International Journal of Engineering Inventions
e-ISSN: 2278-7461, p-ISSN: 2319-6491
Volume 14, Issue 5 [May. 2025] PP: 43-47

Optimizing smart grid performance using machine learning and IoT technologies

Nguyễn Thị Mai Hương
Thai Nguyen University of Technology

Abstract
The transition to a sustainable energy system requires advanced smart grid technology to improve efficiency and reliability. This study suggests an integrated framework that combines machine learning (ML) and Internet of Things (IoT) to optimize the performance of intelligent grids. This framework uses IoT sensor data in real-time and ML algorithms. This includes deep neuronal networks for load prediction and learning enhancements for optimizing energy distribution. The MATLAB/SIMULINK simulation showed a 12.4% reduction in energy losses, with an average absolute percentage rate error for the forecast, and a system reliability of 98.7%. Pilot testing of 100 kW microgrids validated these results and achieved a loss of 9.8%. Frame adaptability and scalability make it a promising solution for modern energy systems with applications for electrical engineering training. This study contributes to sustainable energy goals by improving grid efficiency and resilience.
***Keywords**: Smart grid, machine learning, IoT, energy optimization, sustainability.*

Date of Submission: 28-04-2025 Date of acceptance: 07-05-2025

I. Introduction

The global energy environment is driven by being driven by the urgent need for sustainable development, energy efficiency and integration of renewable energy sources. Intelligent grids have proven to be the cornerstone of energy transition, as traditional power grids are difficult to meet the requirements of modern energy systems. Smart Grid is an advanced power grid that uses digital communication, automation and real data processing to improve the reliability, efficiency and sustainability of power distribution. By enabling two-way communication between suppliers and consumers, intelligent grids allow for seamless integration of distributed energy resources such as dynamic load management, error detection, and solar power generation. However, the complexity of smart grids poses major challenges, including energy loss, cybersecurity risks, and the need to find real-time decisions in the face of fluctuating demands and offers.

One of the most urgent issues with Smart Grid Management is optimizing energy distribution to minimize losses and at the same time ensure system stability. Traditional approaches to network management are based on static models and manual interventions that are not suitable for the dynamic nature of modern power systems. For example, energy losses in transmission and distribution can account for 5-10% of total energy generation worldwide, which corresponds to important economic and ecological costs. Furthermore, the integration of naturally intermittent renewable energy sources complicated load prediction and grid compensation. These challenges underscore the need for innovative solutions that process large amounts of data, predict system behavior, and make autonomous decisions in real time.

Recent advances in machine learning (ML) and the Internet of Things (IoT) provide promising ways to address these challenges. Algorithms for machine learning, such as deep neural networks and reinforcement learning, have shown significant success in analyzing complex data records and optimizing decision-making processes in a variety of fields, including energy systems. In the meantime, IoT technology will allow for the provision of interconnected sensors and devices to collect real-time data on network performance, such as voltage, power, and power consumption. By combining ML and IoT, we can develop intelligent systems that can predict demand, recognize anomalies, and optimize energy flow with unprecedented accuracy and efficiency.

The aim of this study is to propose a new framework for optimizing the performance of intelligent grilles by integrating machine learning algorithms into IoT-based data collection systems. The proposed model seeks to master key challenges in smart grid management, such as reducing energy loss, accuracy of load prediction, and system reliability. By using real-time data from IoT sensors and advanced ML technologies, the framework should enable proactive grid management to improve efficient energy distribution and resilience to failures. This research contributes to the broader goal of achieving a sustainable energy future with scalable and customizable solutions for intelligent grid optimization.

The concept of smart grids has been extensively investigated over the past 20 years, reflecting its important role in modern energy systems. According to Fang et al. (2012), intelligent grilles are characterized by their ability to integrate advanced detection, communication and control technologies to improve power supply efficiency and reliability. In contrast to conventional grids, intelligent networks support bidirectional energy flows and enable consumers to act as a professional by feeding exceed energy back into the network. This paradigm shift was due to the increasing penetration of renewable energy, which in 2020 made 29% of global electricity generation (IEA, 2021). However, the intermittent character of renewable energy represents significant challenges for the stability of the networks and requires progressive management strategies.

Machine learning has been developed as a powerful tool to address these challenges. In their pioneering work, Zhang et al. (2018) considered the use of ML technology in power systems and highlighted its effectiveness in load prediction, error detection and energy management. For example, deep neural networks (DNNs) have often been used for short-term load prediction. This means that predictive predictions with 95% or more in a controlled environment are achieved (Li et al., 2019). Similarly, reinforcement learning (RL) is promising in optimizing energy transport through dynamically adapted changes in grid conditions (Glavic et al., 2017). The RL algorithm learns the best guidelines through experiments and errors. In other words, it is suitable for real-time decisions in dynamic environments. Despite these advances, many ML models rely on historical data and struggle to adapt to real-time fluctuations in grid performance, highlighting the need for integration with real-time data sources.

IoT technology has revolutionized data collection in smart grids by enabling the delivery of interconnected sensors and devices. From Gungor et al. (2013) IoT systems promote real-time monitoring of grid parameters such as excitement, electricity, and performance quality through logs such as MQTT and COP. These protocols ensure degraded communication. This is extremely important for time-critical applications such as error detection and load compensation. For example, Shakeri et al. (2020) showed that IoT-based smart measurement devices can reduce the peak load caused by demand meter programs by up to 15%. Additionally, IoT systems allow for the recording of granular data that can be used to train ML models for predictive expectations and anomaly detection. However, the scalability of IoT deployments is Kim et al. (2021).

The integration of ML and IoT in a smart grid has been examined in several studies, but there is an important research gap. For example, Wang et al. (2019) proposed a hybrid model that combines IoT data and ML with ML for load prediction, achieving improved accuracy compared to conventional methods. Similarly, Liu et al. (2020) developed IoT ML frames for error detection, reducing downtime in pilot research by 20%. However, these studies often focus on specific applications such as prediction and error detection, and are not comprehensive grid optimization. Furthermore, many existing models assume idealized conditions such as: B. Complete data quality and unlimited computing resources that are not always realistic in a real environment.

Another important gap is the lack of a comprehensive framework that combines IoT data with advanced ML techniques for end-to-end grid management in real-time. Most studies treat ML and IoT as separate components with limited synergy between the two. For example, in data collection, IoT systems are confident, but often lack analytical capabilities to effectively process large data records. Conversely, ML models require high-quality real-time data to achieve the optimal performance that IoT systems can provide. By incorporating these technologies, systems can be created in closed circuits that continuously learn from grid data and adapt to changing conditions.

In summary, while considerable advances have been made when using ML and IoT for intelligent networks, existing research still fully addresses the challenge of optimizing the overall network. The proposed study attempts to close this gap by developing an integrated ML-IT framework that uses real-time data and advanced algorithms to improve lattice performance. By addressing key challenges such as energy loss, load forecasting and system reliability, this study aims to contribute to the development of sustainable and efficient energy systems.

II. Methodology

The proposed research develops a framework for optimizing smart grid performance by integrating machine learning algorithms (ML) and the Internet of Things (IoT). Methodologies include ensuring a comprehensive approach to system design, data collection, development, simulation, and algorithm evaluation, and network optimization.

The system architecture consists of three main components:

IoT-based data collection, data processing platform, and ML modules. IoT sensors used in the grid collect real-time data on parameters such as voltage, electricity, power consumption, and frequency. These sensors communicate using the MQTT protocol. This was chosen for low latency and efficiency in processing large data streams. Data processing platforms aggregate and accurately process raw data and perform tasks such as time-series addiction filtering, normalization, and alignment. The ML module, which is the core of the framework, uses two main algorithms:

Deep neural networks (DNNS) and energy distribution optimization for Amplification learning (RL). The system block diagram illustrates the flow from data collection, making decisions and clarifying component integration.

Data collection includes both real-time and historical data records. Real-time data is taken from IoT sensors that are installed on simulated or pilot smart grids and capture dynamic network conditions. To train the ML model, historical data including load traits, weather patterns, and previous errors are obtained from published data or supply records. Data records are divided into training substrates (70%), validation (20%), and test (10%) to ensure robust model development and evaluation.

For load prediction, the DNN model is implemented in several hidden layers with Python and Tensorflow. This model accepts input features such as historical loads, time of day, and weather conditions, and predicts future demand with high accuracy. The DNN is trained in baking propagation and optimized with the Adam algorithm to minimize errors in the middle square. RL algorithms, particularly deep Q networks (DQNs), are used to optimize energy distributions. DQN learns optimal energy allocation guidelines through interaction with a simulated grid environment, balancing supply and demand, and at the same time minimizing losses. Reward functions aim to prioritize energy efficiency and system stability.

The framework is evaluated by Matlab/Simulink simulations that model intelligent networks with distributed energy resources and variable loads. This simulation tests the performance of the model in a variety of scenarios, including topics and variations in renewable energy. A real feasible test involves a pilot network running to validate the simulation results. The most important valuation metrics include prediction accuracy (measured with medium absolute error), reduced energy loss (acceptance of percentage relative to starting base), and system reliability (percentage of terminology).

This methodology guarantees a systematic approach for the development and investigation of the proposed ML IoT framework dealing with the challenges of real-time grid management, while simultaneously providing a scalable solution for smart grid optimization.

III. Results and discussion

3.1. Simulation and pilot test

The proposed framework, which integrates machine learning (ML) and the Internet of Things (IoT), was evaluated by extensive simulations and limited real-world pilot tests to assess its effectiveness in intelligent grill optimization. Simulations were performed using MATLAB/SIMULINK. MATLAB/Simulink was performed using an intelligent grille with distributed energy resources, variable loads and inputs for renewable energy being modeled. Pilot tests are conducted on small grids at university research facilities and cause actual verification. The load prediction deep neural network (DNN) model achieved an average absolute percentage error (MAPE) of 3.2% in the test data records, exceeding the traditional time series model (e.g. Arima, Maape 5.8%). DNN predicted fluctuations in demand, particularly during peak times and in a variety of weather conditions. The reinforcement learning (RL) model based on deep Q networks (DQNs) reduced energy losses by 12.4% compared to conventional energy filling systems. This improvement was most prominent in scenarios with high penetration of renewable energy, as RL models are dynamically stopped and transmission losses are minimized. The system reliability measured as operational behavior achieved 98.7% compared to 96.2% of the basic system. This indicates an increase in resistance to error.

In real-world pilot tests, this framework was used in a 100 kW microgrid with solar collectors and IoT sensors. The DNN model contains 4.1% maps, slightly higher than the simulation results from actual data noise. The reduction in energy loss was 9.8%, lower than the simulation, but still significantly compared with a 3.2% reduction in the base. The system was 97.9% reliable, which reflects robust performance despite hardware limitations. The most scalability challenges were found in the pilot, but the most responsible was confirmed in the pilot.

The results show the effectiveness of the proposed ML-IT frame in addressing the most important challenges in smart grid management, such as load prediction, reduced energy loss, and system reliability. The high prediction accuracy of DNN highlights the value of deep learning in recording complex, nonlinear patterns of energy requirements, especially under dynamic conditions such as B. renewable energy fluctuations. The ability to optimize the energy distribution of RL models highlights the potential for real-time decisions, an important prerequisite for modern smart grids. Pilot test validates to a limited extent, confirms simulation results and forms the basis for actual deprivation in the future.

The main strength of the framework lies in the integration of IoT data in real time with advanced ML algorithms, enabling systems with closed circuits that continuously learn and adapt. In contrast to traditional grid management systems that rely on static models, the proposed framework uses detailed, real data to make positive decisions. This adaptability is especially valuable in scenarios with high penetration of renewable energy, where traditional systems are difficult to compensate for supply and demand. Another advantage is the scalability of the framework to extend the IoT infrastructure and cover large grilles. You can transform your ML models with new data to improve performance over time. Additionally, the modular design of the framework allows for easy integration into existing grid systems and reduced provisioning costs.

Despite its strengths, the frame has some amazing limitations. High initial costs for IoT sensor use and maintenance are obstacles to widespread acceptance, especially in resource-related environments. The complexity of computational DNN and RL models requires critical processing services that require cloud-based or powerful computer infrastructure. Pilot testing reduced data noise and hardware limitations. This indicates that robust pre-processing and quality control mechanisms are important for real applications. Furthermore, cybersecurity remains an issue as IoT devices are susceptible to attacks that can affect grid operations. Future iterations of the framework should include encryption and secure communication protocols to mitigate these risks.

Compared to previous studies, the proposed framework offers several unique contributions. For example, Wang et al. (2019) IoT ML hybrid model achieved 10% improvement in load prediction accuracy, but focused only on predictions without energy distribution. Similarly, Liu et al. (2020) reported 20% by reducing downtime with IoT-based error detection, but did not optimize energy flow. The current framework combines these features to provide a holistic approach to network optimization. The 12.

% energy loss simulation reduction is 8-10% above the reductions registered in similar studies, possibly due to the dynamic optimization skills of the RL model. However, a 9.8% reduction in pilot tests corresponds more closely to the real world of literature, indicating a practical limiting temperature theoretical benefit.

3.2. Application in teaching at university

The proposed framework has important potential to improve electrical engineering training, particularly at the university level. By integrating this research into the curriculum, the gap between theoretical knowledge and practical application can be bridged and prepared for careers in the rapidly developing energy sector. Below you can find specific options for how to use frames in your class. The Matlab/Simulink model used in this study can be adapted to teaching exercises so that students can explore the dynamics of smart grids. For example, students can modify the DNN architecture or RL reward functionality to observe the effect of prediction accuracy and energy efficiency. These exercises encourage critical thinking and make students familiar with the tools of industry-dependent tools. The IoT components of the framework provide a practical context for education and processing. Students can manipulate simulated or real IoT sensor data to learn more about protocols such as MQTT, data preprocessing, and real-time analysis. This practical experience is invaluable as the Internet of Things for electrical engineering is becoming increasingly important. Trust in the ML framework promotes interdisciplinary learning and combines electrical engineering with computer science. Machine learning courses for energy systems can be introduced that cover topics such as neural networks and learning learning. Students can implement simplified versions of DNN or RL models using Python. This allows you to acquire programming and algorithm design. The frame serves as the basis for a capstone project or research task. Students can replicate parts of the study. B. Analysis of actual data to develop microgrid simulation or research skills. Cooperative projects can mimic industry work processes and prepare students for teamwork in professional environments. Framework education exposes students in the state of ART technology that form energy sectors such as smart grids, IoT, AI and more. Guest lectures and workshops from industry experts can add learning in the classroom and give insight into real-world applications. This exposure improves student employees' capabilities in areas such as renewable energy and grid moderation. The frame's focus on energy efficiency corresponds to global sustainability goals and is an ideal tool for teaching the social impact of electrical engineering. A case study based on pilot test results shows how technical solutions contribute to reducing CO2 footprints and how they contribute to encouraging students to pursue sustainable energy careers.

Containing frameworks in your curriculum requires careful planning. Teachers can develop laboratory modules with open source tools such as Python and Tensorflow to keep costs low. Partnerships with industry and research institutes can provide access to real datasets or pilot grills for advanced projects. Integrating the framework into existing courses on power systems or control technologies requires focus to focus on program goals without extensive curriculum overhaul.

Frame's success to reduce energy loss and improve reliability has an impact beyond technical services. By minimizing waste, we support global efforts to combat climate change and support in accordance with initiatives such as the Paris Agreement. Its adaptability makes it suitable for a variety of contexts, from urban bars in developed countries to system systems in development regions. In education, this framework serves as a model for how research informs lessons and ensures that students are ready to address real challenges.

Finally, the proposed ML-IT frame represents a major advance in intelligent grid optimization using robust simulations and pilot test results. Applications in class can change electrical engineering training by promoting hands-on skills, interdisciplinary knowledge and commitment to sustainability. The struggle against identified restrictions such as costs and cybersecurity is important to scale frames to larger networks and broader educational contexts.

IV. Conclusion

This study developed an IoT framework to optimize the performance of smart grids and achieve a significant reduction in energy losses (12.4% in simulation, 9.8% in pilot test), high load prognostic accuracy (3.2% MAT), and system reliability (98.7% period). The combination of real-time IoT data and advanced ML algorithms is considered in key challenges in smart grid management, contributing to energy efficiency and sustainability goals. The electrical engineering training application further improves its effectiveness and further upgrades students with practical skills in IoT, ML, and sustainable energy systems. Future work will focus on improving frame scalability and robustness. The model's integration of renewable energy sources such as wind and solar improves applicability to modern networks. Implementing Spring-based learning can improve data security by activating distributed model training and accepting concerns about IoT cybersecurity. By extending the actual tests to a larger network, frame performance is verified under a variety of conditions. Development of frame-based open source training modules, introduction to university curriculum, promotes and promotes the next generation of engineers in smart grid innovation.

References

[1]. Mazhar, T., Irfan, H. M., Haq, I., Ullah, I., Ashraf, M., Shloul, T. A., ... & Elkamchouchi, D. H. (2023). Analysis of challenges and solutions of IoT in smart grids using AI and machine learning techniques: A review. *Electronics*, *12*(1), 242.

[2]. Tang, Z., Xie, H., Du, C., Liu, Y., Khalaf, O. I., & Allimuthu, U. K. (2022). Machine learning assisted energy optimization in smart grid for smart city applications. *Journal of Interconnection Networks*, *22*(Supp03), 2144006.

[3]. Mishra, R., Desai, V. V., Krishnamoorthy, R., Begum, M. A., Ranga, J., & Taqui, S. N. (2023, November). Energy-efficient IoT with deep learning: optimizing resource allocation in smart grids. In *2023 9th International Conference on Smart Structures and Systems (ICSSS)* (pp. 1-6). IEEE.

[4]. Chahal, A., Gulia, P., Gill, N. S., & Chatterjee, J. M. (2022). Performance analysis of an optimized ANN model to predict the stability of smart grid. *Complexity*, *2022*(1), 7319010.

[5]. Jamberi, K., Venketbabu, T., Chinthamu, N., Vennila, V., Chauhan, R., & Krishnaiah, N. (2025). Machine learning based optimization of resource management with control strategies in smart grid using IoT. In *Challenges in Information, Communication and Computing Technology* (pp. 375-380). CRC Press.

[6]. Alkanhel, R. I., El-Kenawy, E. S. M., Eid, M. M., Abualigah, L., & Saeed, M. A. (2024). Optimizing IoT-driven smart grid stability prediction with dipper throated optimization algorithm for gradient boosting hyperparameters. *Energy Reports*, *12*, 305-320.

[7]. Bashir, A. K., Khan, S., Prabadevi, B., Deepa, N., Alnumay, W. S., Gadekallu, T. R., & Maddikunta, P. K. R. (2021). Comparative analysis of machine learning algorithms for prediction of smart grid stability. *International Transactions on Electrical Energy Systems*, *31*(9), e12706.

[8]. Massaoudi, M., Abu-Rub, H., Refaat, S. S., Chihi, I., & Oueslati, F. S. (2021). Deep learning in smart grid technology: A review of recent advancements and future prospects. *IEEE Access*, *9*, 54558-54578.

[9]. Dahmani, S. (2024). Energy optimization and smart grids: IoT-based smart grid solution and smart grids applications. In *Harnessing High-Performance Computing and AI for Environmental Sustainability* (pp. 278-304). IGI Global.

[10]. Hossain, E., Khan, I., Un-Noor, F., Sikander, S. S., & Sunny, M. S. H. (2019). Application of big data and machine learning in smart grid, and associated security concerns: A review. *Ieee Access*, *7*, 13960-13988.

[11]. Mostafa, N., Ramadan, H. S. M., & Elfarouk, O. (2022). Renewable energy management in smart grids by using big data analytics and machine learning. *Machine Learning with Applications*, *9*, 100363.