National Journal of Antennas and Propagation
Research Article

National Journal of Antennas and Propagation, ISSN: 2582-2659 Vol. 8, No. 2, 2026 (pp.60-72)
WWW.ANTENNAJOURNAL.COM

AI-Driven Smart Grid Optimization Using Deep Learning and Iot-Enabled Electrical Systems Framework

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KEYWORDS:

Optimized Resource,
Electrical Systems,
Smart Grid Optimization

ARTICLE HISTORY:

Received: 11.12.2025
Revised: 15.01.2026
Accepted: 07.02.2026

DOI:
https://doi.org/10.31838/NJAP/08.02.05

ABSTRACT

Rising worldwide energy consumption and the integration of renewable energy sources are driving the rapid rise of smart grids, necessitating the use of resource allocation systems that are intelligent, flexible, and energy-efficient. Due to their inability to handle real-time grid dynamics, traditional energy management systems that rely on static models or heuristic algorithms can result in significant energy waste, poor energy distribution, and high operating costs. This study introduces a state-of-the-art solution that combines these issues: GBMIN-QSO (Gradient boosting machine with inception network and Quakka swarm optimization). For proactive power flow control, the framework makes use of both historical and real-time data; however, IoT-enabled sensors use edge and cloud computing infrastructure to provide constant monitoring and low-latency reaction. Predictive modeling, real-time analytics, and artificial intelligence with optimization are the main drivers of these performance improvements. GBMIN-QSO creates a scalable, dependable, and sustainable energy management system by fusing AI-driven decision-making, IoT sensing, and adaptive learning. The framework is a significant advancement in smart grid optimization and establishes the foundation for further innovations including cybersecurity protections, enhancements to reinforcement learning, and integration with edge computing. The effectiveness of GBMIN-QSO is confirmed by experimental findings indicate a total energy demand of 2412.61 MWh, with 1418.51 MWh (94.88% efficiency) met by renewable energy sources. The grid operates stably, with a Grid Stability Index of 97.78%. Predictive models achieve high accuracy (98.12%), enabling efficient energy management. The operational cost is $54,171.28, suggesting effective resource allocation and cost management. These indicators show that the smart grid system is well-optimized, stable, and capable of making predictions. It also uses a lot of renewable energy.

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How to cite this article: Aundhekar DR et al, AI-Driven Smart Grid Optimization Using Deep Learning and Iot-Enabled Electrical Systems Framework, National Journal of Antennas and Propagation, Vol. 8, No. 2, 2026 (pp. 60-72).

1. Introduction

The rising need for energy and the heightened interest of governments, businesses, and academic institutions in creating a smart electric power system of the future. Even while the current power infrastructure has performed admirably in the past, new technologies and solutions are required to create an intelligent smart grid that offers a secure, economical, dependable, and sustainable supply of electricity. Since every component of the grid may be redesigned, equipment makers are creating new platforms, combining and improving existing features, and getting rid of certain outdated goods [1]. More intelligent equipment is needed because the emphasis on equipment design has shifted from producing new energy capacity to focusing on availability, predictability, and efficiency. When digital computer and communication technologies are integrated with the power distribution infrastructure, this upgraded power grid—known as the "smart grid"—will activate.

Electrical energy is essential to society because it maintains economic growth and a high standard of living. In recent years, there has been a steady increase in the demand for electric energy, and this trend is likely to continue. Nowadays, a large portion of electrical energy comes from dangerous and non-renewable sources including coal, natural gas, and oil. An energy problem brought on by a heavy reliance on fossil fuels could eventually result in a gradual increase in the price of gasoline globally. Distributed Renewable Energy Sources (DREs) are thought to be a potent instrument for addressing the world's impending energy and environmental crises. Reducing the production of greenhouse gases is a global priority. Fossil fuel energy produces the majority of the gasses that cause global warming. Fossil fuels can be replaced with sustainable energy. Renewable energy sources seemed to have the potential to be a good alternative to hazardous energy sources. However, depending on the climatic conditions, renewable energy sources can produce electricity that is quite unpredictable. Additionally, they cannot be instantly incorporated into current electrical infrastructures. PV arrays use solar energy to generate electricity [2]. Customers who are the end users install these PV arrays in their homes. PV arrays turn this end-use energy consumer into a producer when they are installed in residential buildings. Consequently, the consumer of a residential building's power generation capacity turns into a prosumer.

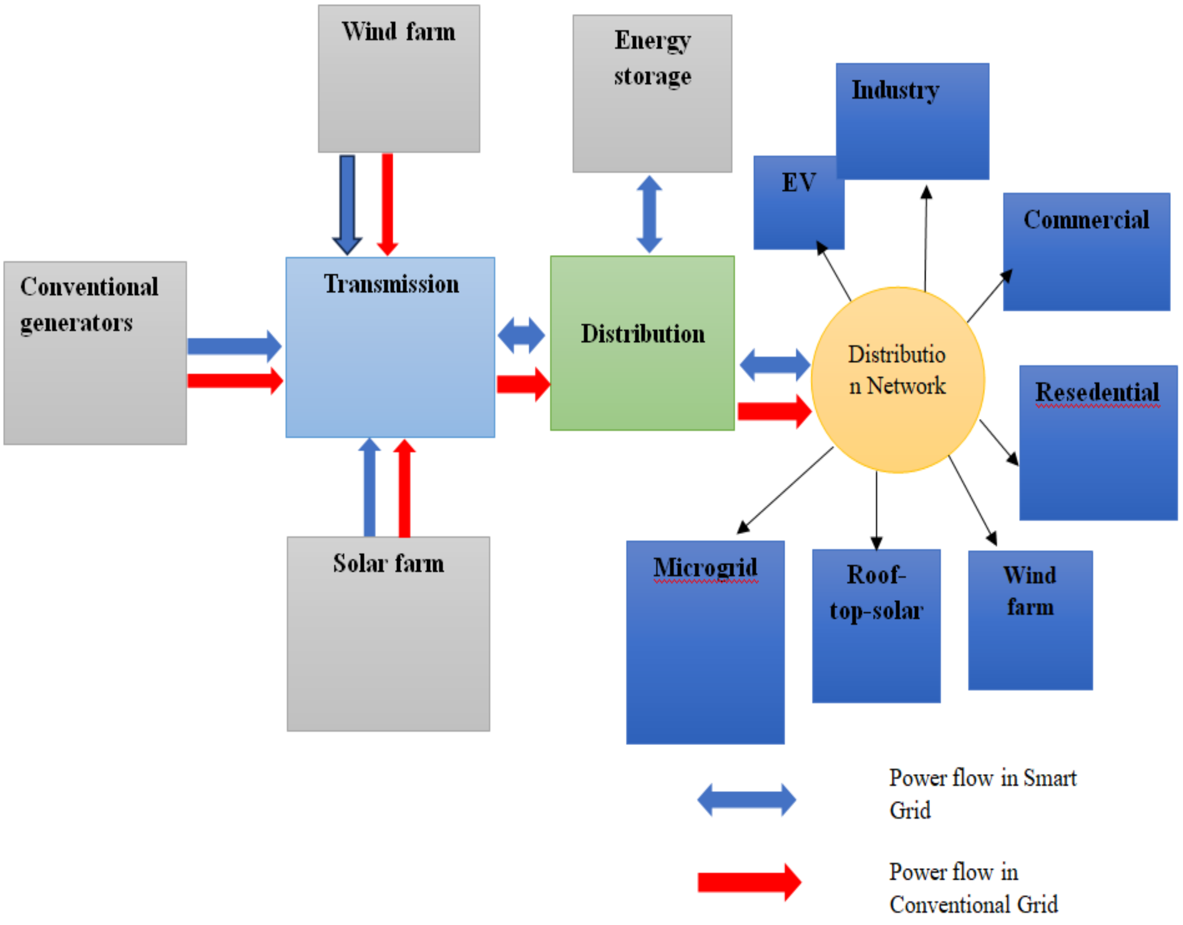

Fig. 1. Architecture of Smart Grid

Since renewable energy sources cannot reliably produce power throughout the day, artificial intelligence (AI) techniques are used to effectively govern the distributed energy sources. To get an accurate PV power projection over the upcoming few to several years, a number of Machine Learning (ML) algorithms have been developed. Often, these forecasting schemes fall into one of three categories: Forecast models that use machine learning, analysis, and physical methods. Utilizing vast amounts of data to gain fresh insights and information that support daily decision-making is the foundation of the contemporary big data scenario. IoT systems, which gather and transmit vast amounts of sensor data, are one of the main sources of this data [3]. Providing end users with a safe and dependable power source is the power system's biggest difficulty.

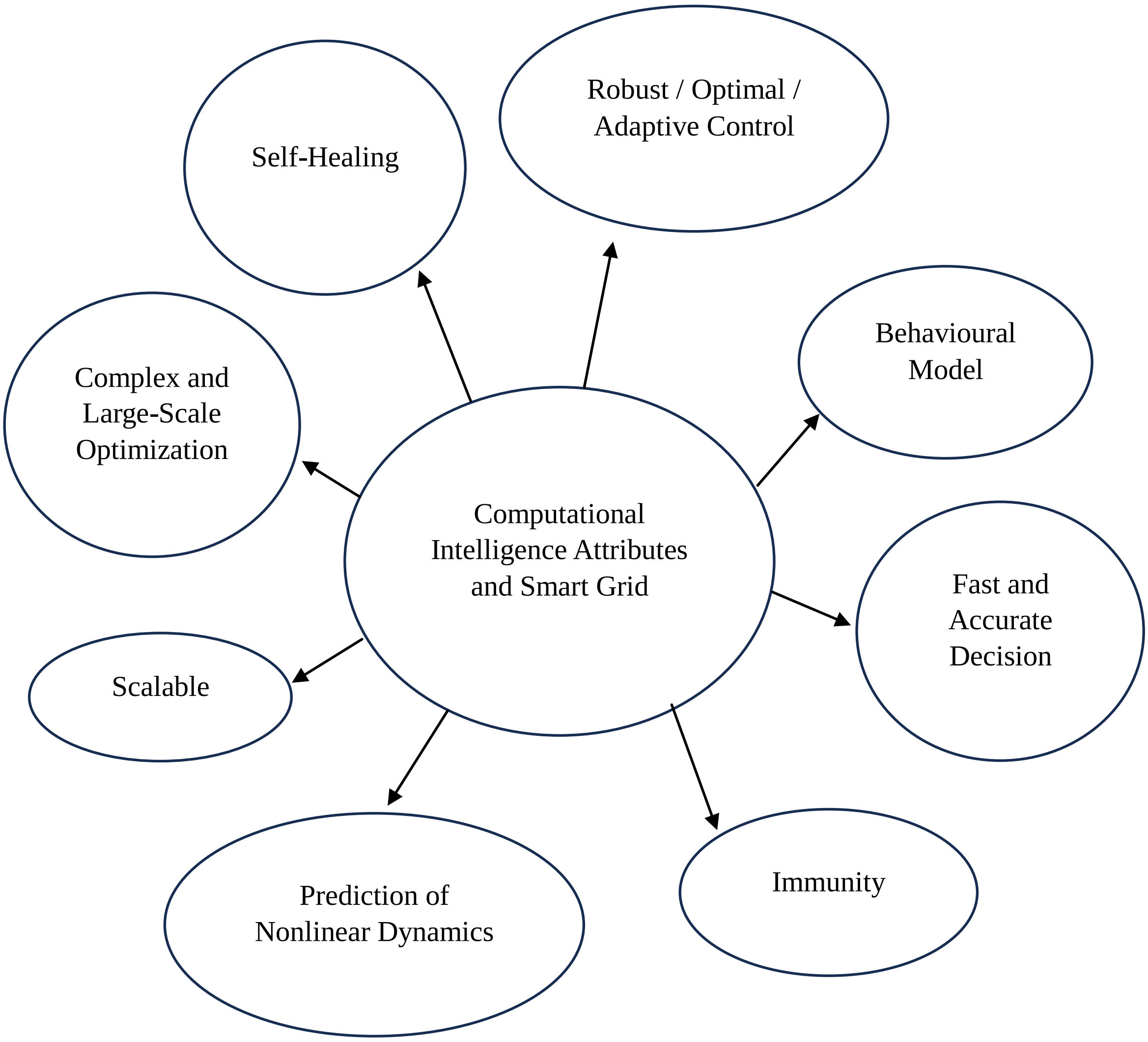

Fig. 2. Attributes of computational intelligence

The goal of enhanced grid dependability is to guarantee that customers receive electricity in a continuous, secure, and stable manner free from unplanned disruptions, voltage swings, or power outages. Since homes, businesses, healthcare facilities, and communication systems all rely on a steady supply of electricity, a stable grid is essential to modern society. Improving the grid's resilience to faults, severe weather, cyberattacks, and abrupt demand spikes while preserving steady operation is known as reliability enhancement [4]. In order to reduce downtime and promptly restore electricity when disruptions occur, advanced technologies like smart grids, automated fault detection, self-healing systems, and predictive maintenance are essential. Reliable service is further ensured by energy storage options, demand response plans, and robust grid infrastructure. Utilities can boost economic growth, boost consumer confidence, lessen outage-related financial losses, and create a strong foundation for upcoming advancements in clean and digital energy systems by increasing grid resilience. Increased sustainability goes beyond energy to include eco-friendly urban planning, sustainable manufacturing, responsible resource management, and circular economy models that emphasize recycling, reuse, and a decreased reliance on non-renewable resources. To guarantee that sustainable growth equitably benefits all populations, social factors such as energy equity, accessibility, and community resilience are equally crucial. Sustainability initiatives are further strengthened by policy frameworks, corporate responsibility, and international cooperation, which synchronize local measures with global climate targets like the Sustainable Development targets (SDGs) and the Paris Agreement. In the end, greater sustainability is not only necessary for the environment but also for long-term societal advancement, technological innovation, and economic resilience [5]. The term "cost savings" describes the decrease in expenses brought about by effective resource management, streamlined procedures, and the use of cutting-edge technology that enhance productivity and reduce waste. Reducing transmission and distribution losses, increasing operational efficiency, incorporating smart grid technology, and increasing reliance on renewable energy sources that cut long-term fuel costs are all ways to save money in the context of the energy and power grid. Implementing energy-efficient machinery, automating processes, utilizing predictive maintenance to prevent expensive malfunctions, and negotiating better energy contracts can all save money for businesses and industries. Customers can save money in a number of ways, including lower power costs, decreased gas consumption, and the long-term benefits of sustainable investments. On a larger scale, governments and utilities save money by investing in new grid infrastructure, preventing costly blackouts, lowering reliance on imported fossil fuels, and lowering pollution-related medical expenses. These savings create a virtuous cycle of economic growth and environmental stewardship by freeing up resources that can be reinvested in infrastructure, social development, and innovation. Numerous technical issues affect the Indian electrical grid, such as a badly designed distribution network, system component overload, a lack of regulatory services and reactive power support, low metering efficiency, difficulties collecting energy bills, and more. Installing rooftop solar to produce their own energy can help customers save even more money, and a smart grid can provide recommendations for when it's ideal to purchase electricity [6]. The implementation of a smart power grid has been facilitated by information and communication technology (ICT), smart meters, relays, Internet of Things devices, communication protocols, and contemporary power converters and DREs (such as solar, wind, etc.).

2. REVIEW OF LITERATURE

Wen et al. used a DL model based on recurrent neural networks (RNN) to determine the power load, optimal hourly electricity rates, and uncertainty in the SG networks. Hafeez et al. suggested a factored conditional restricted Boltzmann machine model based on DL to predict the hourly power load. Ruan et al. proposed a neural-network-based lag range multiplier selection method to maximize the number of neural network iterations for DR prediction in SG. Wang et al. proposed integrating a DRL technique with a duelling deep Q network to enhance the DR management in SG.

Zhang et al. offered an edge-cloud integrated solution for DR in SG using reinforcement learning. An efficient STLF framework addresses the challenges presented by dynamic and erratic consumer behavior patterns on residential campuses.By using aggregated appliance load data and DL approaches to correlate them, the system forecasts patterns in individual electricity demand. The framework comprises learning, load prediction, data preparation, and data collection modules [8].The multiple time series technique is used to model and include the correlations between different load data in appliances. The DNN and Res Block approaches are used to apply the learning.

The problem of high electricity use in industrial sectors is examined by Renhzi Lu et al. A model for the implementation of DR strategies in the management of a particular manufacturing system is built using multiagent DRL. The industrial production system was first developed as POMG. Afterwards, the MADDPG algorithm was used to create the best load consumption strategy for each machine. The effectiveness of the concept was then assessed using a battery production system. The simulation's findings demonstrated that, when compared to the non-DR benchmark system, the DR system could offer the lowest power consumption costs and retain lower production expenses.

Yandong Yand et al. suggested a deep ensemble-learning approach for energy prediction in an SG utilizing a probabilistic model in order to provide reliable energy consumption control. The model with an efficient SG can handle the challenge of accurately forecasting the power consumption of each customer. Current systems are unable to cope with unpredictable load patterns, instability, and the combined load profiles of consumers. Several consumer group profiles are subjected to the ensemble load prediction model. Four phases are planned for the model's operation: deep ensemble learning, which employs ensembled DNNs for probabilistic prediction; multiple task feature learning on the clusters, where the number of tasks is equal to the number of clusters formed; and representation learning, which clusters consumer profiles. Lastly, to achieve revised ensemble projected patterns, the resulting prediction findings are subjected to the LASSO-based quantile technique [9]. To show the efficiency and advancement of the present systems, the framework is implemented for SME clients.In SG homes, it can be applied to DR and electrical needs management systems.

Multiple kernel learning (MKL) was proposed as an alternative to traditional kernels for residential short-term electric load forecasting, as it may provide greater flexibility. Nevertheless, employing traditional techniques leads to intricate optimization issues. Wu et al. suggested a gradient-boosting based MKL that employed a boosting-style technique to address this problem. It also required less computation time. The study also proposed transfer-based learning algorithms to facilitate the transfer of acquired information from source houses to target households. The findings demonstrated that when there was a shortage of data, these transfer methods decreased the forecasting inaccuracy.

Recursive and direct multi-step techniques were used to construct RNN and CNN, which were proposed by Cai et al. Their accuracy and efficiency are compared to those of the traditional ARIMAX. The accuracy of the proposed model improved by 22.6% when compared to ARIMAX, indicating better performance. The aforementioned models are examined using two datasets. In aggregated load forecasting, it has been found that Elmann RNNs outperform GRU and LSTM while costing less [10]. Additionally, temporal CNNs have demonstrated strong performance and are thought to have the potential to boost power system developments in the future.

The load is predicted using a three-layered gated RNN, and load variations are recorded via the shape-based DTW distance. Simulations are conducted using the EUNITE dataset. Ang et al. introduced a multitask PLF framework for residential load forecasting that is based on Bayesian DL. Each step of the model's three-step pipeline involves the utilization of multitask learning, pooling, and clustering. The outcomes show that the overfitting problem is resolved by this approach. Furthermore, this model outperformed more conventional techniques including random forests (RF). Wang et al. proposed an LSTM model driven by pinball loss for residential PLF. In this case, the parameters were trained using pinball loss rather than mean square error. This made it possible to incorporate probabilistic forecasting into the conventional LSTM point-based model. The outcomes showed how effective this model was.

This approach improved and supplemented newer monitoring technologies that can typically analyse a single time series. They offered three data pre-processing techniques with the goal of identifying electricity theft. This approach demonstrated the metric's resilience to manipulated data sources. With over 90% detection rates, the authors demonstrated the primary benefit of utilizing many data sources at once, as opposed to using them separately, which resulted in lower anomaly detection value [11]. This approach also shown that various households can serve as data sources for comparison rather than first classifying the households according to commonalities. Significant inefficiencies, a lack of flexibility in response to real-time grid variations, and excessive energy usage plague current smart grid resource allocation techniques [7]. The main objectives of the GBMIN-QSO framework are:

- Develop an intelligent energy management system that can efficiently allocate resources and predict energy usage in real-time.
- Utilize IoT-enabled sensors and edge-cloud computing infrastructure to provide constant monitoring and low-latency reaction to changes in grid dynamics.
- Create a framework that can scale to meet the needs of growing smart grids, while ensuring reliability and sustainability.
- Establish a foundation for future innovations in smart grid optimization, including cybersecurity protections, enhancements to reinforcement learning, and integration with edge computing.

The organization of the paper is given by the following sections: At Section 1 the introduction about the smart grid is described followed by section 2 describes the existing works of smart grid. Section 3 proposes the proposed work. Section 4 provides the result analysis. Finally, section 4 gives a conclusion of the given work.

3. METHODOLOGY

In an effort to lower carbon emissions and other air pollutants, grid integration of renewable energy and other clean distributed generation is gradually growing However, increasing electricity use and the integration of dispersed energy sources exacerbate system instability. Techniques for electrical load forecasting are essential for controlling peak electrical demand, strengthening grid demand, and balancing generation while lowering costs.

This paper employs short-term electrical demand forecasting approaches to improve the grid's resilience and power quality while lowering grid volatility. However, because electrical data is non-stationary and nonlinear, it is extremely difficult to forecast with any degree of accuracy. Based on past load data, artificial intelligence has identified more accurate and trustworthy load forecasting techniques. Better energy management, grid stability, and peak load control management are all greatly aided by this study. A smart grid, on the other hand, is a more advanced electrical grid that monitors and controls the distribution of electricity using advanced control systems and digital communication technology. It uses sensors, meters, and other devices to gather information about electricity use and grid conditions so that it can decide how best to distribute power in real time. Additionally, the smart grid can let end users and power generators communicate in both directions, allowing users to produce and sell electricity back to the grid [12]. A smart grid's advantages include lower carbon emissions, increased resilience and dependability, and more effective energy utilization. In summary, a smart grid is a more sophisticated and technologically advanced electrical system. It uses digital communication technologies and sophisticated management systems to monitor and manage power distribution, enabling the integration of renewable energy sources and more economical energy use. Conversely, a conventional grid is a more conventional electrical system that supplies customers with power from centralized power plants.

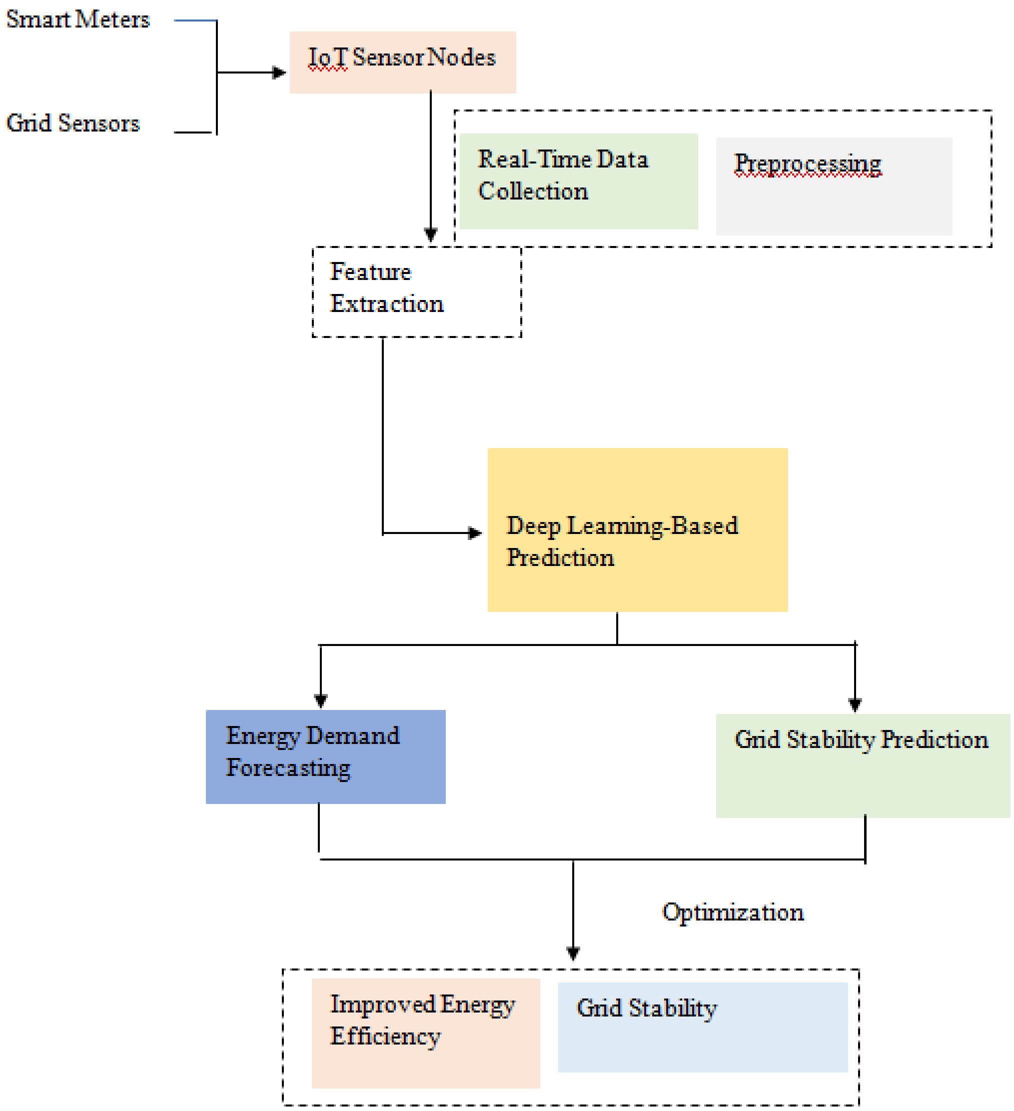

Fig. 3. Proposed flow

- Conventional Grid: This network of interconnected systems distributes electricity across a large region, but it has drawbacks such as outdated infrastructure, security risks, and a lack of RES integration.
- Smart Grid: By integrating RES and exchanging real-time data, the SG is an advanced electrical distribution system that increases dependability, sustainability, and efficiency. Despite challenges like hacking, the SG has a lot to offer in terms of cost reductions, grid resiliency, and energy management.
- Microgrid: A microgrid is a self-contained electrical distribution system that uses local energy resources to produce, store, and distribute electricity within a specific area. Although it increases energy efficiency, resilience, and self-sufficiency, it struggles to handle massive power needs.
- Real-time monitoring, optimization, and trading are made possible by virtual power plants (VPPs), which are integrated networks of dispersed energy resources that function as a single, cohesive system. VPPs offer advantages including

grid stability and effective RES utilization, even if they depend on a strong communication infrastructure.

To design and develop an AI-driven smart grid optimization framework that leverages deep learning and IoT-enabled electrical systems to improve grid efficiency, reliability, and sustainability.Develop and train deep learning models,to predict energy demand, detect anomalies, and optimize grid operations.Integrate the developed deep learning models with IoT-enabled electrical systems.Evaluate the performance of the proposed framework using various metrics, including energy efficiency, grid stability, and cost savings.

3.1. Gradient boosting machine with inception network

By merging the outputs from several trees, gradient boosted trees—like Cat Boost—are ensemble techniques that carry out regression or classification [13]. Random Forest is another well-liked decision tree-based machine learning technique for a variety of prediction problems; however, it is not the same as gradient boosted trees in the way that its individual trees are built. Different decision trees are constructed in parallel by random forests, which then merge them. In contrast, gradient boosted trees employ a technique known as boosting, which involves gradually combining weak learners so that every new tree fixes the mistakes of the one before it. "Decision stumps," or decision trees with only one split, are usually poor learners. Fitting a single decision tree with an initial value is the first stage. Next, the effectiveness of the tree's use of the loss function is assessed. For regression or multiclass classification, there are multiple loss functions (L) to select from. When the second tree is added to the first tree after evaluation, there should be less loss.

The model must construct terminal areas once the first regression tree fits the residual R_{ij} Where, i and j are the sample and tree leaf indices, and m is the index of the tree that is currently being constructed. Instead of the forecast value, the residuals' leaves in built trees contain information (rjm) which needs to be mapped back in the testing phase according to Eq. (9).

$$rjm = argmin(r) \sum_{x_{i \in R_{ij}}} L(y_i \,, F_{m-1}(x_i) + r)$$

The little distinction is that, in contrast to the initiation stage, when no prior prediction existed, models are now accounting for the prior prediction (from a produced model). The other distinction is that this stage's summation is sample-based, incorporating some samples (I) from the terminal region R_{ij} rather than all samples (x) The value of r is chosen to minimize the summation in each step, as seen in the beginning phase [14].

$$F_t\ (x) = \ F_{t-1}\ (x) + p_t h_t(x),$$

where p_t is the weight of the t^{th} function, $h_t(x)$. The approximation is built step-by-step, meaning that a new model is created at each iteration h_t is constructed without altering any of the earlier models that are part of F_{t-1}(x). Initially, a constant approximation is used to initialize the additive expansion.

$$F_0\ (x) = argmin \sum_{i=1}^{N} L\ (y_i, \alpha)$$

and the following models are built in order to minimize

$$(p_t h_t(x)) = argmin_{p,h_t} \sum_{i=1}^{N} L\ (y_i, F_{t-1}\ (x_i) + ph_t(x_i))$$

Nevertheless, rather than solving the optimum for ρ and h_t, There are two steps to the problem. Initially, every model h_t is taught to recognize the gradient vector of the loss function depending on the data. To do that, a fresh dataset is used to train each model, ht $D = \{x_i, r_{ti}\}_{i=1}^{N}$ where the loss function's negative gradient at rti is the pseudo-residuals Ft−1(xi)

$$r_{ti} = \frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} |_{F(x) = F_{t-1}}\ (X)$$

The function, h_t, is anticipated to produce values that are near the pseudo residuals at the specified data points, which run parallel to the gradient of L at $F_{t-1}\ (x)$. However, keep in mind that square-error loss, which may differ from the specified objective loss function, typically directs the h training process. Notwithstanding, the value of p_t is then calculated using the provided loss function and a line search optimization problem [15].

$$pt = \underset{p}{argmin} \sum_{i=1}^{N} L\ (y_i, F_{t-1}\ (x_i) + ph_t(x_i))$$

In certain final derivations, gradient boosting's initial formulation is limited to decision trees. Here, we describe how to combine this method to train a single neural network, which is the primary goal of the article. We also offer an extension of the gradient boosting formulation that permits the base model to be any possible regressor.

3.2 Quakka swarm optimisation

Effective algorithms known as metaheuristics are made to handle a wide range of optimization problems and provide satisfactory answers, even when processing power is constrained or information is lacking. No single metaheuristic algorithm has been found to be optimal for every application. This insight highlights the potential for creating new metaheuristic algorithms or improving ones that already exist.The QSO can be used to solve optimization problems by emulating quokka animals' cooperative behaviour [16].The strength of the suggested method is illustrated using a set of standard unconstrained and restricted test functions. Popular test functions used as benchmarks in optimization were utilized to evaluate QSO's performance. The solutions have been honing their positions in addition to continuously searching for the greatest option.QSO can also substitute the best offspring found so far for the worst quokka in order to improve the solutions. Performance was also compared using the gravitational search method, particle swarm optimization, biogeography-based optimizer, blue monkey swarm optimization, gray wolf optimization, and artificial bee colony.

$$D^{new} = \frac{(T+H)}{(0.8 \times D^{old})} + \Delta W \times rand \times \Delta X,$$

$$X^{new} = X^{old} + D^{new} \times N,$$

(Where D^{old} shows the drought and its value between [0,1]), The temperature ratio, T, is between 0.2 and 0.44, and the humidity ratio, H, is between 0.3 and 0.65. These ratios were selected because quokka animals can tolerate temperatures and humidity levels in between them. Rund is a random number that ranges from 0 to 1, w is the leader's and Quokka I's weight difference, and X is the leader and Quokka I's position difference. Quokka's new position is represented by X^{new} while the old position is represented by X^{old} and N, which stands for the nitrogen ratio and ranges from 0 to 1, was chosen because quokkas need this amount of nitrogen [17]. A value close to zero will be harmful to the quokka since it would hasten the rate of dehydration; conversely, a value close to one will be advantageous.

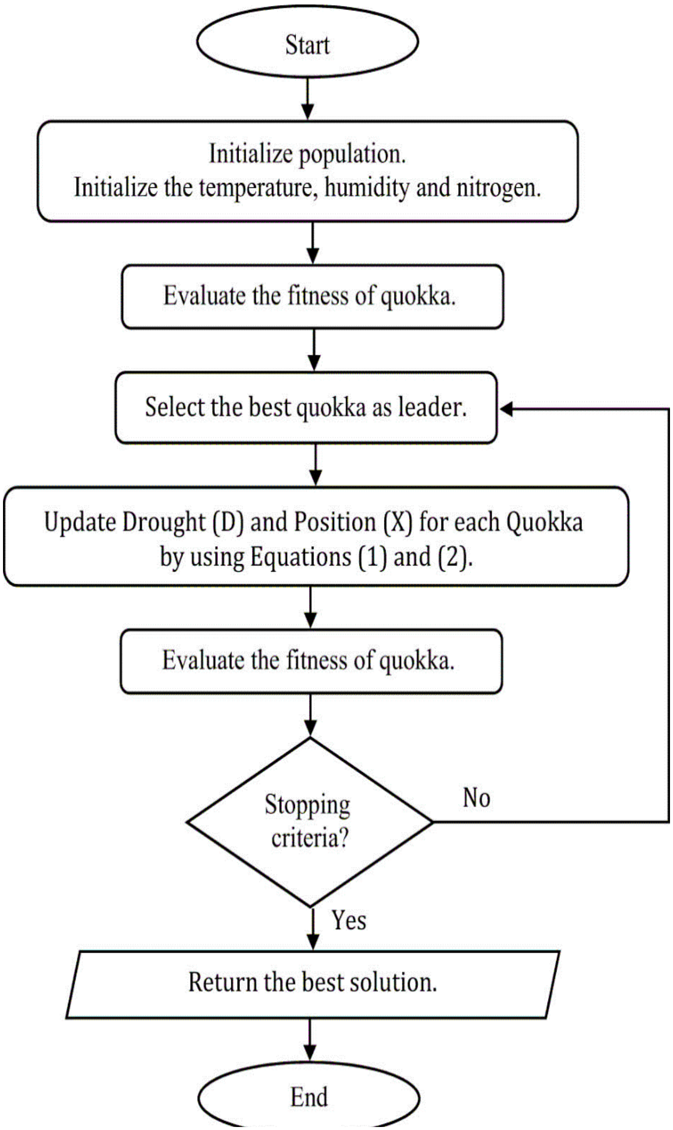

Fig. 4. Flowchart of QSO algorithm

After then, the leader stands for the optimal answer to optimization issues. The search agents enter a new stage of exploitation and return to their exploratory activities. Optimizing the operations of power generation, transmission, and distribution to minimize energy losses, lower operating costs, and improve the overall sustainability and dependability of the electrical grid is known as improved grid efficiency. A more efficient grid ensures that customers receive electricity with the least amount of waste and allows for better integration of intermittent renewable energy sources, such as wind and solar. Power utilities may better manage load, lessen the burden on infrastructure, and balance supply and demand by utilizing cutting-edge technology including smart grids, energy storage systems, automation, and real-time monitoring. Improved grid efficiency also helps combat climate change globally by reducing greenhouse gas emissions and dependency on fossil fuels. Additionally, it improves energy security and resilience, making sure that power systems are resilient to interruptions brought on by cyberattacks, natural disasters, or abrupt changes in demand. Enhancing grid efficiency has become essential to creating a sustainable, dependable, and future-ready energy infrastructure that benefits economies and societies globally as urbanization and industrialization fuel increased energy use.

4. RESULT AND DISCUSSION

In addition to meeting the need for electricity, the future electrical system must be able to address security and environmental problems. However, current grids are under strain to provide the rising demand for a sustainable, high-stability electric supply.

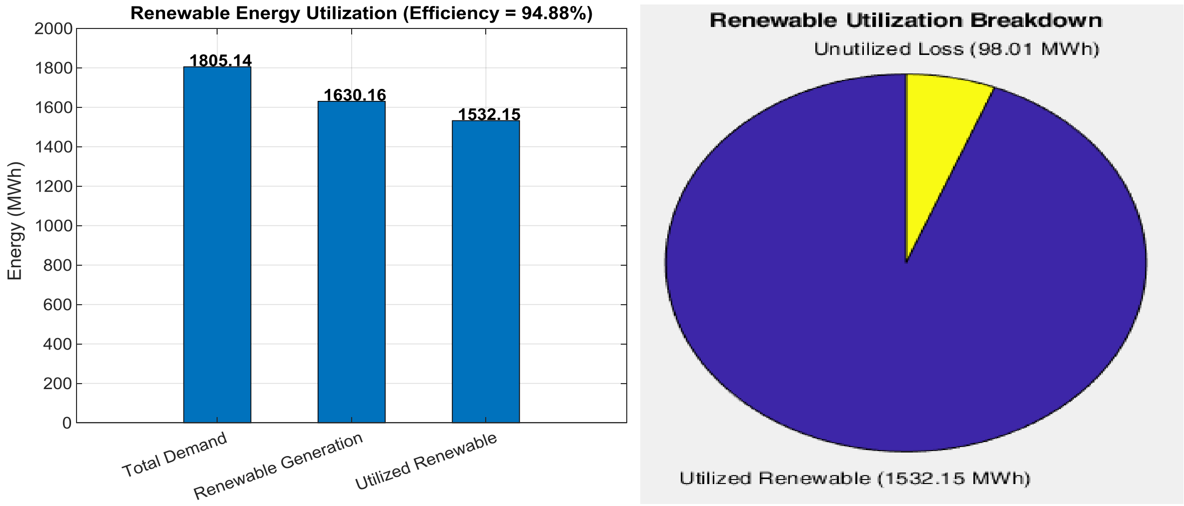

Fig. 5. renewable energy utilization

Therefore, national and international efforts to improve energy efficiency, switch to a sustainable economy that guarantees prosperity for present and future generations depend on modernizing the current electric grid (figure 5).

Table 1. Transmission Line Losses

Line	Current (A)	Resistance (Ω)	Loss (W)
1	120	0.12	1728
2	100	0.09	900
3	140	0.15	2940
4	90	0.10	810
5	110	0.08	968
Total			**7346**

The development of smart grid technology is being propelled by these intricate problems. the scattered use of non-traditional energy sources, such wind and solar (figure 6). It becomes considerably more challenging to predict, control, and optimize a smart grid when plug-in hybrid electric vehicles are added.

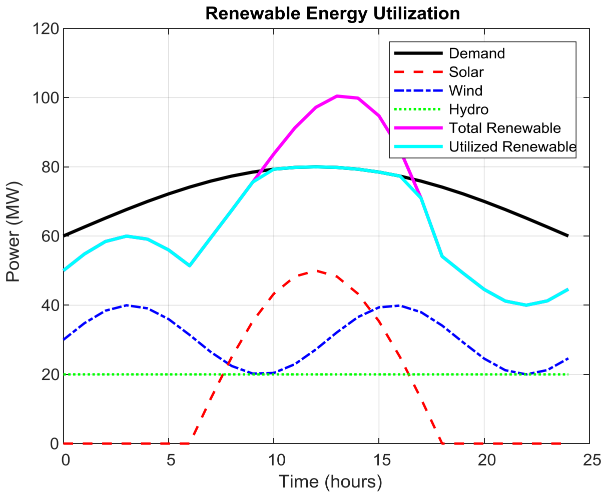

Fig. 6. Renewable Energy Utilization

The need for solutions from various disciplines of expertise is driven by the growing interest in smart grids and their multidisciplinary nature. Given the complexity and diversity of the smart grid, artificial intelligence and computational intelligence techniques appear to be some of the enabling technologies for its future development and success.

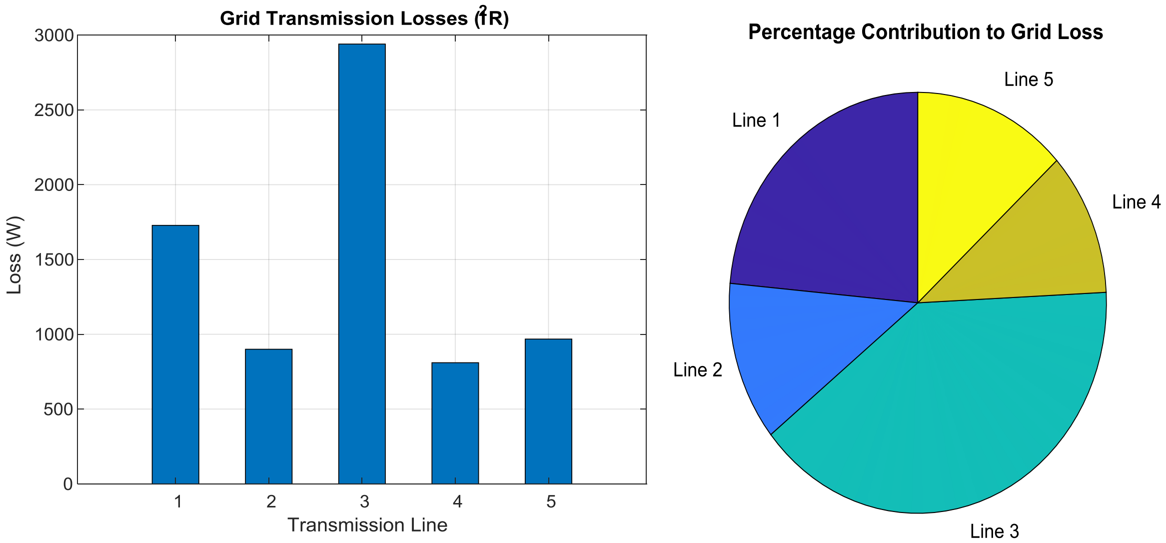

Fig. 7. Grid Losses

The goal of this study is to identify new problems related to smart grid technology and explore how the most pertinent computational intelligence methods might be used to address the various problems that emerge throughout the development of smart grids (figure 7). The thesis specifically discusses the main issues with smart grids, including cyber security issues, integration of Plug-in Hybrid Electric Vehicles (PHEV), and economical power dispatch using unconventional energy sources.

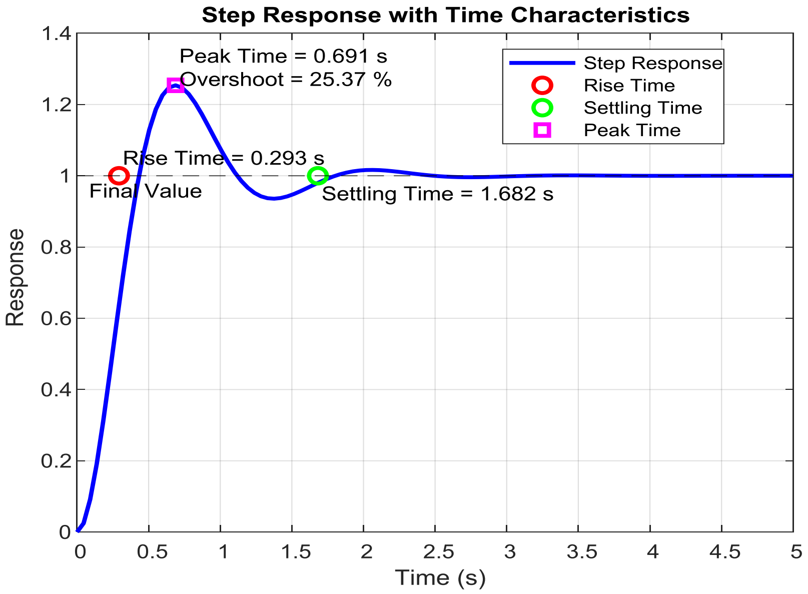

Fig. 8. System step response

Smart grids are being transformed by the combination of deep learning and energy-efficient IoT, which improves automation and optimizes energy distribution (figure 9). However, problems like inefficient resource allocation and wasteful energy use still exist.

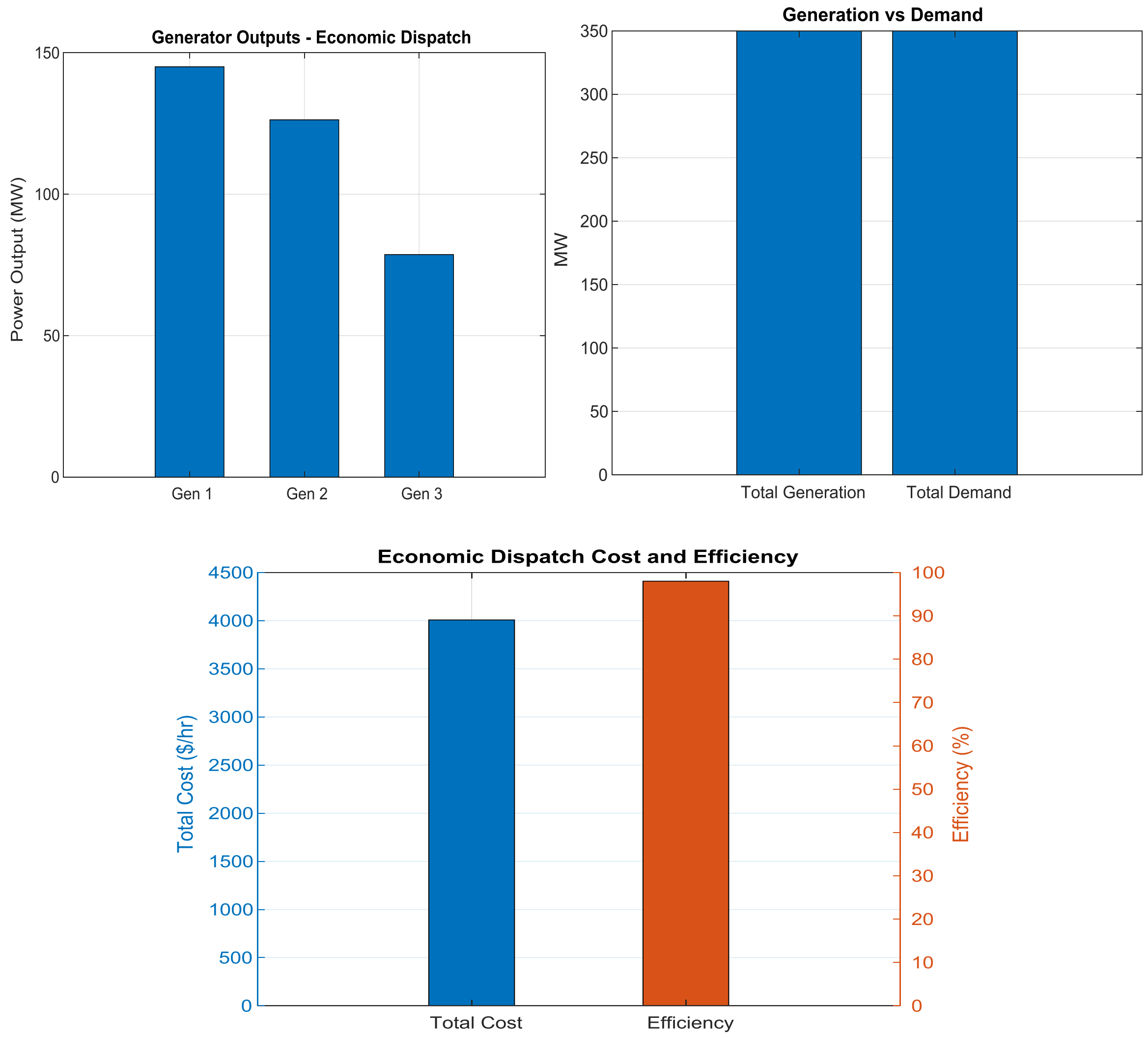

Fig. 9. Economic Dispatch Cost and Efficiency

For patterns of variable power demand, an optimal DR system is offered to control interruptible load (IL) under the time-of-use pricelist. The practical implementation of DR was made possible by the GBMIN-QSO. The state, operation, and reward function of the DR system are defined by the Markov decision process that is used to solve the IL issue, which aims to maximize profit over an extended period of time.

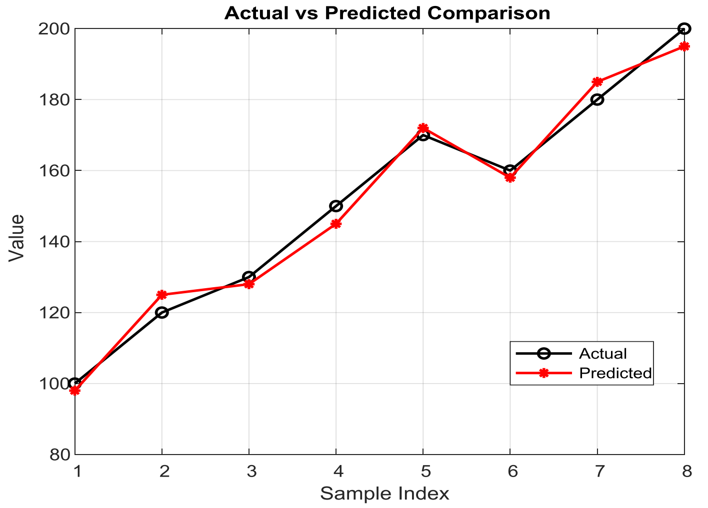

Fig. 10. Actual Vs predicted comparison

Lastly, the model achieved a decrease in the demand for peak electricity consumption and operating costs of voltage regulation within the limit without sacrificing safety. The ORA-DL architecture maintains superior performance in dynamic grid environments by employing a periodic retraining method.

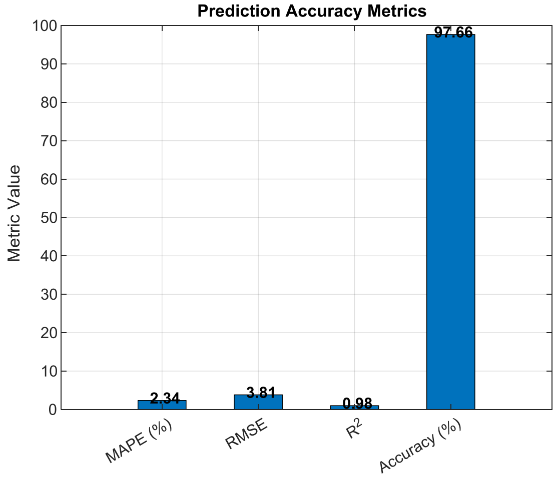

Fig. 11. Prediction Accuracy Metrics

The model can be updated using both previously collected data and newly collected real-time data at predetermined intervals, typically weekly or based on recognized shifts in demand patterns. This guarantees that the model can continue to adjust to evolving grid architectures and trends in energy consumption. Additionally, incremental learning techniques are used to modify the model without requiring total retraining, reducing processing burden and ensuring deployment continuity.

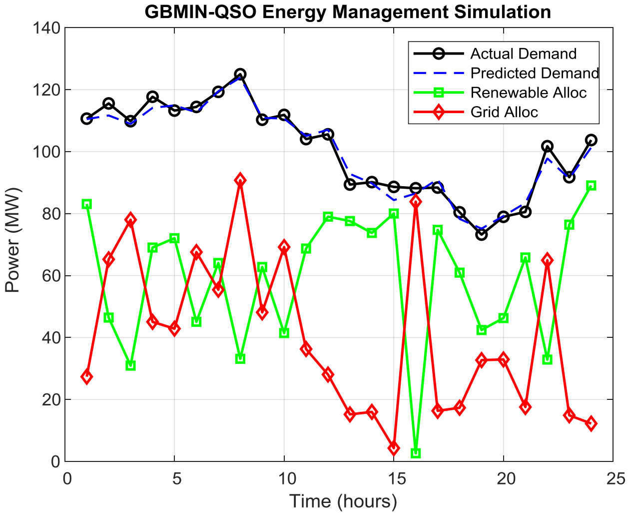

Fig. 12. GBMIN-QSO Energy Management Simulation

4.1. Discussion

The experimental results clearly highlight the effectiveness of the GBMIN-QSO framework in optimizing smart grid operations. The system successfully managed a total energy demand of 2412.61 MWh, of which 1418.51 MWh was supplied through renewable energy sources, reflecting a remarkably high utilization efficiency of 94.88%. This demonstrates the framework's ability to maximize the integration of renewables into the grid, thereby reducing dependency on conventional energy generation and supporting sustainability goals. In addition to renewable integration, the system ensures robust operational reliability, achieving a Grid Stability Index of 97.78%, which indicates that energy flow and supply-demand balancing are maintained with minimal fluctuations or instability.

The predictive modeling capabilities of GBMIN-QSO further enhance its performance, delivering an accuracy of 98.12% in forecasting energy demand and generation patterns. This high precision not only minimizes forecasting errors but also contributes directly to improved scheduling and proactive resource allocation. From an economic perspective, the framework demonstrates cost-effectiveness, with the operational cost measured at $54,171.28. This suggests that the optimization algorithms employed by GBMIN-QSO effectively reduce unnecessary expenditures while ensuring reliable service delivery. The combination of high renewable energy utilization, strong grid stability, accurate predictions, and optimized cost performance underscores the framework's ability to balance sustainability, reliability, and economic efficiency in modern power systems. Overall, these results confirm that GBMIN-QSO provides a well-optimized and intelligent energy management solution, making it highly suitable for next-generation smart grids where adaptability, scalability, and sustainability are critical.

5. CONCLUSION

AI is a well-known technique for predicting electric load based on historical data. With improved decisions based on these predicted loads, the traditional electrical system might become a smart grid. Even if gradient boost modelling has the least amount of error, decision trees are producing optimal results when the model error and runtime are taken into account at the same time. The electric grid's stability is improved and losses are reduced thanks to the model. Inception network of the deep learning is the foundation of our investigation. However, out of all the trained models, GBMIN-QSO computation time was incredibly low. In order to forecast energy demand, identify any issues, and optimize energy distribution, this study makes use of cutting-edge technology such as machine learning algorithms, data analytics, and real-time monitoring. By integrating renewable energy sources and managing distributed energy resources, AI-driven smart grids reduce energy waste, lower costs, and mitigate environmental impact. Even if gradient boost modelling has the least amount of error, decision trees are producing optimal results when the model error and runtime are taken into account at the same time. It benefits society by making the electricity market transparent, competitive, and guaranteed to produce clean energy. Demand-side management may potentially benefit from this technology.

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