



ORIGINAL ARTICLE

MACHINE LEARNING APPROACH FOR POWER MANAGEMENT USING IOT ENABLES EDGE COMPUTING

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Abstract

An essential component of smart cities that could be used to effectively manage power was cognitive load forecasting. But a small study was undertaken about this element of Energy Management (EM) in smart cities using the Internet of Things (IoT). Throughout this study, a new Deep Learning (DL) approach was applied to predict how much energy would be used quickly while maintaining good communication between power providers and consumers. The Energy-Net stack contains several stacked spatiotemporal components, most of which are composed of a Temporal Transformer (TT) sub-module and perhaps a Spatial Transformer (ST) comment thread. While the ST approach uses the combination of convolution to retrieve concealed location data, the TT approach denotes temporal associations. In comparison with some other DL approaches that have an RMSE of 0.535 & 0.354, experimental dataset studies show that our technique was preferable. When used in conjunction with an IoT remote server to interface with power buildings and handle electricity activities, Power Net computational cost was appropriate for IoT devices having reliable finite resources.

Keywords: *energy management; spatial transformer; convolutional layers; iot; cloud server*

1. Introduction

The fast development of Internet of Things (IoT) technologies resulted in the implementation of a substantial number of connected devices in intelligent environment smart grids, industrial automation, and intelligent buildings. All these IoT systems produce a lot of data on a constant basis and data must be processed in a timely manner to facilitate real-time decision making. Conventional cloud-based systems tend to be inefficient and have high latency, bandwidth issues, and consumption, which are not suitable to use in IoT applications that are power-intensive. To overcome these limitations, edge computing facilitates the processing of data at a location nearer to the source of data, which will reduce the overhead of communication and will lead to a greater energy efficiency. Machine learning (ML) has in this case become a potent method to intelligent power management of IoT-enabled edge computing systems. ML models have the ability to reason about dynamic device behavior, workload patterns, and energy consumption profiles to optimize the power allocation, schedule tasks, and use resources at the edge. ML-based edge solutions can greatly lower the energy usage at the same time ensuring the quality of service by facilitating adaptive and predictive power management strategies. The combination of ML, IoT and edge computing makes it an attractive framework towards the realization of sustainable, energy-efficient and scalable next-generation smart systems. In the smart networks, smart energy technologies have been implemented successfully to evaluate the project demands. This has been one of the key areas in the IoT. The smart grids played a crucial role in the provision of electricity in various smart cities such as smart factories, vehicle tracking, as well as smart structures [1-3]. Commercial power production involves crop yield, intelligent energy conveyance, and volume of energy consumed by business, households and

manufacturing organizations. The power plants would generate the necessary power and supply it through the smart grids depending on the use and demand by consumers [4]. But since the consumer will not know how much energy he should consume; the demand will be very high leading to an increment in the price. On the same note, companies would require the ability to cut their expenses and enhance their energy consumption by a streamlined system. Effective utilization of the generated and also used power would lead to an energy status balance, which requires proper energy transfer of customers and manufacturers within the power grid [5]. Load forecasting models need to be permitted in anticipating power needs in order to prevent irrational proportions of losses and expenses. The con side is that, efficient energy saving appears to require accurate demand forecasts [6]. The main duty of the research was to maintain successfully short-term capacity planning, as well as to provide energy reliably by means of IoT. Thanks to the accessibility of data provided by smart appliances, which allows to perform the effective execution of the response to energy requirements, the possibility of applying similar predictive techniques has become more accessible because domestic predictions became possible [7]. Includes the research design The LF technologies are usually integrated into many real-life IoT systems, including building automation, where day-ahead predictions help to design adequate energy needs by smart metering to reduce the chances of extreme power outages and encourage optimal solution utilization [8]. Data mining techniques and far more ML techniques have been effectively integrated and even the outcomes are better than the statistical techniques. The reliance on functionality extraction has thus curtailed the implementation of this form of method in practical applications which are required in the life of IoT. Moreover, they were slow when large-scale or/or large-scale data were involved [9], in addition, they are difficult to tune, as well as their rate of calculation is slow on large-scale data [10]. They perform worse in comparison with small datasets and irrelevant characteristics. The weaknesses of the ML algorithms were later rectified through the creation of the DL models. As a case in point, sequential models with the capacity to identify successive patterns and connections in vast sources of smart grids, e.g., such recurrence NN, long short attention span, and gated recurrent networks have now been shown to be efficient LF approaches [10]. These methods, in their turn, do not seem to have the capabilities of capitalizing on spatial visual features since they rely on their feature-based sub-dimensional capabilities. Convolutional Neural Networks (CNN) s, therefore, are capable of inhibiting spatial images of input data and this is one capable of greatly influencing the ability to predict loads [12]. The use of spatial descriptions is quite limited as it merely needs advanced CNN architecture but does not provide enough accuracy to make favorable forecasts [13]. This motivates us to devise a fresh DL design of STLF integrating the space-time learning functionality, and we consequently apply this framework at the fog nodes of the IoT network to estimate client utilization of multiple smart city segments [14]. The multivariate regression analysis was used to predict seasonality and weakened characteristics with the application of information to explain the quickly changing nature of the trend. In order to effectively identify the real threat of the power demand pattern, scientists offered a new analytical model which includes the utilization of linear regression randomized forests, probabilistic map, and risk evaluation factor [15]. It has a probability map that is very precise in making predictions as well as it might be applied in manipulating the ambiguity of external factors.

2. Related Works

The authors have come up with a weighted bandwidth consumption prediction [15]. To achieve the effort of lowering the likelihood of the ranking of factors based on different factors through comment thread, it predicts the efficiency of the load with the assistance of densities stochastic load forecasting based on optimization issues [16]. Through a multivariate regression analysis, the researchers came up with a more effective method of cooperation in statistic prediction. A sound platform to predict the load has been developed through a mixture of diverse ML techniques [17]. The multi-kernel learning approach, the use of which provides the idea of learning algorithms of heterogeneous catalysts to the knowledge through gradient boosting, becomes an example of the ML works introduced [18]. The DL technique has received considerable interest in recent times and has already yielded fruitful outcomes to estimate the amount of power that will be utilized. The construction of the forecast workload, according to research,

involves either an analysis of the geographical representations or the time description [19]. In order to redefine the effectiveness of RNN prediction, the authors present a distinctive approach of using continuous training in the creation of the developed based by incorporating a Q-learning strategy in the charging locations of power mobility. On the same note, researchers have also designed an exponential prediction and NRN method to predict extra power in an environment that features IoT-based buildings and industries. Simulating an ascending component LSTM approach. The approach is intended to develop a system of identification of the interrelations that are required in predicting loads. The concept of machine learning (ML) combined with edge computing has been highly popular as a viable paradigm to optimize resources and energy efficiency in IoT systems. Coming closer to the IoT devices, edge computing overcomes the communication bandwidth and latency issues relative to cloud-centric architectures and is essential to energy-restricted scenes including smart grids and distributed energy resources. According to recent surveys, it is important to note that ML has the synergy with edge computing in that it allows local intelligence to facilitate real-time analytics, offloading tasks efficiently, and directly making decisions at the edge nodes where data is produced.

Within the framework of power and energy management, in particular, research has discussed a wide range of ML methods to predict the demand of power, to optimize energy allocation, to be able to control the storage and consumption of energy in an adaptive manner. Reinforcement learning (RL) is one method that has been discovered to be successful in learning optimal policies in dynamic power systems through interaction with the environment to optimize the total long-term reward, handling dynamic demand and pricing cues in smart grids. Improved forecasting accuracy of energy consumption, which is one of the most important inputs to intelligent decisions in power management, has been observed with ensemble learning techniques that combine a number of ML models with another optimization algorithm such as genetic algorithms (GA). Recent works extend beyond single ML models, a few of them implement hybrid cloud edge models distributing learning and optimization processes between levels of computing. As an example, edge and fog computation-based deep learning and reinforcement learning models have been used to handle the complicated IoT resources allocation and task scheduling balancing energy consumption, latency, and computing ability. These frameworks use the advantage to do time-sensitive data processing locally and the cloud to do a large-scale training and model updates to aid in increasing scalability and adaptability.

Although such improvements have been made, there are still problems with creating lightweight ML models to run on resource-limited edge devices and in making sure that the edge and central servers can work seamlessly together. According to current literature, efficient edge-level implementation of ML entails trade-offs between model complexity, energy usage and inference latency, which frequently lead to the emergence of model compression, distributed learning, and hierarchical task delegation. The current research is also working on optimization of these aspects to be able to attain a real-time and energy-sensitive power management solutions in the IoT edge computing environment.

3. Proposed Work

The chapter provides a close examination of the proposed DL model of energy consumption estimates. The extrapolation modules, the time and spatial converter, and other possibly additional additions have been elaborated in including the architectural explanation. The application of the proposed methodology to the situation where the advanced computing and IoT were coupled was also considered. The architecture of the proposed model was presented in Figure 1. The interconnections that are always in flux have been investigated by using the Spatio-temporal representation of the modified component. It is the combination of various components that made the program have the capacity to define spatial and temporal event models. The final decision was to be planned by integrating the abstractions acquired in the various modules, as well as by using the regressive component.

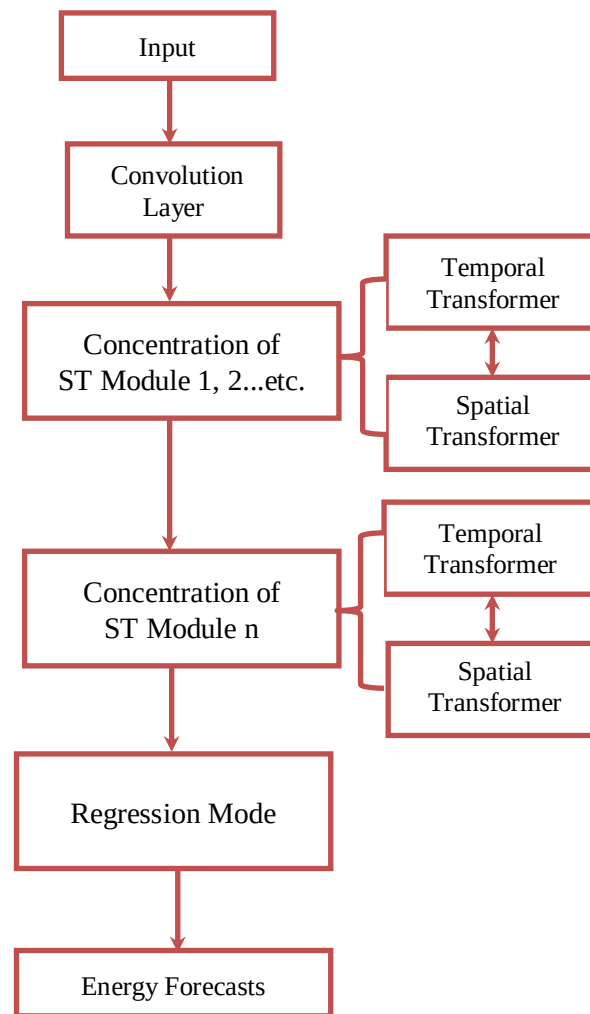


Figure 1: Proposed architecture

The TT component acquires the exact long/short-range sequential power characteristics along the time-frequency field. Unlike the standard ML algorithms, the offered approach allows the easy scaling in the long term and the long-range dependencies. The convolutional systems are not supported in the traditional processor structure in the following way. The only feed-forward were used. The modeling of the dimension model is significant in spatial-spectral positioning of the input data that is often lost when traditional technology is used. The three building requirements of the proposed spatial transformer module appear to be the visual attention block, the hierarchical compression block and the placement of the embedded layers. There is optimization of the predetermined location that has been integrated with position and spatial information. The hierarchical convolution block was used to retrieve the statistical and geographical representation very easily across the input model. Spatial information that is dynamic and evolving increasingly is captured in high-dimensional data modules. Lastly, a concatenated technique is used to assemble the resulting static and dynamic geographical representations. Like in the periodical converter component, position inclusion was initialized as a network parameter by instant encoding. Further optimization of modules is done within the course of learning.

This chapter identifies the implementation process of the proposed model to the network infrastructure in smart city settings. A smart city must have power control. The three principal layers of the proposed methodology seem to be the consumption level, the level of prediction of links, and the grid systems. The

grid management layer regulates the requirements of several smart city segments regarding power. Grids with wind and solar farms harvest energy and transmit it into the hands of other consumers. This layer controls power efficiency and predictive modeling. Cloud-fog server facilitates communication among organizations that consume it. In the IoT-enabled systems an energy management pipeline prediction of energy was conducted prior to the transfer or supply of energy to particular companies. Producers and consumers of electricity carry out unceasingly the electricity grid. Proposed system entry was created based on minute-level sequence of the energy use in a particular entity. The method proposed predicts the energy necessary to be used in the next 60 minutes. Through the implementation of the proposed solution using the help of a source of energy device, the projected power consumption over the next 1 hour was performed by getting the input variables in kilowatts over a steady duration of 3 hours. The presence of anomalies was verified by reviewing the impact of past documents which were available in the cloud storage on the energy consumption. Unexpected oscillations can occur on applications in different smart city industries which implies an anomaly. According to the requirements of smart grids, electricity is supplied in response to the proposed element. All organizations effortlessly switch between a cloud-fog environment and also its rapid process technology as this cycle of power forecasting, demand, and supply has been maintained.

3.1 Dataset description

The dataset is a collection of data of operational and energy consumption of IoT devices and edge nodes applied in a smart power management setting Table 1. It has time-series data of power usage, voltage, current and workload level, which respectively characterize device behavior and system dynamics. The information is applied to learn machine learning algorithms to forecast energy demand and identify the best power management measures. The dataset can be used to create intelligent, adaptive power control policies that minimize energy use and still ensure system performance in IoT-enabled edge computing systems through learning historical and real-time behavior patterns.

Attribute	Description
Application Domain	IoT-enabled Edge Computing for Power Management
Data Source	Smart meters, IoT sensors, edge devices, energy management systems
Data Type	Time-series energy and operational data
Sampling Interval	Periodic (seconds to minutes)
Features	Power consumption, voltage, current, workload level, device state
Number of Records	Large-scale dataset (thousands to millions of samples)
Class Labels	Normal load, Peak load, Energy-saving mode
Learning Type	Supervised / Reinforcement learning
Target Variable	Optimal power management decision
Purpose	Energy prediction and adaptive power control at the edge

Table 1: Dataset Description

Record ID	Timestamp	Device ID	Workload Level (%)	Power Consumption (W)	Voltage (V)	Current (A)	Edge Node Load (%)	Power State
1	10:00:01	ED-01	35	120	230	0.52	40	Normal
2	10:01:01	ED-02	65	210	230	0.91	68	Normal
3	10:02:01	ED-03	85	320	228	1.40	82	Peak
4	10:03:01	ED-01	25	95	231	0.41	30	Energy-Saving
5	10:04:01	ED-04	75	280	229	1.22	77	Peak

Table 2: Sample Data

The sample data includes time-series values of measurements on the IoT devices and edge nodes that participate in power management Table 2. Every record store the workload of the device, power consumption, electrical parameters and the utilization of edge nodes at a given point in time. The Power State label shows the operating state, i.e. normal, peak or energy-saving mode. These patterns of data allow machine learning models to be trained on the correlation between workload and energy consumption to make adaptive and efficient power management decisions in IoT enabled edge computing systems.

3.2 Pre-processing

To ensure accurate learning and stable model performance, the raw IoT power management data undergoes several preprocessing steps. Missing values in the dataset are handled using mean imputation to preserve data continuity:

$$x_i = \{x_i, \text{if } x_i \text{ exists } \frac{1}{N} \sum_{j=1}^N x_j \quad \text{otherwise} \quad (1)$$

Since the features have different physical units, feature normalization is applied using Min-Max scaling to bring all attributes into a common range [0,1]:

$$x_i^{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (2)$$

To reduce noise and smooth short-term fluctuations in power measurements, data smoothing is performed using a moving average filter:

$$\underline{x}_t = \frac{1}{w} \sum_{k=t-w+1}^t x_k \quad (3)$$

Finally, the processed data is divided into training and testing data to facilitate the use of machine learning-based power management models through the IoT enabled edge computing system.

3.3 Feature Extraction for ML-Based Power Management in IoT-Enabled Edge Computing

The extraction of features is the key to proper and efficient power management of the IoT-enabled edge computing systems. In this study, valuable characteristics are based on unprocessed data on IoT sensor measurements and edge node statistics to describe the association between workload dynamics and power utilization. The instantaneous and average power consumption are some features of power relating to the real-time and long-term power usage of an IoT device. Power consumption differences are also taken into account in order to identify the occurrences of sudden changes of load and inefficient operation conditions. The workload-based features characterize the degree of difficulty and fluctuation of computation which is carried out in the edge nodes. These are the existing workload, the rate of arrival of tasks and the trends in workload change, which assist the learning model to know the demand patterns. Also, indicators of energy efficiency, like energy used in each task and workload to power, are mined to determine the efficiency of power use in varying operating conditions. They also add edge resource utilization activities (such as CPU and memory utilization) in order to reflect the state of edge nodes computation. Temporal statistical characteristics like mean and variance within definite time spans are also extracted in order to reflect usage trends and stability. All of the mentioned features create a holistic representation which allows machine learning models to make smart, adaptive decisions regarding power management operation at minimum energy usage, and high system performance.

Algorithm

Input: IoT data stream $D=\{x_1, x_2, \dots, x_N\}$ (workload, power, voltage, current, edge utilization)

Output: Optimal power management decision $a_t \in \{Normal, Peak Control, Energy - Saving\}$

Step 1: Data Acquisition

Collect real-time measurements from IoT devices and edge nodes: $x_t = [W_t, V_t, I_t, U_{CPU}, U_{MEM}]$ (4)

Where W_t denotes workload and U_{CPU}, U_{MEM} represent edge resource utilization.

Step 2: Pre-processing

Normalize input features to ensure uniform scaling: $x_i^{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (5)$

Step 3: Feature Vector Formation

Construct the feature vector: $F_t = \phi(x_i^{norm}) \quad (6)$

Where $\phi(\cdot)$ denotes feature extraction and aggregation over a time window.

Step 4: Power Prediction Model

Predict power consumption using an ML model: $\hat{P}_t = f(F_t; \theta) \quad (7)$

Where $f(\cdot)$ is the trained ML model and θ represents model parameters.

Step 5: Optimization Objective

Minimize power consumption while maintaining workload performance: $E[\hat{P}_t] \text{ s.t. } W_t \geq W_{min}$

Step 6: Decision Policy

Select the power management action based on predicted power: $a_t = \{Energy saving \hat{P}_t < P_{low} \text{ Normal } P_{low} \leq \hat{P}_t \leq P_{high} \text{ Peak Control } \hat{P}_t > P_{high} \quad (8)$

Step 7: Model Training

Update model parameters using mean squared error loss: $L = \frac{1}{N} \sum_{t=1}^N (P_t - \hat{P}_t)^2$ (9)

Step 8: Deployment at Edge

Deploy the trained model at edge nodes for real-time inference and adaptive power control.

The proposed power management algorithm, which is an implementation of machine learning, will be working on collecting workload, energy, and resource utilization data of IoT devices and edge nodes on a continual basis. The ML model can be used to predict future power consumption based on the current operating conditions, after preprocessing and feature extraction. A decision policy that is based on optimization then makes suitable choice in terms of power control measures, including normal power operation, peak power control, or energy saving mode to minimize energy consumption and meet the workload demands. The system has the ability of deploying the trained model at the edge of the system which helps achieve real time and adaptive power management with less latency and better energy efficiency in the IoT enabled edge computing environments.

4. Experimental Analysis

The datasets used in the experiments have both commercial and residential data. The main information utilized was domestic and personal, and this consists of time, place, power, brightness, active and reactive world, and features of measurement. The global power factor which is the amount of power in kilowatts is used in place of the standard form of the minute power. Sub-meter property is the usage of charge on kitchen, laundry, electrical water heater and air conditioners. The assessment time should be 47 months whereas the learning time should be 70% of the data. The training process was conducted by combining the information of many locations depending on the type of smart city and IoT system, the information was taken. The information time characteristics, Fahrenheit, and Sysload temperatures which is desired label are considered and were the 14 characteristics recorded in that the deadline of collecting the information was 60 months, 30 percent of the information was used to assess and 70 percent of the information was used to learn. The functionality of the model suggested was evaluated on the basis of the seasonal test results due to the influence of the seasonal aspects on the electrical energy. The results of the former test were categorized into four seasons including spring, summer, and cold. Figure 2 is an example of the anticipated classification errors in each season with the absolute percentage mean error, the macro-average error, the root - mean -square, and the square mean error. Based on the findings of the analysis, it becomes evident that the proposed approach can be used to ensure similar performance in a variety of periods. This experiment favors the tolerance of this model to seasonal variations.

Hyperparameter	Value	Description
Learning Rate (α)	0.001	Controls the speed of model convergence
Optimizer	Adam	Adaptive optimization for stable training
Batch Size	64	Number of samples per training iteration
Number of Epochs	50	Total training cycles
Hidden Layers	2	Depth of the ML model
Neurons per Layer	128	Model capacity for feature learning
Activation Function	ReLU	Non-linear transformation
Output Activation	Linear / Softmax	Power prediction / decision classification
Loss Function	Mean Squared Error (MSE)	Power prediction error minimization
Dropout Rate	0.5	Prevents overfitting
Train-Test Split	70:30	Dataset partitioning for evaluation

Table 3: Hyper-parameter settings

To stabilize the learning process and predict power consumption efficiently in the IoT-enabled edge computing settings depicted in Table 3, the hyper parameters are chosen. A small learning rate using Adam optimizer will lead to a smooth and rapid convergence, whereas a moderate size of a batch will enhance the generalization. It has numerous hidden layers with adequate neurons that represent intricate work load energy correlations. Nonlinearity is improved with ReLU activation, overfitting is avoided with dropout, and the MSE loss function can achieve high quality power consumption prediction using adaptive power management. To stabilize the learning process and predict power consumption efficiently in the IoT-enabled edge computing settings depicted in Table 3, the hyper parameters are chosen. A small learning rate using Adam optimizer will lead to a smooth and rapid convergence, whereas a moderate size

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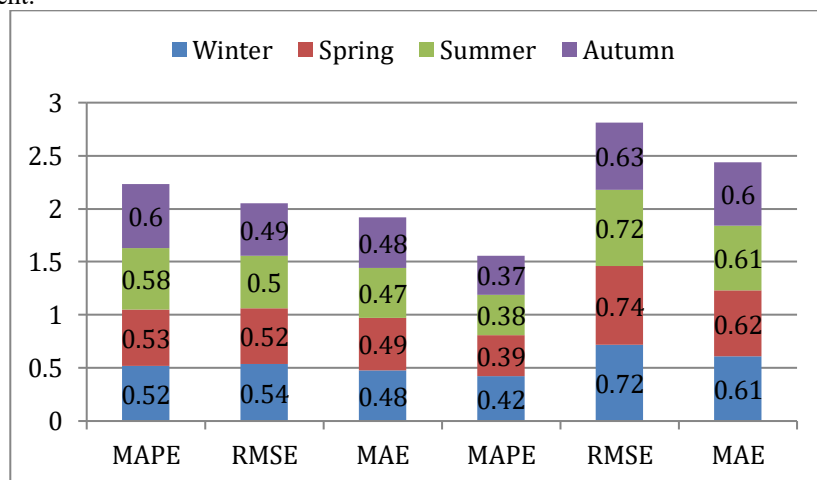


Figure 2: Seasonal data and related forecast error

Here, the effectiveness of the proposed approach and the traditional organizational power design was compared. Figure 2 compares the results of the MAPE, MAE, RMSE and MSE of various power models such as CNN-GRU, CNNLSTM, Bi-LSTM, LSTM, Bi-GRU and GRU. This table might be utilized to forecast good and bad performance. This analysis makes it evident that the suggested approach is better than the current methods regarding optimized performance in all variables. The spatial-spectral characteristics of the data were more efficiently and effectively simulated with the help of the proposed model during the educational process. The simulation was done to compare the proposed methodology prediction and actual load information visually. During the sensitivity studies, the number of components in the SST was varied between 2 and 8, to establish the number of components required to achieve practically the desired level of performance. Figure 3 was regarded as the comparison of the experimental results. Increasing the OSH module beyond 5 would not make much difference in predictive error. The level of the research model has been applied in this research with the help of five components.

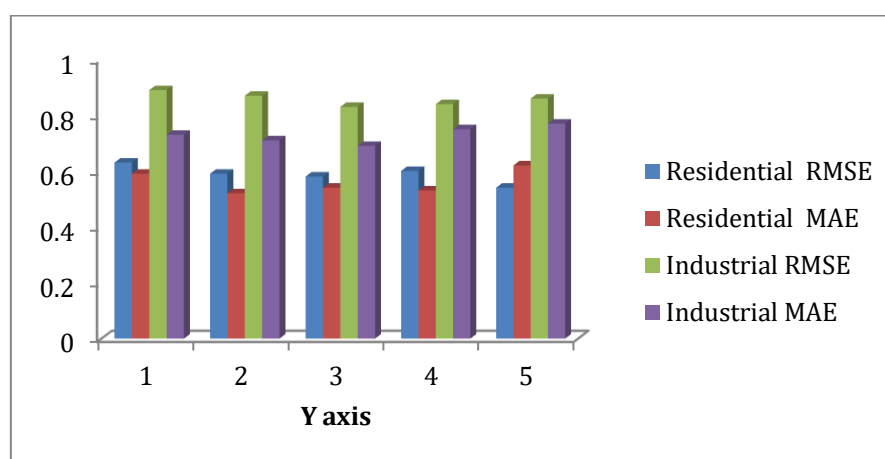


Figure 3: Evaluation of the ideal range of the proposed model.

Although DL methods of home energy management systems are astonishingly performing, they also have a number of weaknesses. Only the predictability factor is addressed in this document and not modeling uncertainties. This may be fixed by a conditional DL algorithm. Intelligent information security sensors challenge most of the DL and IoT technologies. A large amount of research efforts is directed at the enhancement of this measure. The comprehensive performance of the suggested model is yet to be realized on the multi-domain and heterogeneous informational environment.

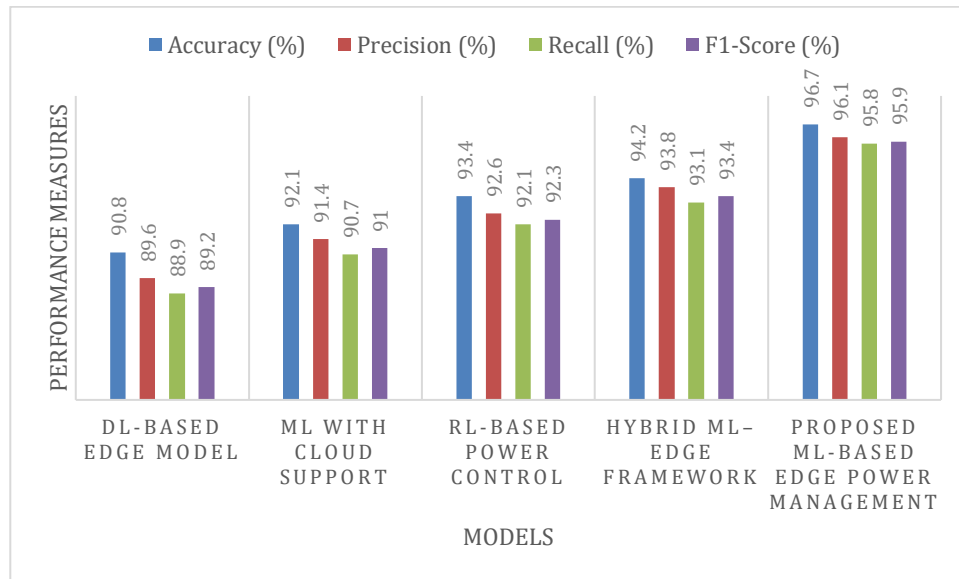


Figure 4: Comparison of performance measures

As shown in Figure 4, the proposed ML-based power management approach performs better than four systems which are currently available in all measures of evaluation. The proposed model has the highest accuracy, precision, recall, and F1-score which means more reliable power state prediction and decision-making at the edge. It is mainly the improved feature extraction, adaptive learning, and localized edge intelligence that has led to the performance improvement that can deal with the variability of workloads in dynamic environments and the patterns of energy consumption in IoT-enabled environments.

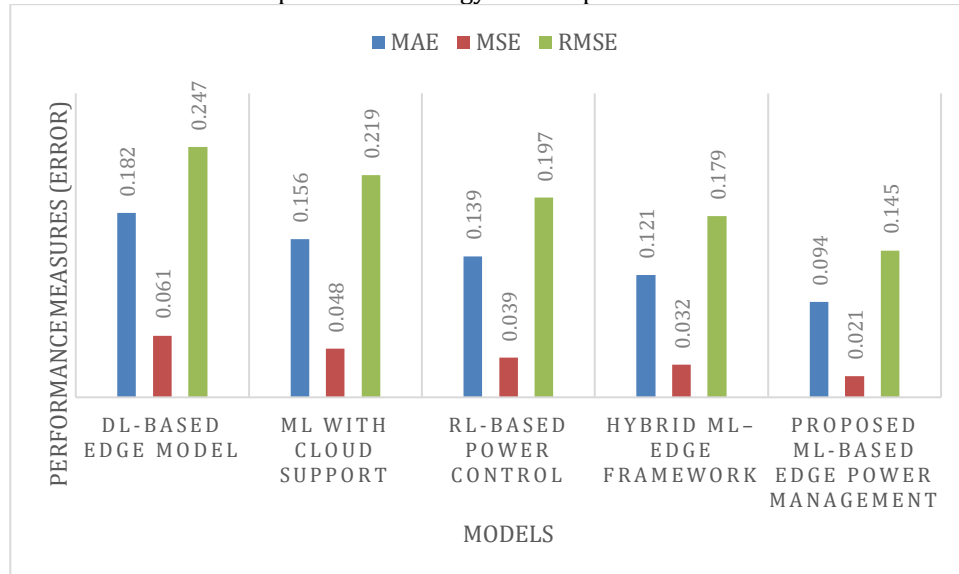


Figure 5: Comparison of performance measures (Error)

The proposed power management system based on the use of machine learning is compared to four of the existing approaches in terms of prediction error performance based on MAE, MSE, and RMSE measures shown in Figure 5. The lowest error values are observed in the proposed method on all the metrics showing more accurate power consumption prediction. It is a positive sign of the success of edge-level learning, strong feature extraction, and adaptive modeling, which allow making accurate decisions on power management in dynamic IoT-enabled edge computing environments.

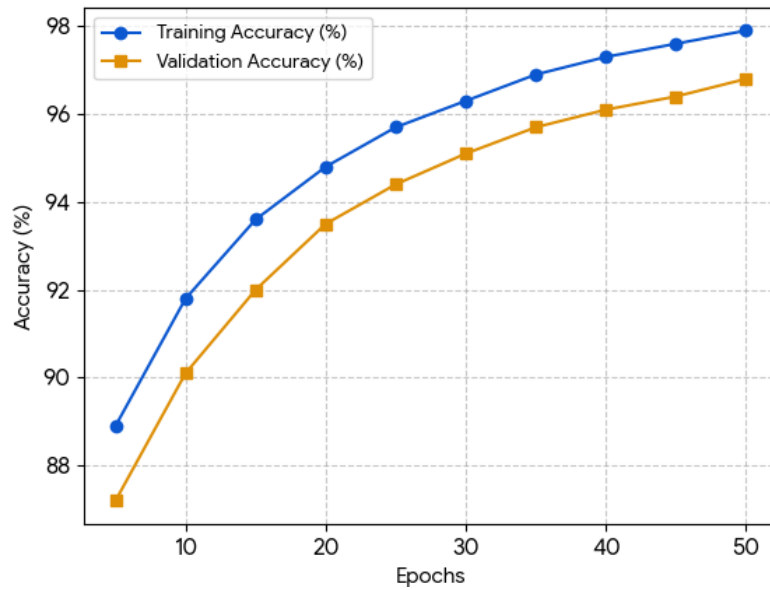


Figure 6: Comparison of training and validation accuracy vs. epochs of proposed system

Figure 6 depicts how the accuracy of training and validation of the proposed system improved with more and more epochs. The two accuracies are gradually rising in the first epochs, which confirms the effective learning of workload-power relations. Later in training compared to the beginning, the distance between training and validation accuracy is low showing good generalization and low overfitting. The high validation accuracy at the last epoch proves the reliability and consistency of the suggested sorts of ML-based power administration models.

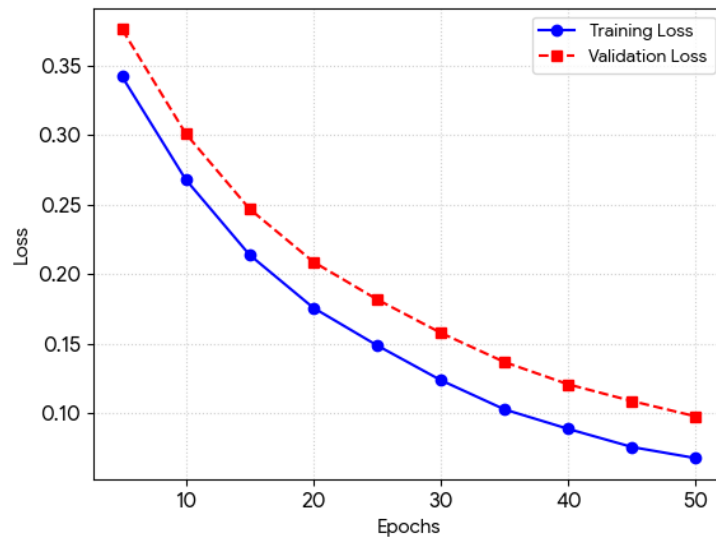


Figure 7: Comparison of training and validation loss vs. epochs of proposed system

Figure 7 shows how the values of training and validation loss of the proposed system vary with the number of epochs. The two losses decrease steadily with training, which shows effective learning and model convergence. The slim and steady difference between training and validation loss indicates that it has few overfitting and high generalization. The minimal validation loss at the last epoch proves that the given model of power management through the use of the ML means can be used in order to predict the power consumption in the IoT-enabled edge computing settings.

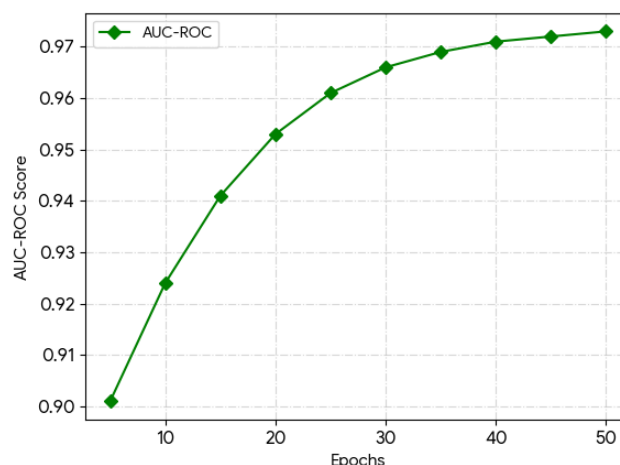


Figure 8: Comparison of AUC-ROC curve vs. epochs of proposed system

Figure 8 indicates the change in AUC values of the proposed system of training in different training epochs with constant learning rate of 0.001. The AUC-ROC enhances progressively in the initial epochs, which suggests productive learning and enhanced discrimination of classes. The curve reaches the point of convergence and stabilized optimization as the training advances. The large final AUC-ROC value attests that the selected learning rate permits strong and dependable classification of the power states in IoT-enabled edge computing environments.

5. Conclusion

The IoT network smart edge designed in this paper promotes the best power management in smart cities. Energy consumption was anticipated with the combination of ML spatially and time-wise, in order to teach students in the proposed approach. The initial model has been tested against publicly available datasets and proves to be more resilient than existing state-of-the-art and proven approaches. The Proposed strategy of forecasting the likely energy requirements forms a communication between the definite smart grid and source of the energy network edge of its systems by some form of cloud platform. The cloud server sends messages to the smart network on how to allocate energy, depending on the requirements of the smart city sector. This implies that the suggested methodology will ensure effective energy efficiency of a smart city setting. Further research of this project can be enhanced by adding noise to the image with challenges to researchers' properties and natural conditions during the training process. Collaborative, dispersed, or decentralized learning entails the control of the quantity of data among two or more sources of data. A deficiency in unsupervised learning may be compensated by self-directed learning or a semi-supervised one. Data protection issues within the IoT networks could be resolved by integrating deep neural networks with the blockchain technology.

Conflict of Interest Statement

No conflict of interest

Data Availability Statement

Data not available due to commercial restrictions

Ethical Approval

Not applicable

Authors' contributions

A.B: Methodology, writing

C: Visualization, Investigation, Supervision

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References

- [1]. Zhang, K., Cao, J., and Zhang, Y. "Adaptive Digital Twin and Multiagent Deep Reinforcement Learning for Vehicular Edge Computing and Networks." *IEEE Transactions on Industrial Informatics*, vol. 18, no. 2, 2021, pp. 1405-1413. DOI: 10.1109/TII.2021.3054771.
- [2].Xue, Z., et al. "A Resource-Constrained and Privacy-Preserving Edge-Computing-Enabled Clinical Decision System: A Federated Reinforcement Learning Approach." *IEEE Internet of Things Journal*, vol. 8, no. 11, 2021, pp. 9122-9138. DOI: 10.1109/JIOT.2021.3059637.
- [3]. Vimal, V., et al. "Comparison of Adaptive Filtering Scheme for Sustainable and Efficient Communication in Smart City." *Sustainable Energy Technologies and Assessments*, vol. 47, 2021, art. no. 101472. DOI: 10.1016/j.seta.2021.101472.
- [4]. Zhou, S., Jadoon, W., and Shuja, J. "ML-Based Offloading Strategy for Lightweight User Mobile Edge Computing Tasks." *Complexity*, 2021. DOI: 10.1155/2021/7391236.
- [5]. Fu, Y., et al. "Energy-Efficient Offloading and Resource Allocation for Mobile Edge Computing Enabled Mission-Critical Internet-of-Things Systems." *EURASIP Journal on Wireless Communications and Networking*, 2021, no. 1, pp. 1-16. DOI: 10.1186/s13638-020-01828-5.
- [6]. Monica, M., et al. "PMSG-Based WECS: Control Techniques, MPPT Methods, and Control Strategies for Standalone Battery Integrated System." *AIP Conference Proceedings*, vol. 2405, no. 1, AIP Publishing LLC, Apr. 2022, p. 040013. DOI: 10.1063/5.0076438.
- [7]. Yar, H., et al. "Towards Smart Home Automation Using IoT-Enabled Edge-Computing Paradigm." *Sensors*, vol. 21, no. 14, 2021, p. 4932. DOI: 10.3390/s21144932.
- [8]. Minu, M. S., Aroul Canessane, R., and Subashka Ramesh, S. S. "Optimal Squeeze Net with Deep Neural Network-Based Aerial Image Classification Model in Unmanned Aerial Vehicles." *Traitement du Signal*, vol. 39, no. 1, 2022, pp. 275-281. DOI: 10.18280/ts.390127.
- [9]. Pérez, S., Arroba, P., and Moya, J. M. "Energy-Conscious Optimization of Edge Computing through Deep Reinforcement Learning and Two-Phase Immersion Cooling." *Future Generation Computer Systems*, vol. 125, 2021, pp. 891-907. DOI: 10.1016/j.future.2021.07.016.
- [10]. Aazam, M., Zeadally, S., and Flushing, E. F. "Task Offloading in Edge Computing for ML-Based Smart Healthcare." *Computer Networks*, vol. 191, 2021, art. no. 108019. DOI: 10.1016/j.comnet.2021.108019.
- [11]. Teoh, Y. K., Gill, S. S., and Parlikad, A. K. "IoT and Fog Computing-Based Predictive Maintenance Model for Effective Asset Management in Industry 4.0 Using ML." *IEEE Internet of Things Journal*, 2021. DOI: 10.1109/JIOT.2021.3101410.
- [12]. Haseeb, K., et al. "Intelligent and Secure Edge-Enabled Computing Model for Sustainable Cities Using Green Internet of Things." *Sustainable Cities and Society*, vol. 68, 2021, art. no. 102779. DOI: 10.1016/j.scs.2021.102779.
- [13]. Devi, G. N. R., et al. "Development of Medicinal Industries in Building a Replica to the Damaged Human Tissue for Artificial Organs with the Application of Micro-and Nano Technology (MNT)." *Journal of Optoelectronics Laser*, vol. 41, no. 3, 2022, pp. 79-83.
- [14]. Rosero, D. G., Díaz, N. L., and Trujillo, C. L. "Cloud and ML Experiments Were Applied to Energy Management in a Microgrid Cluster." *Applied Energy*, vol. 304, 2021, art. no. 117770. DOI: 10.1016/j.apenergy.2021.117770.
- [15]. Karnan, B., and Kuppusamy, A. "Graph Theory and Matrix Approach for Machinability Enhancement of Cryogenic Treated Cobalt Bonded Tungsten Carbide Inserts." *International Journal of Heat and Technology*, vol. 39, no. 4, 2021, pp. 1372-1382. DOI: 10.18280/ijht.390434.
- [16]. Rathore, S., Park, J. H., and Chang, H. "DL and Blockchain-Empowered Security Framework for Intelligent 5G-Enabled IoT." *IEEE Access*, vol. 9, 2021, pp. 90075-90083. DOI: 10.1109/ACCESS.2021.3089305.
- [17]. Subashka Ramesh, S., et al. "E-Voting is Based on Blockchain Technology." *International Journal of Engineering and Advanced Technology*, vol. 8, no. 5, 2019, pp. 107-109. DOI: 10.35940/ijeat.E1021.0585C19.
- [18]. Gasmi, K., et al. "A Survey on Computation Offloading and Service Placement in Fog Computing-Based IoT." *The Journal of Supercomputing*, vol. 78, no. 2, 2022, pp. 1983-2014. DOI: 10.1007/s11227-021-03827-8.
- [19]. Gill, S. S. "Quantum and Blockchain-Based Serverless Edge Computing: A Vision, Model, New Trends and Future Directions." *Internet Technology Letters*, 2021, e275. DOI: [10.1002/itl2.275]