with the accuracy of depicting energy poverty. Therefore, the algorithms using smart meter data to detect disconnection can be refined more in future studies, which will help study energy poverty more accurately.

5. Research gaps

We summarize several areas that need to be further improved in the existing literature. First, most research currently focuses on developed economies, possibly because smart meters are widespread in these regions. However, as smart meter adoption increases, it is also worthwhile to study higher-frequency electricity usage patterns in underdeveloped areas as the differing consumer behaviors, as well as institution and market conditions in developing countries, might imply different electricity usage patterns compared to those in the developed regions. Second, for research on household service disruptions using smart meter data, the existing literature did not clearly distinguish power outages (a disruption in the supply of electricity to a specific geographic area) and power disconnections (a disruption in the supply of electricity to a customer due to non-payment of bills). As higher frequency and longer duration smart meter data become available, there is an opportunity to use machine learning models in conjunction with demographic data to identify electricity disconnections. Third, there are few empirical studies that estimate the impact of new technology adoption such as battery storage and electric vehicle in-home charging, partially due to the lack of data on such technology adoption. More studies are needed to empirically evaluate the impact of these new technologies because the actual consumer behaviors after adopting these technologies may deviate from those predicted by engineering models. Lastly, few studies have focused on the dynamic tracking of electricity consumption behavior and the exploration of interannual regularities in electricity consumption behavior. This helps understand the patterns and reasons for changes in behaviors over time, which provide implications for better optimization of consumer electricity consumption behaviors.

6. Conclusion

High frequency smart meter data increases the breadth and depth of the analysis of household energy consumption patterns. Firstly, a rich amount of studies in recent years applied high frequency electricity data to explore the overall impact of COVID-19 on household energy consumption and transition in pre- and post-pandemic. They focused on examining the policy interruptions such as the "STAY AT HOME" order in different states. Other studies, with the help of high frequency electricity data, could explore the private and social benefits of household new technology adoption, such as EV, PV, and battery energy storage systems. With smart meter data, these new findings provide reliable information and empirical evidence for residents and communities to better plan for the adoption of new technologies. Also, these empirical studies and scenario analyses can help the government optimize interventions and design more targeted policies to improve the social benefits of adopting these technologies. Secondly, the data boosts the accuracy of various energy prediction models with data-driven algorithms and underpins household and utility companies' dynamic energy management. Better forecasting also supports the government in infrastructure planning and investment. Besides, integrating high-frequency smart meter data with information about household characteristics, as well as natural and socio-economic factors, can facilitate a deeper understanding of their interrelationships. By doing so, it may be possible to target households with potential energy poverty and inform the development of energy assistance policies and programs. This approach can serve as a foundation for more effective policymaking and program design. Current federal and state energy assistance programs, such as the Low Income Home Energy Assistance Program and the Weatherization Assistance Program, focused on low-income households instead of energy poverty households. Evolving energy poverty studies could provide targeted energy vulnerability household assessment methods, not only based on income.

Moving forward, there are a few important research areas worth further exploring with the assistance of smart meter data. First, the pandemic has changed the way people work, such as working from home and online education. In the post-pandemic era, what will the new normal bring to energy transition and energy consumption? Some evidence has shown that residential electricity demand increased more than before; the peak time for electricity demand shifted; people could increase EV charging after the pandemic (Jiang et al., 2021). High prices and volatility caused by political instability have placed an excessive burden on consumers. How is this reflected in residents' electricity consumption patterns and consumer behavior through smart meter data? These findings are important for utility companies for better grid operation and management. For example, utility companies could design a wider choice of contracts such as the option for long-term prices to avoid excessive risks. Second, smart meter data, especially household sub-meter data, can help innovate dynamic pricing contracts. Designing real-time demand response programs relies on smart meters and dynamic pricing plans. This is promising for residential customers to take advantage of price variability with increasing penetration of technologies such as electric vehicles, solar panels, and battery storage. Third, with the promotion of smart meters, policymakers can better answer questions such as how to accurately define energy poverty, identify households who are in energy poverty in a timely fashion, and implement targeted assistance. This could significantly enhance the protection of vulnerable groups. We also need to inclusively understand and evaluate the impact of current energy poverty programs, refine energy poverty determination and the analysis of influencing factors, and based on this, prompt policy action to better address energy poverty. And distinguishing the disconnection caused by energy poverty helps make policies to protect vulnerable consumers in arrears from being disconnected. The fourth is to apply smart meters to indicate broader social behaviors. Electricity smart meters can evaluate and track population migration and housing vacancy rates. Lastly, a promising research direction is to utilize smart meter data to study the threat of natural disasters and extreme weather to vulnerable communities and find ways to reduce negative effects. Determining the optimal timing for the restoration of services is an area that warrants further investigation. The electricity consumption patterns revealed by smart meter data (such as energy limiting behaviors) combined with factors such as the severity of weather conditions, poor quality housing, income status, and poor health conditions will imply different degrees of energy restoration urgency and the extent to which vulnerable households are affected. Therefore, further research is needed to identify best practices for restoring power in a timely and equitable manner using smart meter data, especially for vulnerable communities.

Author contributions

XY and ZZ: writing—original draft and investigation. YQ: writing—review and editing, supervision, and conceptualization. All authors contributed to the article and approved the submitted version.

Funding

Funding for this research was provided by Alfred P. Sloan Foundation.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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