# Leveraging Smart Meter Data for Advanced Analytics: A Review of Techniques and Comparative Analysis


Sandeep Kumar
*Dept of ECE*
*IIIT Kota*
Kota , India
2021krec2005@iiitkota.ac.in

Dr. Parikshit Kishor Singh
*Dept of ECE*
*IIIT Kota*
Kota , India
parikshit@iiitkota.ac.in

Anukram Mishra
Independent Technical Advisor
Jaipur , India
anukram@gmail.com

Tushar Gautam
*Dept of ECE*
*IIIT Kota*
Kota , India
2021kuec2008@iiitkota.ac.in

Harshit Arora
*Dept of ECE*
*IIIT Kota*
Kota , India
2021kuec2014@iiitkota.ac.in

Aman Verma
*Dept of ECE*
*IIIT Kota*
Kota , India
2021kuec2006@iiitkota.ac.in



***Abstract*— The modern adoption of smart metering infrastructure in the energy market has allowed creation of Advanced Metering Infrastructure and smart grids, giving electricity traders important insights into consumer habits and achieving optimal energy usage. This paper provides a review of the techniques employed in smart meter data analytics, discussing some applications of smart meters along with analysis methods such as time series analysis, machine learning methods and big data techniques. A comparative analysis of smart meter data based on factors like scalability and data granularity is also performed to a degree. Additionally, some challenges related to computational requirements and data quality are discussed, along with security and privacy issues in smart grids. This review seeks to illuminate the current state of smart meter data analytics, offering insights for academic purposes.**



***Keywords*— *Smart meters, data analytics, machine learning, time series, load forecasting, demand response.***


## I. Introduction

Modern world is highly dependent on technology and smart devices, due to which energy consumption has gone up drastically. This raises a need for better resource management and a shift towards renewable energy. This is especially difficult due to highly diverse modern energy mix, which includes solar, nuclear, wind, among other sources. The complexity and functionality of the energy grid has therefore widened a lot. With a traditional grid system, it will be difficult to collect so much information in the first place, smart grids have come into play. Some differences between traditional and smart grids can be seen in Figure 1.

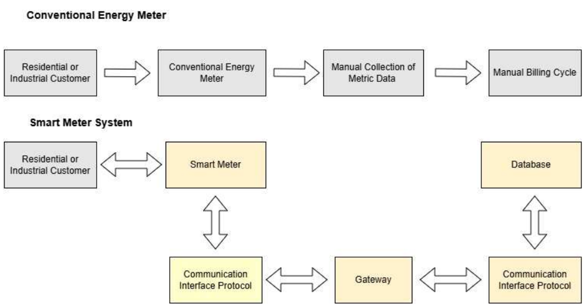


*Figure 1: Traditional vs. smart metering systems, adapted from [28]*

Smart grids and meters make it possible for service providers to assess client behaviour in a much more accurate manner. It helps them to make better decisions and operate efficiently. Use of smart meters enable the information to flow out from the grid in a seamless manner, along with the possibility of real-time monitoring and grid management [1]. As per the organizations deploying and supporting the smart grid movement, smart meters also give rise to other low-carbon advancements [2]. This includes renewable energy, demand response, energy efficiency and integration with the Internet of Things.

Demand Response is perhaps the most important aspect of smart metering. There are works which aim to estimating demand reduction or increment on basis on client consumption patterns [3]. Such analysis is just one step towards achieving net-zero and sustainability goals, and is done using various machine learning or statistical techniques like K-means [4].

This paper aims to discuss and compare prominent smart meter data analysis techniques, mentioning their strengths, weaknesses and applications, touching on topics like relevance of time series, machine learning, big data, edge computing, blockchain, and statistical approaches to analysis of smart meter data. Comparison is made based on the dimensions of accuracy, complexity, granularity of data, scalability, and privacy. With this review, we try to provide aid to academic work in the field of smart meter data analysis.

## II. Applications of Smart Meter Data

### *A. Load Forecasting*

Load forecasting forms the backbone of electricity trade operations by forewarning traders about meeting future requirements on the basis of expectations of consumers. Data from smart metering systems is essential for load forecasting in both the short and longer terms, avoiding the overproduction of energy. Artificial Intelligence-based load forecasting methods, including machine learning and neural network models, usually yield the best forecast performance [5].

## B. Anomaly Detection

Anomaly detection refers to detection on irregularities in the consumption patterns of users, which might indicate energy theft or faulty equipment Common models for this purpose are support vector machines and K-means clustering [6]. Many times, unsupervised learning and deep learning techniques like LSTMs are also deployed on smart meter data in order to identify strange patterns [7]. Some examples of anomalies include sudden increase(spikes) or decrease(dips) in energy consumptions, excessive consumption, etc. Using this, the energy trader can launch an investigation and resolve any issue as soon as possible. This can result in huge cost-savings for the energy trader and consumers don't have to face any issues like overcharging in bills due to faulty equipment.

## C. Demand Response

The topic of flexibility in energy demand is subject of significant interest in modern economies, especially where transmission is difficult. Flexibility of demand helps reduce the load peaks, which in turn allows the system to breathe in terms of energy generation. This also results in lower network congestion [8].

Demand Response not only helps the electricity trader avoid costly network modifications [9], but also contributes to tariff optimization. Clients are also alerted at the time of peak load, so that they can control their electricity consumption during peak. Demand Response programs can be implemented using Internet of Things [10], but may also utilize Machine Learning methods. For example, supervised learning using artificial Neural Networks is widely utilized for short-term load demand response [9].

## D. Tariff Optimization

With true consumption information, electricity traders can construct optimal tariffs that mirror actual usage. Using Demand Response, Smart meter tariff pricing is done dynamically, different at different times of day – during peak and off-peak hours. This means fair prices during off-peak hours, which is better from customers' perspective and better load factor during peak hours, which is better for the electricity trader [11].

# III. Techniques of Smart Meter Data Analysis

The smart metering system is being rapidly adopted globally. With different size of networks and different requirements of a grid deployment, multiple techniques can be utilized to process the meter data into information useful for the electricity trader or the consumer. Figure 2 shows the general procedure for processing data from the grid.

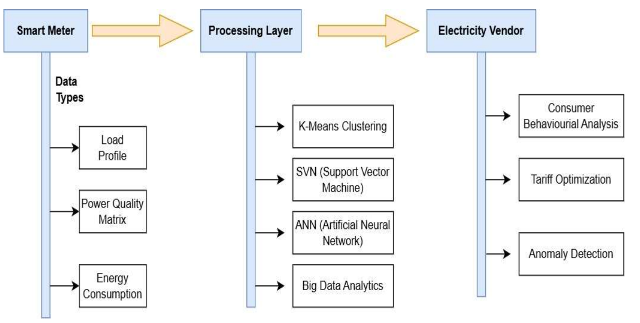


*Figure 2: General process of data analysis of smart meter data, adapted from [29]*

## A. Time Series Analysis

Time series analysis techniques help study and forecast energy consumption patterns. Remote data metering is possible for various granularities, from 15 minutes to an hour, hence analysing every household's profile vary greatly, making it harder to analyse. Such problems call for "*time-series clustering methods using Euclidean distances and Dynamic Time Warping distance*" [12]. Classical models for performing time series analysis include ARIMA, which stands for auto-regressive integrated moving average , ARIMAX meaning ARIMA exogenous, SARIMA or seasonal ARIMA, etc. They provide baseline methods for trend analysis, in contrast to machine learning (ML) and neural network methods enhance accuracy by capturing nonlinear relationships.

Analytics by means of time series analysis can help the energy vendors or traders to improve energy resource management and consumer services by utilizing techniques like accurate forecasting and anomaly detection [13].

## B. Machine Learning Methods

1) *Supervised Learning:* Regression models (e.g., Linear, Ridge, Lasso) are widely used for load forecasting due to their simplicity and interpretability. For the same, purpose artificial neural networks (ANNs) are widely used for Bad Data detection by modelling it as hypothesis testing on the residual extremes *[14]*. Using classification algorithms like Decision Trees and Random Forests on top of feature extraction is useful for tasks like anomaly detection including Energy Theft Detection, where clear decision boundaries are advantageous.

2) *Unsupervised Learning:* Unsupervised clustering algorithms like K-means, DBSCAN are also helpful in Energy Theft Detection (anomaly detection) by clustering together load profiles. This method is generally preferred as obtaining a labelled dataset for theft detection is both costly and difficult.

3) *Deep Learning:* Deep Learning Analytics include use of Recurrent or Convolutional Neural Networks (RNNs or CNNs), Long short-term memory (LSTMs) for long-term load forecasting. Unlike classic supervised learning, deep learning provides the additional benefits like the ability to address the issue of long-term load forecasting using additional hidden layers in the deep networks. Deep Neural Networks (DNNs) also give the provision of handling a very large volume of data, making it the efficient choice for load forecasting, fault identification and price optimisations *[15]*. Recurrent Neural Networks (RNNs) generally perform much better in load forecasting than LSTMs *[16]* or classic supervised learning techniques like regression.

## C. Big Data Analytics

Platforms like Hadoop, Spark and Cassandra facilitate the handling and processing of the huge amounts of data (big data) produced by smart meters. These platforms enable batch and real-time processing. By using big data analytics with cloud, electricity traders can scale their analytics capabilities in accordance with data growth.

For big data analytics, electricity consumption data derived from a smart meter at some fixed sampling rate is sent to a platform like Hadoop and then exported into a general programming language like R or Python for doing the load profile analysis using ML models like ARIMA [17]. The flexibility of the programming language on top especially aids the forecast analysis.

### D. Edge Computing and IoT integration

Advanced Metering Infrastructure (AMI) produces a lot of information which is useful both for the consumer and for the electricity trader. The information is produced at a very high sampling rate; thus, it is very huge in volume. Transmission of such high amounts of data to cloud will require huge amount of processing and bandwidth.

"Edge computing is a distributed computing approach", which implies processing data near to where it is required, and aims to reduces the latency associated with cloud-based analytics [18]. In our case, processing of data is done locally on smart meters or edge devices, accelerating response times and reducing bandwidth requirements.

### E. Distributed Ledger Technologies (Blockchain)

When we talk about distributed ledger technology, blockchain emerges as the most popular. It records asset transactions in a peer-to-peer network. It generates massive amount of interest in almost every field due to its decentralized data processing, i.e., transferring of assets between entities without a centralized ledger [19].

While blockchain implementation of transactions has some limitations, it can still be utilized for energy transactions between clients and energy providers while preventing unauthorized access and data tampering [20]. Application of blockchain in smart meter data emphasize immutability, which is crucial for regulatory compliance and enhancing consumer trust.

### F. Statistical Methods

Load curves are essential for operating any power system but they naturally always contain abnormalities and deviations. For extracting useful information like load factor, loss factor, etc from load curves derived from smart grid data, statistical expressions are used. We can directly define factors like Peak, maximum and minimum loads, root mean squared load, maximum loss duration using statistics. Furthermore, outlier detection can also be performed on smart meter data using probability techniques related to the Gaussian Distribution [21]. Removing the outliers help achieve more realistic load curves.

## IV. Comparative analysis

### A. Data Granularity

Different techniques perform variably with data granularity; higher granularity (e.g., 15-minute intervals) typically enhances accuracy for load forecasting but demands more computational resources.

For low granularity, deep learning models perform decently [13] but as the data gets more fine-grained, they require lots of computational power. At this stage, big data analytics tool like Hadoop and Spark integrated with some programming language perform much better [17]. Even with these tools, response time tends to get worst and worst with the increase in size of data.

### B. Scalability

As we discussed previously, there are millions of smart meters deployed globally containing fine grained data about consumer behaviour. Given the sheer volume of this data, there is a need for scalability. In smart grids, the legacy way of managing the data from the infrastructure using normal relational database systems. As a consequence, many of these systems have begun to suffer severe issues in dealing with the data deluge that has resulted from the application of advanced metering and infrastructure and meet the scalability needs of such systems [22].

Distributed systems, particularly Hadoop and Spark, help in handling large volumes of data with ease, which are therefore preferred over deep learning models frequently require mammoth parallel processing capabilities. With a big experiment dataset, Hadoop-Hive response time is anywhere from 1 to 5 times faster than Spark with Cassandra [22], because Hadoop is independent of in-memory processing, which is more efficient when data during processing do not fit in memory. Spark performs 7.5 times slower compared to Postgres-XL with 0.55 million meters but is almost 26 times slower once the number of meters reaches a 4 million scale [22].

*Table 1: Comparison of different data analysis methods for smart meters, adapted from [5], [14]*

| Method | Techniques | Applications | Advantages | Disadvantages |
|---|---|---|---|---|
| **Machine Learning Approaches** | *Supervised Learning*: SVM, Decision Trees *Unsupervised Learning:* K-Means [4], DBSCAN | Load forecasting, anomaly detection including Energy Theft Detection | Adaptable to variety of datasets with mixed attributes, provides flexibility in classification and regression tasks | Results depend on quality of dataset: computationally intensive |
| **Deep Learning Techniques** [16] | Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Autoencoders | Long-term load forecasting, fault identification, tariff optimization | Great for detecting complex non-linear patterns; suitable for handling large data volumes | Computationally intensive; requires large datasets for accurate results |
| **Hybrid Techniques** | Ensemble Learning, Self-Supervised Learning, Deep Learning with Feature Engineering [15] | Enhanced forecasting accuracy, Anomaly detection | Combines strengths of statistical ML and DL techniques for improved accuracy | Complex to implement |
| **Big Data Analytics** [17] | Hadoop. Spark | Real-time and batch data processing for grid management | Can handle large volumes of data (scalability), adaptable with cloud-based solutions | High data processing and storage requirements |
| **Edge Computing** [18] | Edge processing on smart meters | Anomaly detection near data source | Reduces latency and bandwidth requirements | Limited by processing power of edge devices |
| **Distributed Ledger Technologies** | Blockchain Technology [19] | Secure energy transactions, Data integrity | Tamper-resistant data storage; ensures data integrity and consumer trust | Limited by scalability and government policies |
| **Statistical Methods** | Z-score Analysis, Moving Average Models, Time-Series Decomposition | trend analysis, load factor estimation and load curve parameters | Simple to implement; effective for analyzing and evaluating basic metrics | Face difficulty in detecting complex patterns |

## C. Dataset Linearity

Smart meter datasets are highly non-linear due to dynamic nature of power consumption.

For this reason, techniques based on clustering like K-means, or neural networks learning perform especially well on smart-meter data, while linear techniques like regression and time series analysis using ARIMA somewhat struggle with it.

## D. Energy Efficiency

In traditional grids, energy savings are cultivated through self-management. In contrast, Advanced Metering Infrastructure cultivate energy savings using variable tariffs or tariff optimization and use of In-Home displays to make the consumer aware of their usage. A pilot demonstration for showcasing the effectiveness of In-Home Displays was conducted in South Korean winter for 2 months - Dec. 2008 to Feb. 2009. 77 households in 2 different regions volunteered to participate in the study. 53 of the households in one city showed an average 15.9% decrease in consumption and 22 of the households in the other city showed a dip in consumption of average 7.5% [23]. As can be concluded, smart metering infrastructure directly helps in energy savings, even in households with greater purchasing powers [24].

## E. Security and Privacy

In traditional grids, delivery of power was the most important element. As the world shift towards smarter grids, the concept of smart meter security and user privacy for ensuring confidentiality and integrity of consumer data, as well as accountability and identification have also become important elements of the grid [25]. Security issues like eavesdropping and network interceptions are more common than ever. Most of the service providers also have to keep themselves prepared for Denial-of-Service attacks.

Mitigation techniques for these attacks can either be cryptographic or non-cryptographic. Non-cryptographic techniques like Battery-based load hiding uses some algorithm to obscure actual demand patterns. "*Cryptographic techniques employ public and symmetric key cryptography, homomorphic encryption or some combination of these approaches [25].* " In general, cryptographic techniques are more scalable than their non-cryptographic counterparts, as non-cryptographic techniques usually depend to prediction methods.

# V. CHALLENGES AND LIMITATIONS

## A. Data Quality

Data Quality issues are prevalent in smart meter data, it may include missing or noisy data caused by transmission losses or anomalous/inaccurate data caused by faulty hardware. These quality issues affect the dataset, therefore directly impacting the performance of the ML models that are utilized in the above discussed applications of the smart grid.

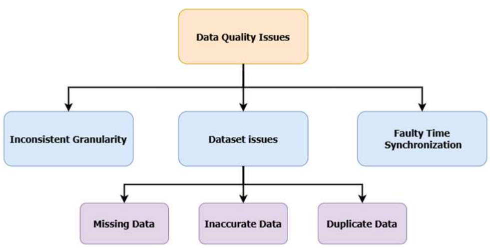


*Figure 3: Some data issues faced while dealing with smart meter data*

Other issues related to data include inconsistent data granularity and high data latency in transmission, which can impact the real time analysis performance. Moreover, data duplication may affect the dataset quality as well. Over time, smart meters may undergo wear and tear, causing a calibration drift, affecting the synchronization of data with time. Figure 3 summarizes the data quality issues faced during smart meter data analysis.

## B. Computational Challenges

Often smart meter data is used for predictive analysis. However, the real time data produced by the meters is not pure and usually needs to be pre-processed or cleaned before the machine learning models can utilize the data. No analytics team can ignore this step and not only does the cleaning step takes around 70% to 80% of the total time spent by a team working on the dataset [26], it also usually requires a lot computational power to go through the raw data.

Moreover, as previously discussed in the paper, the deep learning models require more and more parallel computing resources as the size of the dataset keeps increasing. With the smart grid expanding rapidly, this need for computing power is only going up. Some relaxation can be taken by using tools specifically designed for big data analytics like Spark but even they require massive computing powers, although not as much as the classical analysis models.

## C. Privacy Concerns

Privacy issues like confidentiality of user behaviour data, restricted access and profiling are under more and more consideration as smart meter network increases. We have already discussed various security and privacy related issues above along with some mitigation techniques for the same.

## D. Interoperability

Since smart meter networks are scaling up rapidly, they are sure to expand over multiple countries soon. Even within a country or a state, different neighbouring cities might have their Advanced Metering Infrastructure managed by different vendors and they may follow different standards and protocols. Standards regarding data collection and storage, data processing and transmission must be set and followed to ensure that all the different smart grids stay interoperable.

To aid in this cause, meters are so designed for data collection and inter transmission following certain fixed protocols, even the privacy standards are already in place in some European countries. Most of the implementations of smart grids are versatile and have a lot of common functionality; however, electricity traders might stray away from them to provide exclusive features to the users. "*Among the various functionalities, Time-of-use (TOU) and Bi-directional communication have been found to be the two top most functionalities [27].*"

# VI. FUTURE DIRECTIONS

## A. AI and Hybrid Models

The future of smart metering analytics includes hybrid models, which usually intermix several traditional techniques of analysis. For example, ARIMA may be combined with Neural Networks. This is particularly helpful for energy demand forecasting, where they can enhance the accuracy of predictions by blending time series analysis with ML algorithms. Similarly, combining Random Forests for feature selection and LSTMs or Long Short-Term Memory networks for time-sequenced forecasting, can efficiently detect anomalies and forecast energy loads. They can better predict peak demand and identify unusual consumption patterns that could indicate technical issues or tampering.

### B. *Enhanced Privacy*

AI driven modern ML techniques like Federated Learning allow data analysis without transferring consumer data to centralized locations, preserving privacy while improving model performance by training across multiple decentralized sources. By only transmitting encrypted model updates, federated learning significantly reduces privacy risks while enhancing security.

Modern cryptographic techniques like Homomorphic cryptography [25] allow computations to be performed on encrypted data, meaning that sensitive information never needs to be exposed.

### C. *Policy and Regulatory framework*

Governments need to form updated regulations regarding smart grid operations and deployment to promote competition in market and ensure standards are being followed so that interoperability can be maintained.

Moves by electricity vendors which can lead to sustainability should also be recognized and promoted by means of legal policies and framework. For example, implementation of demand response program should be promoted as it can help in achieving the goal towards forming a sustainable model of the grid.

## VII. Conclusion

Smart meters define the present and future of the modern grid and data analytics is an important element in its efficient management. It can help in achieving greater energy efficiency, real-time monitoring, and demand response.

In the paper, we reviewed and compared analytical techniques at a high level and highlighted mostly on how the traditional techniques like time series analysis hold up to the advantages of modern techniques involving big data analytics. We also touched on the topic of scalability and the use of cutting-edge techniques, such as edge computing and blockchain, in improving the factors involved in the grid such as latency, security and privacy of user data, etc. We also touched on some challenges like data quality issues. The paper aimed at providing a review of these techniques as a contribution to academia and other scholarly work.

## VIII. References


[1] M. H. Raza, Y. M. Rind, I. Javed, M. Zubair, M. Q. Mehmood and Y. Massoud, "Smart Meters for Smart Energy: A Review of Business Intelligence Applications," *IEEE Access,* vol. 11, pp. 120001-120022, 2023.

[2] B. K. Sovacool, A. Hook, S. Sareen and F. W. Geels, "Global sustainability, innovation and governance dynamics of national smart electricity meter transitions," *Global Environmental Change,* vol. 68, no. 0959-3780, 2021.

[3] S. Valovcin, N. Abe and B. Massey, "Using Smart Meter Data to Estimate Demand Reductions from Residential Direct Load Control Programs," *2022 IEEE International Smart Cities Conference (ISC2),* pp. 1-6, 2022.

[4] X. Wang, H. Li, X. Yi, J. Kong and X. Wang, "Analysis of User's Power Consumption Behavior Based on K-means," *2022 4th International Conference on Machine Learning, Big Data and Business Intelligence (MLBDBI),* pp. 39-42, 2022.

[5] H. Habbak, M. Mahmoud, K. Metwally, M. M. Fouda and M. I. Ibrahem, "Load Forecasting Techniques and Their Applications in Smart Grids," *Energies,* vol. 16, no. 1996-1073, 2023.

[6] M. A. Shaukat, H. R. Shaukat, Z. Qadir, H. S. Munawar, A. Z. Kouzani and M. A. P. Mahmud, "Cluster Analysis and Model Comparison Using Smart Meter Data," *Sensors,* vol. 21, no. 1424-8220, 2021.

[7] Á. Hernández, R. Nieto, L. de Diego-Otón, M. C. Pérez-Rubio, J. M. Villadangos-Carrizo, D. Pizarro and J. Ureña, "Detection of Anomalies in Daily Activities Using Data from Smart Meters," *Sensors,* vol. 24, no. 1424-8220, 2024.

[8] G. Di Leo, C. Liguori, V. Paciello, A. Pietrosanto and P. Sommella, "Smart meters and demand response: A double challenge," *2015 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA),* pp. 1-6, 2015.

[9] M. A. Khan, A. M. Saleh, M. Waseem and I. A. Sajjad, "Artificial Intelligence Enabled Demand Response: Prospects and Challenges in Smart Grid Environment," *IEEE Access,* vol. 11, no. 1477-1505, 2023.

[10] M. M. Luambano, A. Kondoro, I. B. Dhaou, N. Mvungi and H. Tenhunen, "IoT enabled Smart Meter Design for Demand Response Program," *2020 6th IEEE International Energy Conference (ENERGYCon),* pp. 853-857, 2020.

[11] P. Farhadi and B. Taheri, "Smart meter tariff pricing using load demand response model," *2017 5th International Istanbul Smart Grid and Cities Congress and Fair (ICSG),* pp. 135-139, 2017.

[12] H. Kim, S. Park and S. Kim, "Time-series clustering and forecasting household electricity demand using smart meter data," *Energy Reports,* vol. 9, no. 2352-4847, pp. 4111-4121, 2023.

[13] M. H. Rashid, "AMI Smart Meter Big Data Analytics for Time Series of Electricity Consumption," *2018 17th IEEE International Conference On Trust, Security And Privacy In Computing And Communications/ 12th IEEE International Conference On Big Data Science And Engineering (TrustCom/BigDataSE),* pp. 1771-1776, 2018.

[14] Y. Wang, Q. Chen, T. Hong and C. Kang, "Review of Smart Meter Data Analytics: Applications, Methodologies, and Challenges," *IEEE Transactions on Smart Grid,* vol. 10, no. 3125-3148, 2019.

[15] J. Jeyaranjani and D. Devaraj, "Deep Learning based Smart Meter Data Analytics for Electricity Load Prediction," *2019 IEEE International Conference on Clean Energy and Energy Efficient Electronics Circuit for Sustainable Development (INCCES),* pp. 1-5, 2019.

[16] M. N. Fekri, H. Patel, K. Grolinger and V. Sharma, "Deep learning for load forecasting with smart meter data: Online Adaptive Recurrent Neural Network," *Applied Energy,* vol. 282, no. 0306-2619, pp. 116-177, 2021.

[17] P. Mathiyalagan, A. Shanmugapriya and A. V. Geethu, "Smart meter data analytics using R and Hadoop," *2017 IEEE*

*International Conference on Electro Information Technology (EIT),* pp. 623-629, 2017.

[18] T. Sirojan, S. Lu, B. T. Phung and E. Ambikairajah, "Embedded Edge Computing for Real-time Smart Meter Data Analytics," *2019 International Conference on Smart Energy Systems and Technologies (SEST),* pp. 1-5, 2019.

[19] S. Nakamoto, Bitcoin: A Peer-to-Peer Electronic Cash System, 2008.

[20] S. M. S. Hussain, S. M. Farooq and T. S. Ustun, "Implementation of Blockchain technology for Energy Trading with Smart Meters," *2019 Innovations in Power and Advanced Computing Technologies (i-PACT),* vol. 1, pp. 1-5, 2019.

[21] B. C. Neagu, G. Grigoraş and F. Scarlatache, "Outliers discovery from Smart Meters data using a statistical based data mining approach," *2017 10th International Symposium on Advanced Topics in Electrical Engineering (ATEE),* pp. 555-558, 2017.

[22] H. Chihoub and C. Collet, "A Scalability Comparison Study of Data Management Approaches for Smart Metering Systems," *2016 45th International Conference on Parallel Processing (ICPP),* pp. 474-483, 2016.

[23] T.-S. Choi, K.-R. Ko, S.-C. Park, Y.-S. Jang, Y.-T. Yoon and S.-K. Im, "Analysis of energy savings using smart metering system and IHD (in-home display)," *2009 Transmission & Distribution Conference & Exposition: Asia and Pacific,* pp. 1-4, 2009.

[24] H. Amaral, A. N. DE Souza, D. S. Gastaldello and F. Fernandes, "Smart meters as a tool for energy efficiency," *2014 11th IEEE/IAS International Conference on Industry Applications, IEEE INDUSCON 2014 - Electronic Proceedings,* 2014.

[25] L. L. Win and S. Tonyalı, "Security and Privacy Challenges, Solutions, and Open Issues in Smart Metering: A Review," *2021 6th International Conference on Computer Science and Engineering (UBMK),* pp. 800-805, 2021.

[26] S. M. Sulaiman, P. A. Jeyanthy and D. Devaraj, "Smart Meter Data Analysis Issues: A Data Analytics Perspective," *2019 IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS),* pp. 1-5, 2019.

[27] G. R. Barai, S. Krishnan and B. Venkatesh, "Smart metering and functionalities of smart meters in smart grid - a review," *2015 IEEE Electrical Power and Energy Conference (EPEC),* pp. 138-145, 2015.

[28] S. S. S. R. Depuru, L. Wang, V. Devabhaktuni and N. Gudi, "Smart meters for power grid — Challenges, issues, advantages and status," *2011 IEEE/PES Power Systems Conference and Exposition,* pp. 1-7, 2011.

[29] M. K. M. Shapi, N. A. Ramli and L. J. Awalin, "Energy consumption prediction by using machine learning for smart building: Case study in Malaysia," *Developments in the Built Environment,* vol. 5, 2021.