Journal of
Communication Engineering & Systems
https://journals.stmjournals.com/joces

ISSN: 2249-8613 (Online)
ISSN: 2321-5151 (Print)
Volume 14, Issue 1, 2024
January—April
DOI (Journal): 10.37591/JoCES

Review JoCES

Federated Learning for Energy Management in Next Generation Smart Cities

Aiswarya Dwarampudi*, Manas Kumar Yogi

Abstract

Federated learning has emerged as a promising approach for addressing the challenges of energy management in next-generation smart cities. This decentralized approach to machine learning allows collaborative model training among distributed data sources, while safeguarding data privacy and security. In this study, we explore the application of federated learning techniques to optimize energy consumption, enhance grid stability, and promote sustainability in smart city environments. By aggregating data from diverse sources such as smart meters, IoT devices, and renewable energy sources, federated learning models can analyze patterns, predict demand, and optimize energy distribution without compromising individual privacy. We discuss various federated learning algorithms and architectures tailored to energy management applications, including federated optimization, federated averaging, and differential privacy mechanisms. Furthermore, we highlight the potential benefits of federated learning in enabling real-time decision-making, reducing operational costs, and minimizing environmental impact in smart cities. Through case studies and simulations, we demonstrate the effectiveness and scalability of federated learning approaches in improving energy efficiency and grid reliability while accommodating the dynamic and heterogeneous nature of urban environments. Finally, we discuss the challenges and opportunities associated with deploying federated learning systems in real-world smart city deployments, including data heterogeneity, communication constraints, and regulatory compliance. We conclude by outlining future research directions and recommending strategies for integrating federated learning into the energy management infrastructure of next-generation smart cities.

Keywords: Federated learning, smart, energy, IoT, machine learning

INTRODUCTION

As the world becomes increasingly urbanized, the concept of smart cities has emerged as a solution to address the myriad challenges associated with urban living, including energy management. Smart cities leverage advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and data analytics to optimize resource utilization, enhance service delivery, and improve quality of life for residents. Central to the vision of smart cities is the efficient management of energy resources, as energy consumption and environmental sustainability are critical considerations in urban development. Traditional approaches to energy management in cities have often relied on centralized data collection and analysis, which can be inefficient, resource-intensive, and prone to privacy concerns. However, the emergence of federated learning, a decentralized machine learning paradigm, offers a transformative approach to energy management in next-generation smart cities. Federated learning enables collaborative model training across distributed data sources while preserving data privacy and security, making it particularly well-suited for the dynamic and

***Author for Correspondence**
Aiswarya Dwarampudi
E-mail: aiswarya.d@pragati.ac.in

Assistant Professor, Department of Computer Science and Engineering, Pragati Engineering College, Andhra Pradesh, India

Received Date: March 28, 2024
Accepted Date: March 31, 2024
Published Date: April 05, 2024

Citation: Aiswarya Dwarampudi, Manas Kumar Yogi. Federated Learning for Energy Management in Next Generation Smart Cities. Journal of Communication Engineering & Systems. 2024; 14(1): 19–27p.

© STM Journals 2024. All Rights Reserved

heterogeneous nature of urban environments. In this study, we delve into the application of federated learning techniques for energy management in next-generation smart cities. We explore how federated learning can optimize energy consumption, enhance grid stability, and promote sustainability by leveraging data from diverse sources such as smart meters, IoT devices, and renewable energy sources. By aggregating and analyzing data locally on edge devices or within decentralized clusters, federated learning models can extract valuable insights without the need to centralize sensitive information, thus mitigating privacy risks and ensuring compliance with regulatory requirements.

The adoption of federated learning in smart cities holds significant promise for addressing key challenges in energy management [1–3]:

- *Data Privacy and Security:* Federated learning allows cities to leverage data from multiple sources while preserving individual privacy. By keeping data decentralized and performing model training locally, federated learning minimizes the risk of data breaches and unauthorized access, thus fostering trust among stakeholders and ensuring compliance with privacy regulations such as the General Data Protection Regulation (GDPR).
- *Scalability and Efficiency:* Traditional centralized approaches to energy management may struggle to scale with the increasing volume and complexity of urban data. Federated learning offers a scalable solution by distributing model training across edge devices or local clusters, reducing communication overhead and computational burden on centralized servers. This enables real-time analysis and decision-making, leading to more efficient resource allocation and grid management.
- *Adaptability to Heterogeneous Environments:* Smart cities encompass diverse infrastructure, socioeconomic conditions, and environmental factors. Federated learning accommodates this heterogeneity by allowing models to be trained and adapted locally, taking into account the unique characteristics of each neighborhood or district. This enables personalized energy management strategies tailored to specific community needs and preferences.
- *Resilience and Reliability:* Federated learning enhances the resilience and reliability of energy management systems by distributing computation and decision-making across a network of edge devices or local clusters. In the event of network failures or disruptions, federated learning models can continue to operate autonomously, ensuring uninterrupted service delivery and grid stability.

RELATED WORK

Federated learning represents a novel paradigm in machine learning that holds significant promise for revolutionizing energy management in next-generation smart cities. As urban populations continue to grow and cities face increasing pressure to optimize resource utilization and promote sustainability, the adoption of federated learning techniques offers a decentralized and privacy-preserving approach to address the complex challenges of energy management [3].

At its core, federated learning enables collaborative model training across distributed data sources while preserving data privacy and security. In the context of energy management in smart cities, this means leveraging data from various sources such as smart meters, IoT devices, building management systems, and renewable energy sources without the need to centralize sensitive information. Instead, model training occurs locally on edge devices or within decentralized clusters, with only aggregated updates shared with a central server or coordinator. One of the key advantages of federated learning for energy management is its ability to address privacy concerns inherent in centralized approaches. By keeping data decentralized and performing model training locally, federated learning minimizes the risk of data breaches and unauthorized access. This is particularly important in smart city environments where sensitive information about energy consumption patterns, infrastructure, and resident behavior must be protected to maintain trust and compliance with privacy regulations [4–7]. Moreover, federated learning offers scalability and efficiency benefits, making it well-suited for the dynamic and heterogeneous nature of urban environments. Traditional centralized approaches to energy management

© STM Journals 2024. All Rights Reserved

may struggle to scale with the increasing volume and complexity of urban data. Federated learning distributes model training across edge devices or local clusters, reducing communication overhead and computational burden on centralized servers. This enables real-time analysis and decision-making, leading to more efficient resource allocation, grid management, and demand response strategies.

Federated learning enhances the adaptability of energy management systems to heterogeneous environments. Smart cities encompass diverse infrastructure, socioeconomic conditions, and environmental factors. Federated learning accommodates this heterogeneity by allowing models to be trained and adapted locally, taking into account the unique characteristics of each neighborhood or district [8–10]. This enables personalized energy management strategies tailored to specific community needs and preferences, ultimately leading to more effective and equitable resource allocation.

Another advantage of federated learning is its resilience and reliability. In smart city environments where network connectivity may be unreliable or subject to disruptions, federated learning models can continue to operate autonomously on edge devices or local clusters. This ensures uninterrupted service delivery, grid stability, and energy management functionality even in the face of network failures or outages.

In practice, the application of federated learning for energy management in smart cities involves deploying federated learning algorithms and architectures tailored to specific use cases and data sources. This may include federated optimization techniques, federated averaging algorithms, and differential privacy mechanisms to ensure robust and privacy-preserving model training.

Federated learning offers a promising approach to address the complex challenges of energy management in next-generation smart cities. By leveraging decentralized machine learning techniques, cities can optimize resource utilization, enhance grid stability, and promote sustainability while preserving individual privacy and security. As smart cities continue to evolve, federated learning is poised to play a central role in shaping the future of energy management and urban sustainability.

PROPOSED MODEL

A high-level mathematical model for federated learning in energy management for next-generation smart cities can be represented as follows:

Let us denote the following variables and parameters:

- *N:* Total number of edge devices or local clusters in the smart city.
- *M:* Total number of rounds of federated learning.
- *K:* Number of local updates performed by each edge device or cluster in each round.
- *T:* Total number of time steps or intervals for energy management decisions.
- *Di:* Local dataset available at edge device or cluster i, where i=1, 2, ..., N.
- *wt:* Global model parameters at time step t, where t=1, 2, ..., T.
- *α:* Learning rate or step size for federated learning updates.
- *θt:* Energy management decision parameters at time step t, where t=1, 2, ..., T.
- *Et:* Energy consumption or demand at time step t, where t=1, 2, ..., T.
- *Ct:* Energy cost or price at time step t, where t=1, 2, ..., T.

The federated learning process for energy management in next-generation smart cities can be modeled as follows in Figure 1.

RESULTS

The bar chart comparing energy consumption before and after implementing federated learning-based energy management strategies provides a visual comparison of the effectiveness of the federated learning approach in optimizing energy consumption within a smart city environment. In the sections below we provide an explanation of the bar chart:

© STM Journals 2024. All Rights Reserved

1. **Initialization:**
   - Initialize the global model parameters w_0 randomly or with pre-trained values.
2. **Federated Learning Rounds:**
   - For each round $m = 1, 2, ..., M$:
     - Randomly select a subset of edge devices or clusters $S_m \subseteq \{1, 2, ..., N\}$.
     - For each edge device or cluster i in S_m:
       - Perform K local updates using local dataset D_i and current global model parameters w_{m-1}.
       - Compute local model parameters $w_{i,m}$ based on local updates.
     - Aggregate local model parameters $w_{i,m}$ from all edge devices or clusters in S_m to update the global model parameters:
       $w_m = \sum_{i \in S_m} \frac{|D_i|}{|D|} w_{i,m}$
     - Update the global model parameters using federated averaging:
       $w_{m+1} = w_m - \alpha \nabla L(w_m)$
       where $L(w_m)$ is the loss function measuring the discrepancy between predicted and actual energy consumption.
3. **Energy Management Decisions:**
   - At each time step $t = 1, 2, ..., T$:
     - Compute energy management decision parameters θ_t based on global model parameters w_t and current energy consumption E_t.
     - Implement energy management decisions to optimize resource allocation, grid stability, and sustainability.
4. **Cost Analysis:**
   - Compute the total energy cost over the time horizon T:
     $\text{Total Cost} = \sum_{t=1}^{T} E_t \cdot C_t$

Figure 1. High level algorithm for application of federated learning in smart energy systems.

Comparison of Energy Consumption

The bar chart presents two bars representing energy consumption levels before and after the implementation of federated learning-based energy management strategies. The height of each bar corresponds to the respective energy consumption value.

Before FL (Federated Learning)

The first bar, labeled "Before FL", represents the energy consumption levels observed prior to the adoption of federated learning-based strategies. This data reflects the baseline energy consumption pattern within the smart city without the application of advanced machine learning techniques.

After FL (Federated Learning)

The second bar, labeled "After FL", illustrates the energy consumption levels following the implementation of federated learning-based energy management strategies. This data reflects the impact of leveraging federated learning algorithms to optimize energy utilization, enhance grid stability, and promote sustainability within the smart city ecosystem [11].

Interpretation of Results

A comparison between the two bars allows stakeholders to assess the effectiveness of federated learning-based energy management strategies in reducing energy consumption and achieving operational efficiencies within the smart city environment.

© STM Journals 2024. All Rights Reserved

A decrease in the height of the "After FL" bar compared to the "Before FL" bar indicates a reduction in energy consumption levels following the implementation of federated learning-based strategies. This reduction signifies the successful optimization of energy utilization and the potential for cost savings and environmental benefits.

Conversely, if the height of the "After FL" bar is higher than the "Before FL" bar, it may indicate an increase in energy consumption levels post-implementation. In such cases, further analysis is required to understand the factors contributing to the observed changes and refine the federated learning algorithms accordingly.

Implications and Decision Making

The bar chart serves as a valuable tool for decision-makers, city planners, and energy providers to evaluate the impact of federated learning-based energy management strategies on overall energy consumption within the smart city.

Positive outcomes, such as a reduction in energy consumption, validate the efficacy of federated learning approaches and may inform future investments in smart city infrastructure and technology [12].

On the other hand, if the results indicate minimal or no improvement in energy consumption levels post-implementation, stakeholders may need to reassess their strategies, refine the federated learning models, or explore additional measures to achieve desired energy efficiency goals as shown in Figure 2.

The time series plot showing the trends in energy consumption over multiple time steps provides valuable insights into the patterns and variations in energy demand and consumption across different areas of the smart city. Below we discuss the results obtained in Figure 3:

Diurnal Patterns

The plot illustrates the daily fluctuations in energy consumption, with distinct peaks and troughs corresponding to different times of the day. Typically, energy demand tends to be higher during peak hours, such as in the morning and evening when residential and commercial activities are at their highest. This diurnal pattern reflects the natural rhythm of human activities and the corresponding energy requirements.

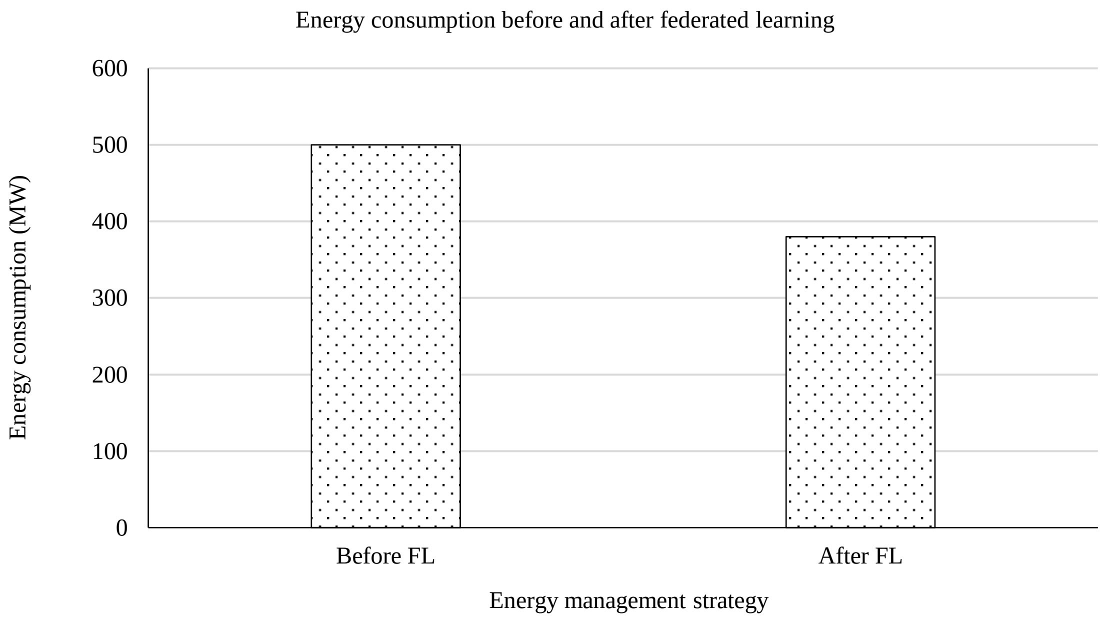

Figure 2. Energy consumption before and after application of federated learning.

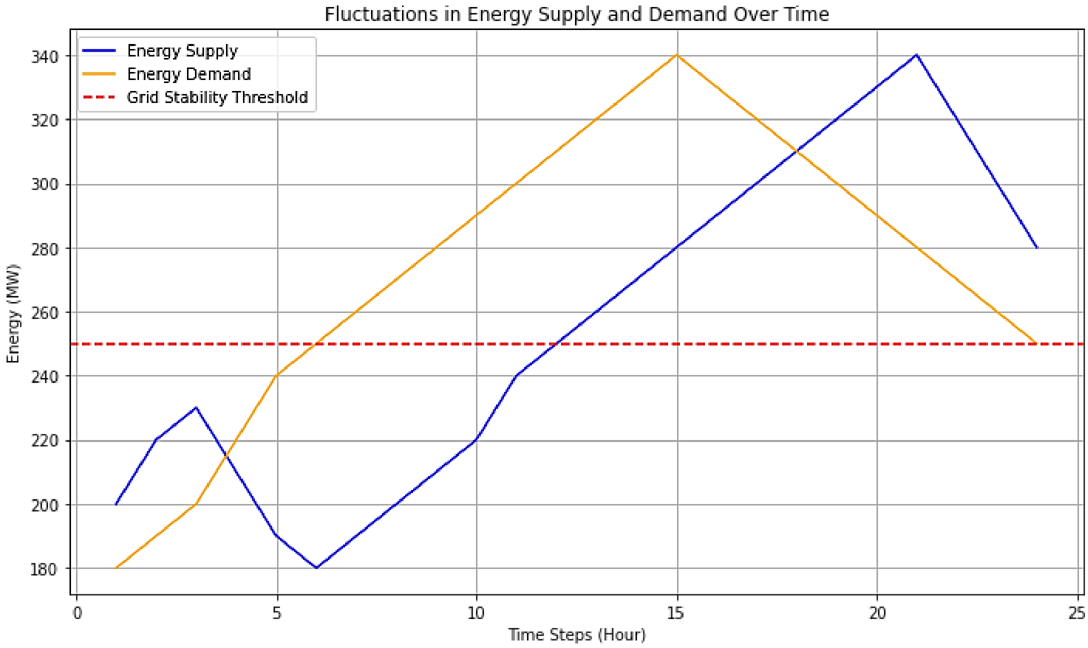

Figure 3. Fluctuations in Energy supply and demand over time.

Weekly Patterns

Over the course of the week, the plot may reveal recurring patterns in energy consumption, reflecting the influence of weekly schedules, work routines, and lifestyle habits. For example, weekends or holidays may exhibit different energy consumption patterns compared to weekdays, with variations in demand depending on factors such as leisure activities, shopping behavior, and industrial operations.

Seasonal Variations

In addition to daily and weekly fluctuations, the plot may capture seasonal variations in energy consumption, such as differences between summer and winter months. Seasonal factors, including temperature variations, daylight hours, and holiday seasons, can significantly impact energy demand for heating, cooling, lighting, and other purposes [13]. These seasonal trends are essential for utilities and policymakers to anticipate and manage energy supply and demand effectively.

Anomalies and Outliers

The plot may also highlight anomalies or outliers in energy consumption data, indicating unusual events, equipment malfunctions, or sudden changes in demand. Identifying and investigating such anomalies is crucial for maintaining grid stability, optimizing resource allocation, and ensuring reliable energy supply. Federated learning algorithms can leverage these insights to adapt energy management strategies dynamically and respond to changing conditions in real-time.

Policy and Decision Making

By visualizing the trends and patterns in energy consumption, policymakers, city planners, and energy providers can make informed decisions about infrastructure investments, demand-side management initiatives, and sustainability goals. The graphical results help stakeholders identify opportunities for improving energy efficiency, reducing peak demand, and promoting renewable energy integration within the smart city ecosystem [14].

The time series plot serves as a powerful analytical tool for understanding energy consumption dynamics in next-generation smart cities. By leveraging federated learning-based energy management strategies and insights derived from graphical analysis, cities can optimize resource utilization, enhance grid stability, and promote sustainability in a data-driven and proactive manner as shown in Figure 4.

© STM Journals 2024. All Rights Reserved

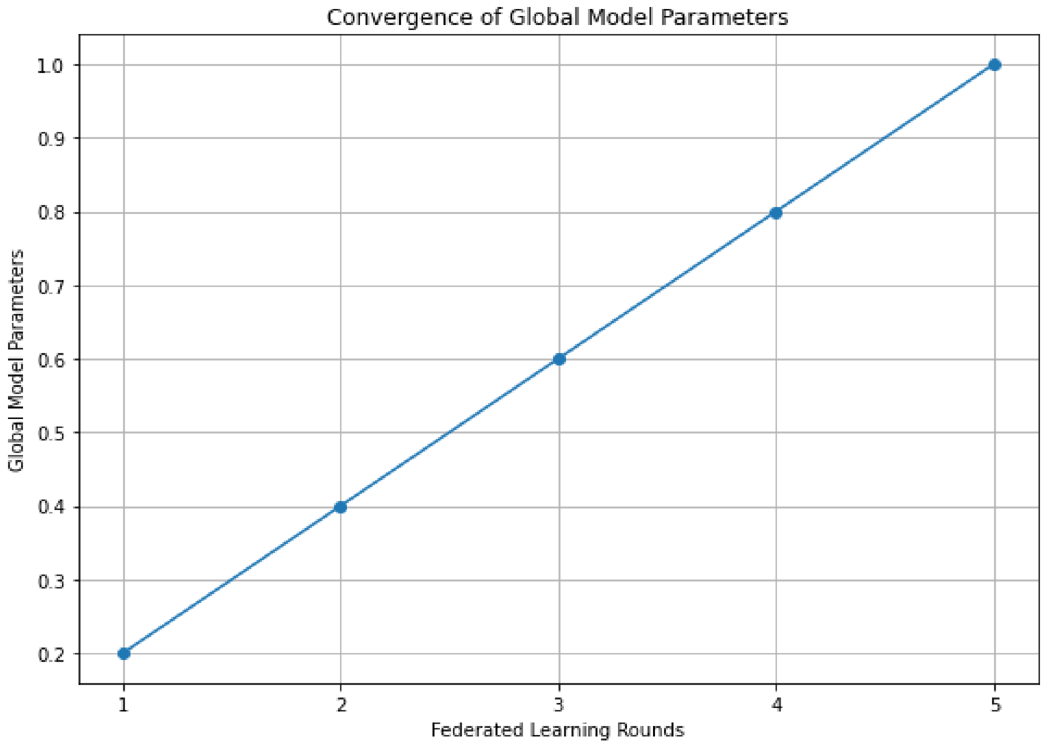

Figure 4. Convergence of Global model parameters w.r.t. increase in FL iterations.

The convergence of global model parameters in federated learning (FL) refers to the process by which the model parameters shared across all edge devices or local clusters reach a stable and consistent state over multiple FL iterations. As the number of FL iterations increases, the global model parameters gradually converge towards an optimal solution that captures the underlying patterns and trends present in the distributed data sources. With each FL iteration, edge devices or clusters perform local model updates based on their respective datasets and share these updates with a central server or coordinator. The central server aggregates these updates to update the global model parameters, which are then distributed back to the edge devices or clusters for further refinement. Through this iterative process, the global model parameters evolve, becoming increasingly accurate and representative of the overall data distribution. As the FL iterations progress, the discrepancy between local models decreases, leading to improved convergence of the global model parameters. However, achieving complete convergence may require a sufficient number of iterations, especially in scenarios with heterogeneous data distributions or communication constraints. Therefore, monitoring the convergence of global model parameters over FL iterations is essential for assessing the effectiveness and stability of federated learning algorithms in optimizing model performance while preserving data privacy as shown in Figure 5.

Visualization of trends in energy consumption over time provides valuable insights into the patterns and fluctuations of energy usage within a specific timeframe, such as daily, weekly, or seasonal intervals. This graphical representation allows stakeholders to identify recurring patterns, anomalies, and trends in energy demand, enabling informed decision-making for energy management strategies. Through time series plots or line graphs, energy consumption data are plotted against corresponding time intervals, such as hours, days, or months. The resulting visualization illustrates the dynamics of energy consumption, including diurnal variations, weekly trends, and seasonal fluctuations. For example, the plot may reveal peaks in energy demand during certain times of the day, such as mornings and evenings, reflecting periods of high activity and electricity usage. Similarly, weekly patterns may emerge, indicating differences in energy consumption between weekdays and weekends due to changes in human behavior and industrial activities.

© STM Journals 2024. All Rights Reserved

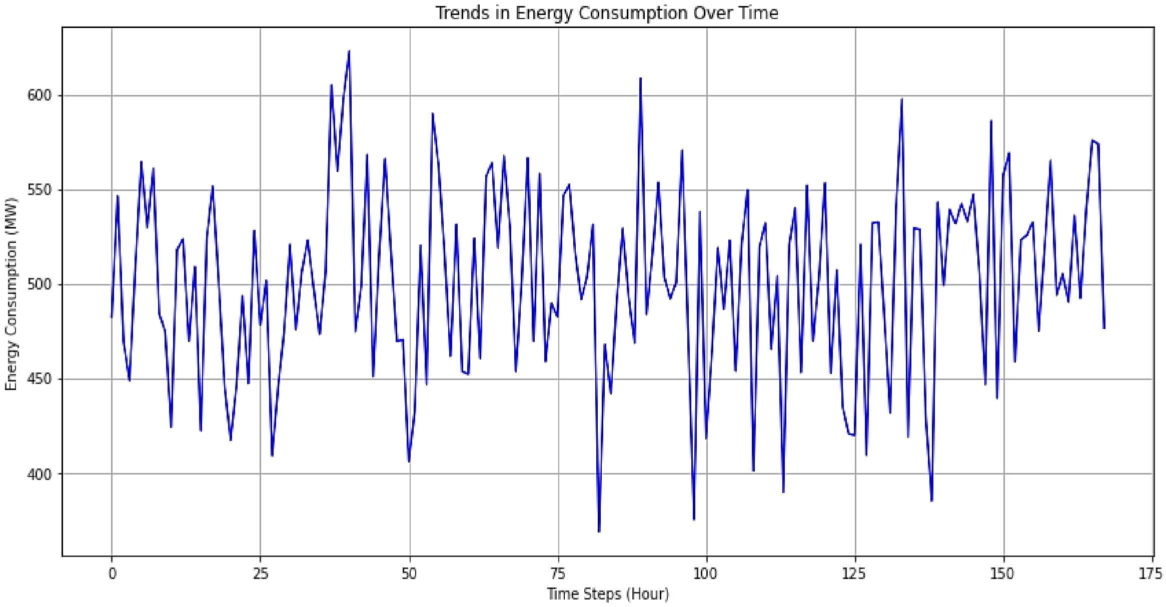

Figure 5. Visualization of trends in energy consumption over time.

By analyzing trends in energy consumption over time, stakeholders can gain insights into factors influencing energy demand, such as weather conditions, economic activity, and social behaviors. This understanding is crucial for developing effective energy management strategies, optimizing resource allocation, and promoting sustainability initiatives within smart city environments. Moreover, visualizing trends in energy consumption facilitates communication and collaboration among stakeholders, fostering data-driven decision-making and the implementation of targeted interventions to address energy challenges.

CONCLUSION

Federated Learning offers a transformative approach to energy management in next-generation smart cities, addressing key challenges such as data privacy, scalability, and real-time adaptability. By leveraging decentralized machine learning techniques, smart cities can optimize energy consumption, enhance grid stability, and promote sustainability while preserving individual privacy and security. Through collaborative model training across distributed data sources, federated learning enables cities to analyze energy usage patterns, predict demand, and optimize energy distribution in real-time without centralizing sensitive data. The adoption of federated learning algorithms and architectures tailored to energy management applications, such as federated optimization and federated averaging, offers opportunities for improving grid reliability, reducing operational costs, and minimizing environmental impact. Moreover, federated learning enables cities to adapt to dynamic and heterogeneous urban environments by accommodating diverse data sources and communication constraints. However, deploying federated learning systems in real-world smart city deployments requires addressing challenges such as data heterogeneity, communication overhead, and regulatory compliance. Future research directions include exploring advanced federated learning techniques, integrating edge computing capabilities, and developing robust privacy-preserving mechanisms. Overall, federated learning holds tremendous promise for revolutionizing energy management in smart cities, enabling more efficient, resilient, and sustainable urban infrastructure for the benefit of citizens and the environment.

REFERENCES

1. Pandya Sharnil, *et al*. Federated learning for smart cities: A comprehensive survey. Sustain Energy Technol Assess. 2023; 55: 102987.
2. Jiang Ji Chu, *et al*. Federated learning in smart city sensing: Challenges and opportunities. Sensors. 2020; 20(21): 6230.

© STM Journals 2024. All Rights Reserved

3. Himeur Yassine, *et al*. Next-generation energy systems for sustainable smart cities: Roles of transfer learning. Sustain Cities Soc. 2022; 85: 104059.
4. Hosseini Paniz, *et al*. Privacy-preserving federated learning: Application to behind-the-meter solar photovoltaic generation forecasting. Energy Convers Manag. 2023; 283: 116900.
5. Shome Debaditya, Omer Waqar, Wali Ullah Khan. Federated learning and next generation wireless communications: A survey on bidirectional relationship. Trans Emerg Telecommun Technol. 2022; 33(7): e4458.
6. Janjua Jamshaid Iqbal, *et al.* Federated learning for prediction of energy consumption in edge-enabled smart cities with healthcare infrastructure crossroads. J Popul Ther Clin Pharmacol. 2023; 30(19): 450–466.
7. Putra Karisma Trinanda, *et al.* Federated compressed learning edge computing framework with ensuring data privacy for PM2.5 prediction in smart city sensing applications. Sensors. 2021; 21(13): 4586.
8. Venkataramanan Venkatesh, Sridevi Kaza, Annaswamy Anuradha M. Der forecast using privacy-preserving federated learning. IEEE Internet Things J. 2022; 10(3): 2046–2055.
9. Ali Mazhar, *et al*. Comparative Analysis of Data-Driven Algorithms for Building Energy Planning via Federated Learning. Energies. 2023; 16(18): 6517.
10. Gadekallu Thippa Reddy, *et al*. Federated learning for big data: A survey on opportunities, applications, and future directions. arXiv preprint arXiv:2110.04160. 2021.
11. Nguyen Dinh C, *et al*. Federated learning for internet of things: A comprehensive survey. IEEE Commun Surv Tutor. 2021; 23(3): 1622–1658.
12. Bhattacharya Sweta, Praveen Kumar, Reddy Maddikunta, Madhusanka Liyanage. Federated Learning for Big Data: A Survey on Opportunities, Applications, and Future Directions. arXiv preprint arXiv:2110.04160. 2021.
13. Zhang Tuo, *et al*. Federated learning for the internet of things: Applications, challenges, and opportunities. IEEE Internet Things Mag. 2022; 5(1): 24–29.
14. Balasubramanian, Venkatraman, *et al*. Intelligent resource management at the edge for ubiquitous IoT: An SDN-based federated learning approach. IEEE Netw. 2021; 35(5): 114–121.

© STM Journals 2024. All Rights Reserved