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Experimental Study and Performance Analysis of Green Smart Grid for Futuristic and Sustainable Energy Management

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ABSTRACT

The Smart Grids (SGs) integrate communication, big data, and ML to boost productivity and "power demand and supply" management. By using ML, smart grids can respond to emergencies in a preemptive manner. In this paper, we provide a study of the smart grid and the application of ML in three parts. (1) First provide an examination to investigate ML methods' application in SGs. Here, we discuss research opportunities and relevant solutions. Additionally, we established the objectives of the proposed work. Moreover, a performance study among several algorithms, including SVM, ANN, and LR (Linear Regression), have been implemented. These algorithms estimate how much power the appliance will need in the HAN. (2) Secondly, we provide data to comprehend the power requirements of commercial and residential consumers in SGs. For this purpose, a smart plug reading dataset has been considered. Two data categories from the dataset have been derived, which are determined by user behavior. Additionally, hourly, and daily power demand is analyzed. Next, the time series problem has been solved to predict the power demand. For this purpose, ANN and LR algorithms are used. Based on the results, we found that LR provides a more accurate prediction. Additionally Compared to daily, weekly, and monthly demand predictions, the hourly demand predictions give better results. Moreover, it is necessary to forecast each pattern separately defined improved model for enhanced accuracy. (3) Finally, design a deep learning model for assisting "power demand and supply" management. In this context, two main types of power consumers are assumed and then the subcategories of consumers have been defined. Here, for each power consumption behavior, a neural network model has been trained and future power demand has been predicted. Further, the predicted power demand is converted into the required amount of power supply. The results have been measured over 33 hours in terms of hit and miss ratio. Based on the results, the proposed model provides an 85% hit ratio for best case and a 71% hit ratio for worst-case scenarios.

Keywords: *Experimental study, Machine learning, Performance comparison, Review, Supervised learning, Smart grid applications.*

1. INTRODUCTION

The Advanced power grid (smart grid) can oversee and control various functions like lighting, road alerts, and early seismic detection. Smart Grid is a network, which contains elements like transmission lines, sensors, software, etc [1]. The aim is to efficiently manage energy demand and supply. Smart Grids (SG) have communication between tools and sensors, so they can quickly meet user needs. The SG is also capable of detecting failures and can provide preference-based power routing. Smarter Energy, controlling the waste of energy, and lowering costs through data management are some of the benefits of SG [2]. Both Cleaner Energy and Smart Grids use less carbon-based energy and are made to handle a lot of work. The researchers are involving green sources of energy to make it sustainable. And Lower Costs, the SG to lower electricity costs by effective routing, rapid power outage management, and monitoring.

In SG demand-side management, supports smart functionality in several areas, including infrastructure development, and decentralized energy management [3]. Additionally, the aim is to minimize overall costs, and carbon emissions, control energy demand profiles, lower total peak demand, and improve sustainability [4]. It is comparatively new and requires more improvements [5]. In SG, a substantial volume of data has been produced. The examination of this data may yield various advantages in comprehending power utilization behavior, trends, and demand patterns [6]. The analysis of the data is necessary to strike a balance between the production and use of power for various industries [7]. This paper discusses the recent advancements in Serious Games utilizing Machine Learning technology. Next, important research areas that have chances for both academic and commercial research were highlighted. Further, to provide an understanding of power "demand and supply", we used a smart plug reading dataset. Additionally, by using this dataset, we explored the power demand patterns, based on time and power consumers. Further, to predict the power needed for various time frequencies of the power consumers under consideration, time series data analysis and machine learning techniques are used. Additionally, the performance is measured.

In addition, the power demand in domestic and industrial domains is increasing. However, the techniques of producing electrical energy are also improving and developing, but appropriate power management is also essential [8]. Because more than 55% of electrical energy is produced using thermal power stations [9]. These power plants are omitting harmful gases, which are also contributing to air pollution. Therefore, the wise use and appropriate management of electrical energy is also essential for the environment [10]. Electrical energy management is mainly focused on electrical energy "demand and supply". The power grid is used for administration of the

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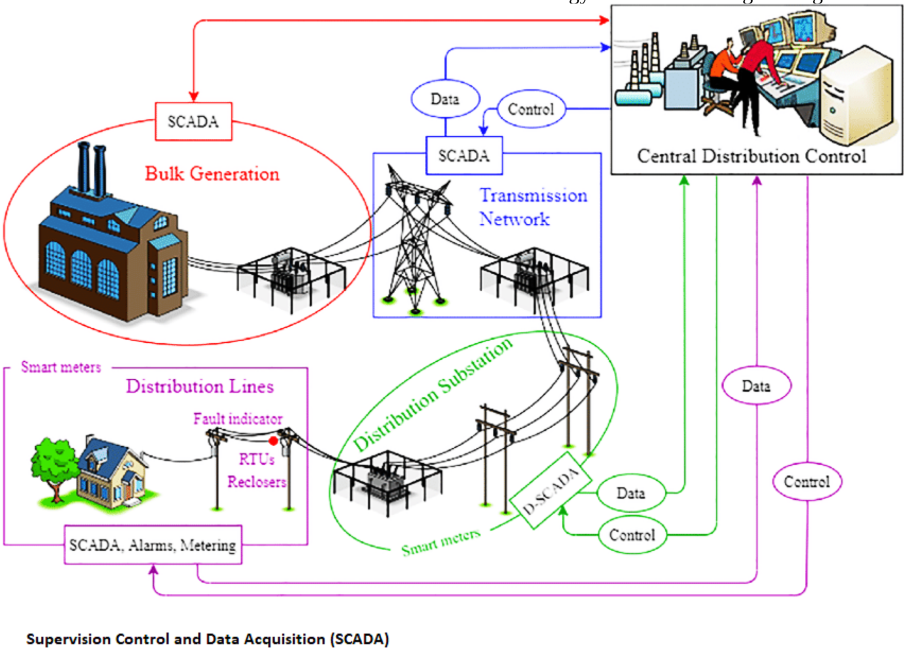


Figure 1: SG power distribution and control [12]

power, from generation to consumption [11]. The supervision control and data acquisition (SCADA) of the smart grid is used for demand and supply management. An example of SCADA is demonstrated in Figure 1 [12].

The SG has connected with all three participants, namely power generation, "transmission and distribution", and consumer [13]. All the units relate to the help of a data and control line. The data line is utilized for gathering real-time data. Additionally, the control lines carry the control commands to regulate the operations, based on decisions made in control centers [14]. The decisions are made in both modes, i.e. manual and automated. The automated decision-making process involves an ML algorithm, which analyzes the data and recovers usual and unusual patterns [15]. Usual patterns include the monitoring data and normal functioning. On the other hand, the unusual pattern includes data related to security, failure, or fault management [16]. Therefore, in this paper, we are also aiming to calculate the electricity usage behavior of the consumers. Additionally, simulates the power scheduling of the consumers to reduce power wastage. The structure of the paper is as follows: the first section provides an overview of the SG and requirements for power management. The next section provides a discussion about the recent development in SG using ML techniques. Additionally, a comparative study among ML algorithms has been discussed. The third section proposes a methodology to perform power demand profiling and perform prediction of future power demand. The fourth section is simulating a power scheduling technique for smart grids. Additionally, includes the concept of power demand and supply management for preserving power. Further, results are provided, and the conclusion and future work has been reported.

2. RELATED WORK

In this section, first we provide a review of recent literature, then the key issues in the current system have been discussed. Further, the objectives are listed and a comparison between predictive ML algorithms has been discussed.

2.1 Literature Review

The literature review of related work has been shown in table 1.

2.2 Research Opportunities

Smart systems with IoT capabilities are revolutionizing electric power systems. That has to do with the latest computational and communication technology. It offers a significant potential and chance to create and build solutions to deal with future sustainable power generation, preservation, distribution, and management because of the fusion of multiple technologies. It also includes renewable energy sources. This presents fresh chances to enhance the development of futuristic smart cities, national security, healthcare, and other areas. That technology is dedicated to offering efficiency and support in a range of real-world application settings. However, there are still several significant problems that need to be resolved if we are to raise the SGs' overall performance. An important area of research is understanding power supply and demand, demand volatility, the impact of the seasons on supply and demand, and intelligent decision-making for achieving the best possible balance between supply and demand. Furthermore, the following are some recognized areas for further investigation in smart grid applications:

- The HEM system needs to be given more attention. An important part of this method for managing energy based on demand and supply is scheduling appliances [4]. Researchers have had to use optimized schedules for machines to find out how HEMSs should work best [18].
- With DSM, it can make sure there is enough supply and use energy more efficiently. Its main goal is to lower CE without limiting power use [6]. It's hard to keep the SG safe [17], so we need to investigate and think about the security issues. In

order to observe things in real time, SG needs a fast connection [26].

- Energy demand will rise exponentially, so we must create strategies for effective energy management [7]. To handle SG consistently in the presence of renewable energies, a load forecasting system is also necessary for smart grids [21, 22].
- Furthermore, we must pay attention to both energy and data [23]. Furthermore, we must adjust the power supply to meet the needs of the consumer [24]. To efficiently manage resource usage and demand, we must also innovate [25] [28].
- To handle renewable energy, we must create an EMM. Furthermore, an algorithm for tracking EMM performance needs to be developed [19]. Using erratic energy sources calls for management. It is also difficult for users to regulate. Furthermore, users find it difficult to regulate. As a result, we must improve control and reliability. When merging renewable energy sources, we require a strategy for resource management [27].
- The detectors are unable to identify the hackers who are carrying out attacks [29]. The impacted devices may present a challenging problem for improved performance [30]. Furthermore, fresh security risks are always emerging [31]. To reduce load, smooth load, and reduce carbon emissions, environmental concerns seek to reduce and shape patterns of energy consumption [32].

Table 1: Literature based on related work.

Reference	Work Contribution	Outcomes
[4]	The multiple knapsack theory has been discussed. In this the comparative performance model has been proposed for the home energy model using heuristic algorithms.	With the integration of renewable energy sources, the system has become more efficient.
[6]	Developed a framework that was both adaptable and portable to cater to a wide range of customers. The design is designed to replace power disruptions with partial load shedding, which may be adjusted according to the user's particular preferences.	The architecture replaces power outages with preferred partial load shedding.
[7]	A method called WBFA, a cross between WDO and BFO, was proposed in this study. They provide a method for controlling home appliances' power usage. They used scheduling to increase sustainability and energy efficiency. In response to price-based DR programs, the WBFA acts.	The models are tested and evaluated in comparison to methods such as GWDO, BPSO, GA, and GBPSO.
[17]	Author discussed a safe DSM engine with machine learning for the Internet of Things grid, to handle breaches. Dishonest devices are recognized by the agent.	The findings of the simulation show that the DSM engine is efficient at consuming less power and is less susceptible to incursion.
[18]	Proposed DRSREOD-based HEMS algorithm. The goal of appliance scheduling is to lower the peak demand. To analyze and provide a range of options, tradeoffs have been estimated.	Based on trade-offs between size, CE, and TBD, this algorithm provides a way to choose a DG that best suits customer needs for size.
[19]	Introduced a security measure using security groups (SG) using decision-making processes and risk assessment.	Identifies and demonstrates the applicability of 5G's security features.
[20]	Introduced a framework for real-time data gathering and utilize RNN and LSTM to forecast energy consumption.	Shows connection among the SG, IoT, and ML components.
[21]	Introduced the STLF online tool for precise forecasting. Weather and electrical load data are utilized for training machine learning systems. Online forecasting is efficient since it utilizes up-to-date data records.	Advanced machine learning methods are recommended for online prediction.
[22]	Made advancements in the infrastructure upgrade of the electric utility. concentrated on how a smart grid differs from a traditional grid. Renewable energy integration is also considered.	The emphasis is on control mechanisms to maintain the supply of electricity and ensuring grid dependability.
[23]	Encourage energy storage as a grid asset by providing administrative and financial support. The workloads and operations of the market would benefit from this. There are chances to enhance grid performance with energy storage.	Improves the user experience, lower execution costs, and produce accurate service rates.
[24]	To forecast the smart grid's stability, an MLSTM is suggested.	After evaluation, the findings demonstrate that the MLSTM

		performs better than the other ML techniques.
[25]	The Internet of Things architecture was presented, and the topics of distribution, transmission, monitoring, and communication were covered.	Utility of IoT based smart grid and functionality has been shown.
[26]	Incorporate GPR and ML into the EMM. Initially, the optimization technique is applied to PES, PEC, and GR. Second, the GA model is utilized in conjunction with price, load, and renewable energy sources to construct the GPR model. There are seasonal differences.	Renewable energy sources are used to construct the energy management model in adoption with ML for better results.
[27]	Explored policy analysis focused on energy management, using the participation of aggregators and users in subsidiary programs.	The goal is to gain insights about usage trends, security threats, and main difficulties.
[28]	Give an IoT and EC-based assessment. The structure and prerequisites for putting the SG system into practice are emphasized.	After analyzing the framework, a few important problems and difficulties are noted.
[29]	The author proposes a technique to identify a cyber-deception assault in a smart grid using a GA for feature selection,	The detection plan is assessed and found to increase the accuracy of covert cyberattack detection.
[30]	The authors suggest a convolution-based classification approach to identify smart grid devices that exhibit malfeasance. By concentrating on the various features, the framework can detect rogue devices.	The framework produces extremely high accuracy in various contexts.
[31]	Presented a study on the use of machine learning to create smart applications for BT. The attacks are analyzed using machine learning techniques.	Future problems and difficulties are then discussed.
[32]	A summary of methods for SG consumers to offer guidance, inspiration, and information about energy saving is provided. The goal is to improve energy savings and manage flexibility by bringing ML techniques closer to SG mobile apps.	Discuss several elements of the designs, including technologies, motivation, consumer profiling, and the use of ML. The objective is to determine how applications integrate these characteristics.

2.3 Objectives

In this paper, we are investigating the utilization of ML techniques in SG, for effective distribution, administration, and conservation of power. The objective is to create, evaluate, and show how well machine learning approaches handle the heavy SG demand. Therefore, we are proposed following objectives for study:

1. **Understanding and predicting power demand:** We are identifying the workload dataset, which can be used with ML. Additionally, analyze SG data for seasonal influence on “demand and supply” of the user requirements (domestic and industrial consumer). Identifying the variations in demand for 24-hour time cycle.
2. **Design power distribution strategy using ML:** A load aware power distribution or scheduling system is proposed to design, which helps to supply energy according to the personalized requirements.
3. **Analysis of energy conservation technique:** The ML model is designed for energy efficient power management. This model considers the different sectors, application, and variations in power demand. Additionally, predict the schedule for managing the power supply.

2.4 Predictive ML Algorithms

Three supervised learning algorithms—ANN, SVM, and LR—have been explored in this work to better understand how machine learning approach’s function. A brief overview of the ML algorithms is given as:

Support vector machine (SVM): This binary classifier uses one or more hyper-planes to categorize the input. It can be applied to regression, outlier identification, and classification. The choice of hyperplane affects the categorization accuracy. We require the largest distance hyper plan for optimal precision. A higher-dimensional space was created by mapping the original dimensions for simpler separation. To facilitate calculation, mappings are designed. The problem specifies that a kernel function k(x,y) defines the mapping. With parameters α_i of the vectors x_i in the dataset, the hyper-planes can be selected using the following relation:

$$\sum_i \alpha_i k(x_i, x) = constent$$

Artificial Neural Network (ANN): This method is predicated on the idea of the nerve systems of humans. It is set up like a network, with neurons connecting to one another. The application—such as recognition, classification, or prediction—determines the setup. Synaptic connections were updated during ANN learning. It is a parallel, nonlinear system. It is composed of N The number of inputs into the network is denoted by x(n), and the connection weight of each input is multiplied by w(n). To produce the output, the weight and input products are added together and passed through an activation function.

Linear regression (LR): It is applied to ML and statistical challenges. Especially in relation to predictive modelling. The goal of this approach is to reduce prediction error. To comprehend the relationship between input and output, utilize this model. It is assumed in linear regression that there is a linear relationship between the input (x) and output (y). The input (x) can be combined linearly to calculate the y. The Ordinary Least Squares approach is used to train the model. Each input is given a scaling factor, or coefficient (B), by the equation. Giving the line a coefficient corresponds to an intercept or degree of freedom. The example may be:

$$y = B_0 + B_1 * x$$

Next, Using the dataset, which includes information on the electricity usage of appliances connected to a home area network (HAN), we are attempting to compare these methods. The Home Area Network Plug Readings [33] dataset is another name for the dataset. The dataset is used by the algorithms to learn about and forecast the power consumption of the appliances. Prior to using the dataset, preprocessing techniques are used to optimize the dataset. We have sorted the data in preprocessing based on the consumer id. Following preprocessing, we train the ML algorithms—SVM, ANN, and LR—that were previously presented. 20% of the samples were used for validation after the algorithms were trained using 80% of the samples. The readings for every test sample instance are predicted by the trained model. The algorithms' performance has been evaluated based on this forecast. Finding a time- and accuracy-efficient machine learning algorithm is the goal.

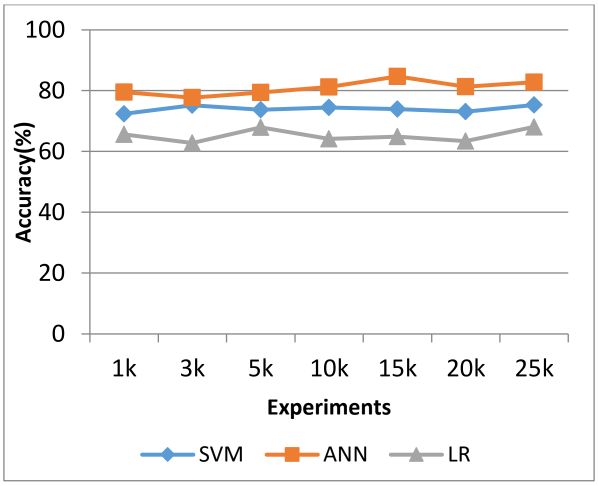
In this context, two parameters, i.e. accuracy and training time have been measured. Accuracy is a measurement of correctness. The accuracy can be computed using:

$$accuracy(\%) = \frac{1}{N}\sum_{i=1}^{n}(1 - |P_v - A_v|) * 100$$

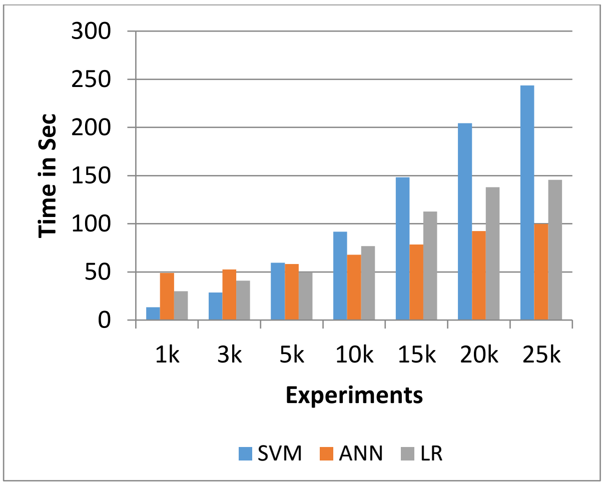
N represents the sample size to be predicted, V is the actual value in the test sample, and predicted value is V. The accuracy of the algorithms is shown in figure 2(A). The results show that as compared to LR, the SVM and ANN algorithms offer superior accuracy. SVR approach is employed here for prediction problem, instead of SVM. The accuracy range for the SVR is 72–75% on average, whereas the accuracy range for the ANN is 76–84%. Higher accuracy can be attained by applying the appropriate parameter tweaking. One crucial parameter system is the amount of time consumed.

$$time\ consumption = End\ time - Start\ Time$$

Figure 2(B) displays the algorithms' time consumption. The findings indicate that SVM and ANN require more time than LR. Furthermore, compared to ANN, the training time of SVR has increased significantly faster as the sample size has increased. Consequently, the SVR outperforms the ANN for short sample sizes. We discovered that the ANN is advantageous for large data by comparing the three techniques. Furthermore, the cost of the other two algorithms increases as the sample size increases.



(A)



(B)

Figure 2: shows the performance of training algorithms in terms of (A) Accuracy in (%) and (B) Time consumption in Sec

3. ANALYSIS OF ENERGY DEMAND OF SMART GRID

Additionally, it is tried to demonstrate the data analysis and recovered trends of the power demand [33]. In addition, by using ML algorithms we are trying to predict future energy demand. The dataset is provided by the Australian Government Department of Climate Change, Energy, the Environment, and Water [34]. The dataset was last updated on 11-04-2022.

The dataset consists of CUSTOMER_ID (Cid), READING_TIME (date), PLUG_NAME (PName), READING_VALUE (Reading), CALENDAR_KEY (CKey) and RECORD_COUNT (Rcount) attributes. The dataset

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Attributes, CKey and Cid are used for the same purpose (identification of the consumer). Thus, we eliminated Ckey from the dataset. Next, Attribute PName describes the product used and has not much relevance thus we eliminate PName. The data has finally been transformed from an attribute to an index and sorted by date; figure 3 displays the preprocessed dataset.

date	Cid	Reading	Rcount
2013-08-19 14:48:40	10014678	0.000	1
2013-08-19 14:48:40	10014678	0.000	1
2013-08-19 14:48:41	10014678	0.000	1
2013-08-19 14:48:41	10014678	0.000	1
2013-08-19 14:48:41	10014678	0.002	1

Figure 3: Shows after data preprocessing.

The dataset is a collection of user side energy demand. It contains more than 800 consumer data. Each user has different demand patterns and appliances use. Thus, some users are consuming less electricity, and some are consuming more. Now, based on the electricity consumption, we categorize the users into two groups: “High consumer group (Industrial)” and “Low power usage group (Domestic)”.

In order to categorize the users, we use a threshold value T, which is derived by:

$$T = \frac{1}{N}\sum_{i=1}^{N} R_i$$

Where, N is number of samples in dataset and R_i is the reading values of i^{th} instance of dataset.

The users, who have total number of samples more than T, is denoted as Industrial or high-power consumer group. On the other hand, the users, who have the entries below T is categorizeed as Low power usage consumer or Domestic user. Based on user categories figure 4(a), shows the total number of industrial consumers, and figure 4(b) shows the number of low power usages consumers. This categorized data is treated as user profile, to study the user specific behaviour. Here, we denote low energy consumer as C_1 and have a total of 9948 instances. With 105520 instances, the consumer C_2 is a commercial user. The duplicate index is present in both the user's group data and the user's individual data. Additionally, distribution of indexes is non uniform. Thus, we performed data re-sampling. Additionally, values are organized by sum of duplicate index. This results in total hourly load of the consumer.

Electricity demand is a time series problem. Time series data analysis is needed to solve and understand before building a prediction model. Therefore, time series decomposition is performed. Using this decomposition, the pattern of a time series is characterized by four components: Level (L) represents the base value, Trend (T) indicates the type and rate of change, Seasonality (S) shows cyclic events, and Noise or residual (R) accounts for random variations.

The interaction of the mentioned components leads to the creation of time series data. Seasonality significantly impacts the predictive value. The forecasted values may differ from the time series used for analysis in the training process. The time series components can be split into two types: Additive or Multiplicative. Additive decomposition involves explaining the link between components by adding them together. An additive time series exhibits a consistent increase or decrease and can be characterised as:

$$y(t) = L + T + S + R$$

The multiplicative time series shows exponential increase or decline in its trend pattern and can be expressed as:

$$y(t) = L * T * S * R$$

This work involves conducting additive time series decomposition. Figure 5 displays the visual time series decomposition. The subplots display the level, trend, seasonal cyclic pattern, and residual components. Figure 5(a) and 5(b) display the total hourly demand-based data components over a 24-hour cycle. The data depicted in the images indicates a rising tendency, however seasonality is not distinctly evident. Moreover, the residual becomes increasingly random over time. When the data is resampled to show daily total demand, the cyclic effect over a 7-day period is illustrated in figures 5(c) and 5(d). The component patterns of total weekly EED and monthly total EED, together with their cyclic relationship, are estimated during a six-month period. The hourly demand forecast is more intricate than other types of demand prediction based on the pattern we identified. Increasing the time period in data enhances the seasonality. Hence, prediction is simplified in comparison to hourly demand prediction.

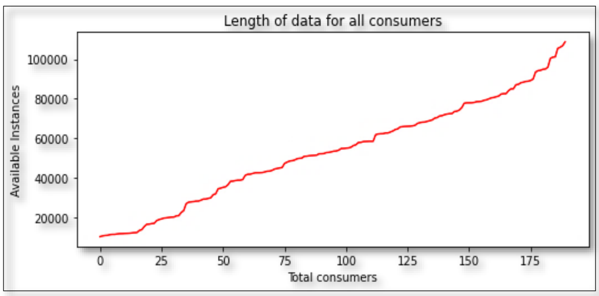

Figure 4(a): shows the industrial consumers

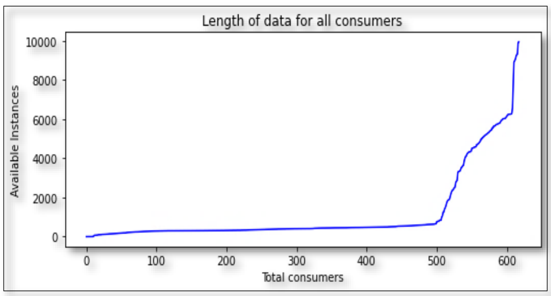

Figure 4(b): shows the domestic consumers

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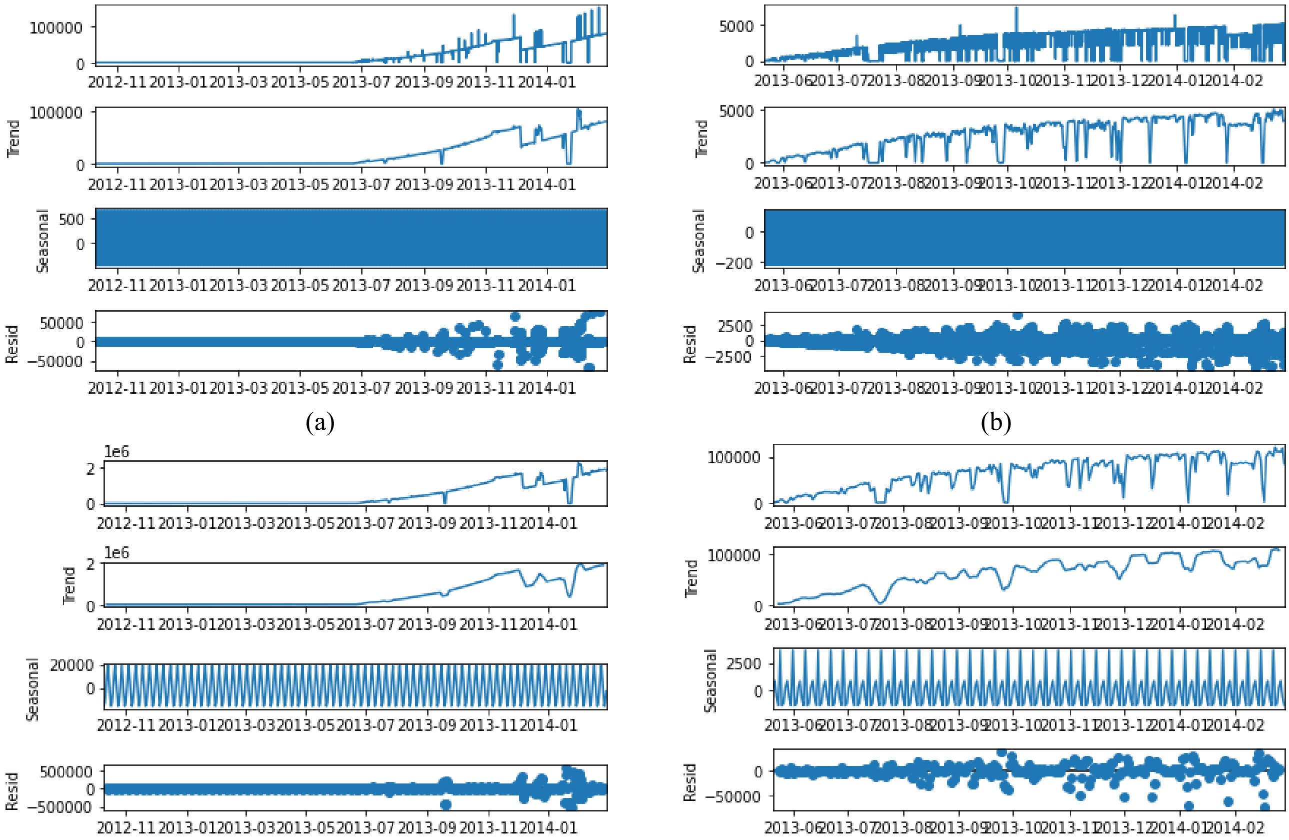

Figure 5: shows the visual seasonal time series decomposition of EED for variation of (a) consumer C_1 and (b) for consumer C_2 for hourly EED in 24-hour cycle, (c) and (d) shows the EED pattern for daily total demand and in 7 days period

3.1 Energy Demand Prediction

Next, we are utilizing the historical electricity demand data for analysis and to predict the future electricity demand for both type of consumers. The system for energy demand prediction is given in figure 6.

According to the figure, first the dataset is preprocessed. The preprocessed data is further categorized according to the energy demand into two user groups. The threshold-based strategy categorizes users. Subsequently, individual consumers from each group were chosen, and the client's data was converted into

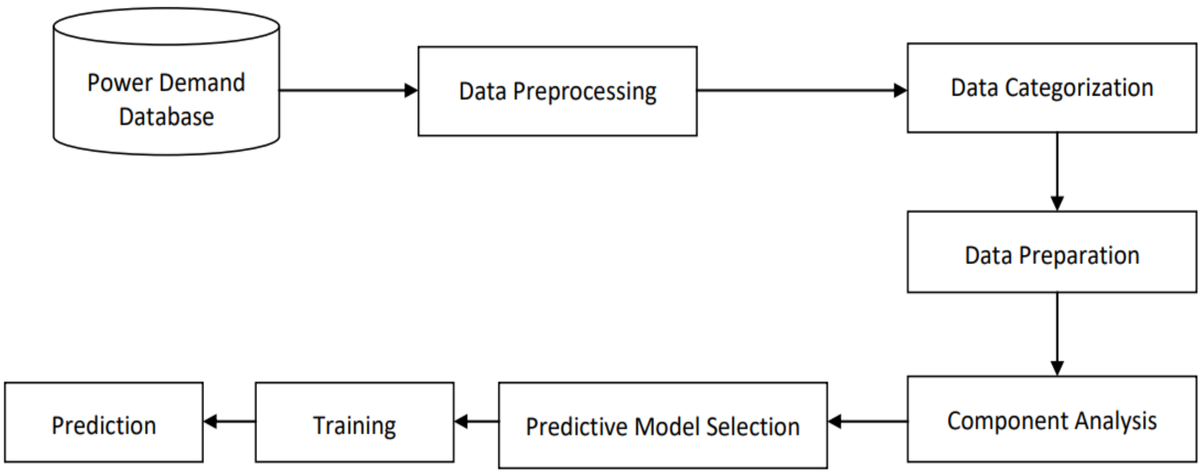

Figure 6: illustrates the proposed model for conducting predictive data analysis to predict EED per hour.

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into a time series problem. Additionally, the analysis includes examining the trend and seasonal effects on the data. We utilize three common machine learning algorithms: Sequential Neural Network (SNN), Long Short-Term Memory (LSTM), and Linear Regression. The ML algorithms have been trained and predictions have been made. Prior to using these machine learning techniques, we convert the data from a linear format to two-dimensional vectors. The vector sequence example is given in table 2.

Table 2: Training Vector

Sequence to train	Predictable
$t_1, t_2, \ldots . t_{24}$	t_{25}
$t_2, t_3, \ldots . t_{25}$	t_{26}
$t_2, t_3, \ldots . t_{26}$	t_{27}

Then, we partition the data into training (70%) and validation (30%) sets. ML algorithms are used for both consumer types, and training of ML algorithms has been conducted. Prediction is carried out after the training process. The SNN setup contains the Sequential model type. Layer 1 is a dense layer with 128 neurons, an input size of 24, and ReLu activation. Layer 2 is dense with 64 neurons and uses the ReLu activation function. Layer 3 is dense with 32 neurons and uses the ReLu activation function. Layer 4 is a dense layer with 1 neuron and uses the softmax activation function. The loss function is Mean Squared Error, and the optimizer is Adam. The LSTM model has been set up and its configuration is detailed in table 4. The experiment assessed the performance of both algorithms for both consumers using Mean Square Error (MSE) and training time on the validation data. Model: LSTM, Layer 1: LSTM, Neurons: 128, Input size: 24, Activation function: ReLu. LSTM network with 64 neurons in the second layer using ReLu activation function. LSTM network with 32 neurons in the third layer using ReLu activation function. Layer 4 is a Dense type with 1 neuron and Softmax activation. The Mean Squared Error loss function and the Adam optimizer are utilised.

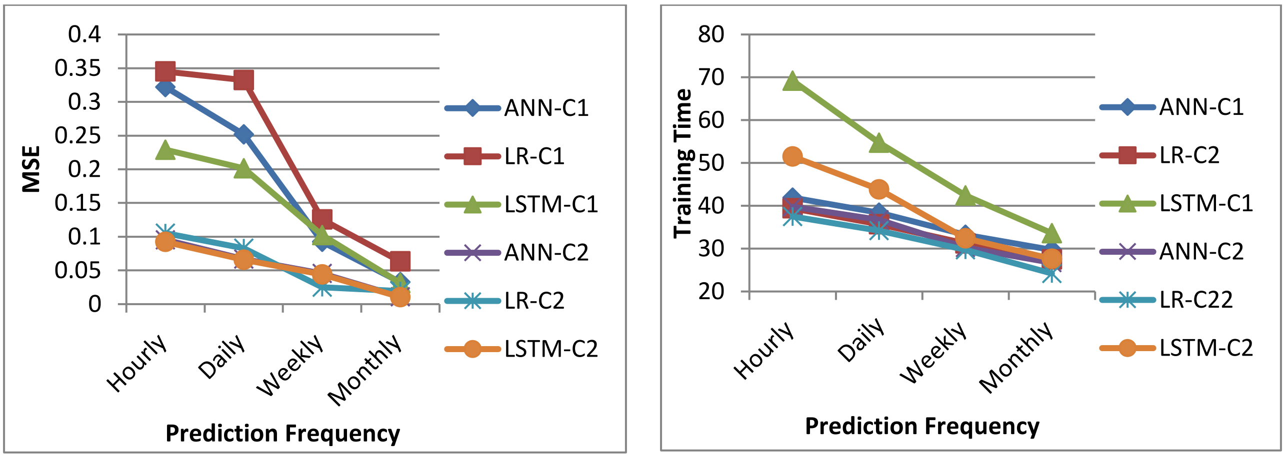
3.2 Results

Electrical energy demand prediction is conducted for two consumer groups: household and commercial. We developed two machine learning models to predict the EED. Performance is evaluated based on Mean Squared Error (MSE) and training time. Mean Squared Error (MSE) quantifies the accuracy of predictions by calculating the average squared difference between predicted and actual values. It displays the mean squared error, which is the average of the squared differences between the actual and anticipated values. That can be measured using:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2$$

Where, y_i' is predicted values and y_i is actual value and n is the total samples for prediction.

The MSE of different experimental scenarios (i.e. hourly, daily, weekly, and monthly demand) are given in figure 7(a). As given in figure, the MSE of the predictive algorithm is reducing with the increasing time of demand prediction. Additionally, the LSTM based prediction is superior as compared to the LR and ANN. Compared to other patterns, hourly patterns are more difficult to predict. Compared to home use, the industrial consumption EED estimate is more accurate. The training time is given in figure 7(b). Here, we have found commercial usage patterns require less training time.



(a) (b)

Figure 7: Evaluating the ML models' performance in predicting EED at different frequencies (hourly, daily, weekly, and monthly) for household and commercial users based on Mean Squared Error (MSE) and Training time.

4. POWER DEMAND AND SUPPLY SCHEDULING

This section introduces a proactive power distribution system. This method first analyzes the power utilization behavior of the client and based on the requirements the load distribution strategy has been prepared. The model is developed using machine learning. It is a power scheduling technique, which is used to preserve energy wastage. The method promises to deal

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with the gap between demand and supply. First it is required to understand the experimental scenario, then proposed power scheduling technique is presented.

4.1 Experimental Scenario

In this experiment, it is assumed that there are two main groups of power consumers, i.e. Industrial and Domestic [35]. The aim is to perform power supply decisions, according to the requirement of the consumer. In this diagram, two different power consumers relate to a central distribution and control system. Both the type of user includes the following properties:

1. **Industrial:** These consumers are involved in some kind of business-like manufacturing and/or service. This user group has involve three kinds of sub power consumers i.e. Low ($I_L = \{d_1^L, \dots, d_n^L\}$), Medium ($I_M = \{d_1^M, \dots, d_n^M\}$) and High ($I_H = \{d_1^H, \dots, d_n^H\}$). According to the demand profile, these subcategories of consumers are utilizing equipment and machinery. Additionally, devices also have different power profiles according to the scale of industry. Therefore, each consumer has defined a specific device power usage pattern.
2. **Domestic:** The domestic user is very different in power consumption profile. This consumer is consuming very fewer amount of power. But the variation in power utilization pattern is significantly varying with respect to the time. Due to higher variation of power usage pattern the five user profiles has been considered like Most high ($D_{MH} = \{d_1^{MH}, \dots, d_n^{MH}\}$), High ($D_H = \{d_1^H, \dots, d_n^H\}$), Average ($D_A = \{d_1^A, \dots, d_n^A\}$), Low ($D_L = \{d_1^L, \dots, d_n^L\}$), and very low ($D_{LV} = \{d_1^{LV}, \dots, d_n^{LV}\}$). Additionally, based on the power profile of home equipment's we define the domestic consumer profile.

In this context, two kinds of networks have been proposed to establish. The configuration of the experimental scenarios for both kind of distribution network is described as:

A. Simulation of industrial power consumption

In these simulations, three types of nodes have been introduced. The configuration of nodes is given in table 3.

Table 3 Simulation parameters

Consumer profile	**No of consumers**	**Active device (D_n)**	**Device rating (D_r)**
Low (I_L)	3	3	1.5
Medium (I_M)	3	4	2
High (I_H)	3	5	2.5

Here, a random function $Ran(x)$ is used to generate the traffic load. The customer profile has been prepared by using number of active devices (D_n) and device rating (D_r). The power demand (U_{pd}) of the consumer profiles are generated based on random number of active devices. Thus, for each user the generated amount of power demand is given by:

$$U_{pd} = Ran(D_n) * D_r$$

In this experiment, the demand profile is divided into 3 types of profiles and the demand profile consists of 3 users. Thus, a total of 9 user nodes are established. Each demand profile is initialized with a random number of devices. The random number is generated between 0 and the maximum number of devices as given in table 3. Additionally, to maintain more randomness, the numbers are regenerated in a specific time interval. Figure 8 demonstrates the power demand by each nine-

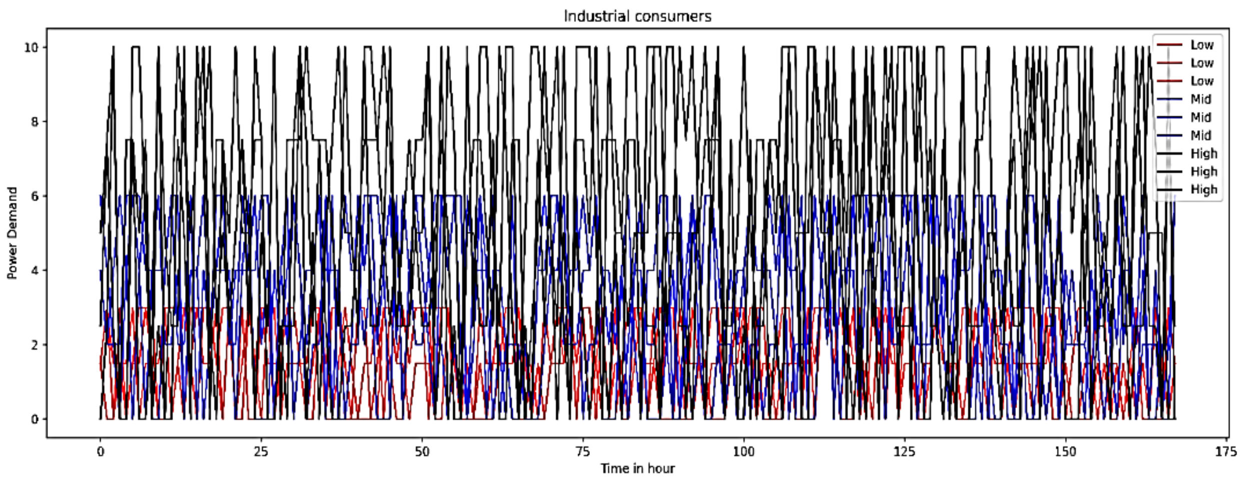

Figure 8: Generated Power Demand By all the Nodes belonging to Industrial sector.

The key details about the device profiles and user profiles are discussed in the next section.

4.2 Simulation scenario

user considered. Additionally, the total load for 168 hours has been generated. In addition, the total load per user profile is also measured. The following formula is used to compute power demand (P_p):

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$$P_p = \sum_{i=1}^{n} U_{pd}^{\,i}$$

B. Simulation of domestic power consumption

The domestic power consumption is small in amount, but the variation is higher. In addition, device utilization is also much random as compared to industrial consumption. Therefore, by considering the volatility in power consumption, there are five profiles considered. The required network configuration is given in table 4.

Table 4: simulation parameters for domestic consumer

Consumer profile	No of consumers	No of device each profile	Power requirement of each device
Most high (D_{MH})	3	7	1.25
High (D_H)	3	6	1.0
Average (D_A)	3	5	0.75
Low (D_L)	3	4	0.50
Very low (D_{LV})	3	3	0.25

As in the previous section, in this scenario each profile also utilizes the random number of devices selection. A total of 15 domestic consumers have been used. The power demand of each user is given in figure 9. Among them each user profile is initiated with the random number of active devices. The power rating of devices based on each user profile has been given in table 4. Additionally, the user profile-based power demand is also measured.

The power demand prediction is essential for a smart grid because proactive management requires the possible future demand and then tries to fulfil the resource demand. Therefore, prediction is an essential component of the proposed model.

In this experimental scenario, a total of 3 user profiles are considered for industry and 5 user profiles are used for domestic user profile. In this complex scenario, a stacked neural network model has been proposed. But, in the proposed prediction technique, we do it differently as given in figure 10. The proposed neural network model produces output for each specific profile of power supply. Therefore, a common neural network model is constructed and trained on different profiles separately. The learned models are saved and used for predicting the future one-hour possible power demand for the user profile. The used neural network is a 1D convolutional neural network and consists of six layers. The first layer is an input layer and consists of the 5 input neurons and activation function is used 'ReLu'.

4.3 Power Demand Prediction

The power demand prediction is essential for a smart grid because proactive management requires the possible future demand and then tries to fulfil the resource demand. Therefore, prediction is an essential component of the proposed model.

In this experimental scenario, a total of 3 user profiles are considered for industry and 5 user profiles are used for domestic user profile. In this complex scenario, a stacked neural network model has been proposed.

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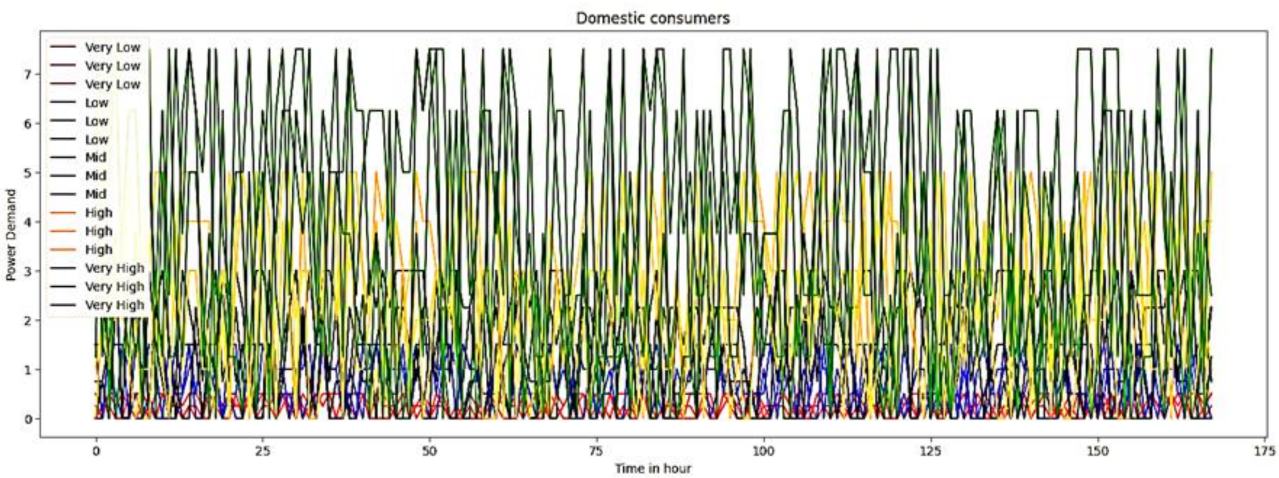

Figure 9: shows the power demand of all the nodes for domestic users

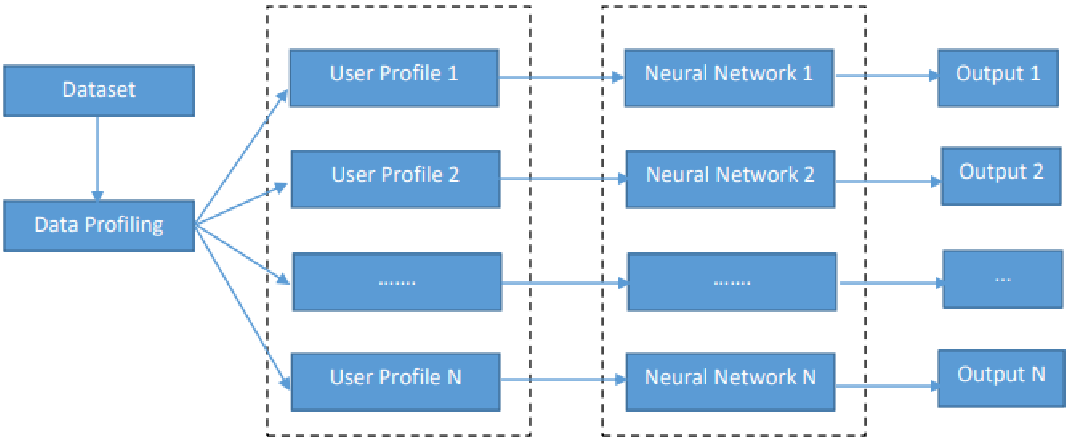

Figure 10: Proposed Neural Network Architecture for user profile-based power demand prediction

The second layer is max pooling layer and having the pool size 2, next a flatten layer has been used. Next a dense layer with 50 neurons and activation function 'ReLu' is used. Finally, the output layer with a single neuron is configured. Additionally, the model is compiled with the 'Adam' optimizer and loss model 'mse' (Mean Square Error) has been used.

4.4 Power Scheduling Technique

Figure 11 demonstrates the working of the proposed model. Additionally, the functional aspect of the model for power demand prediction and power supply management is demonstrated.

The model can also work with the smart meter datasets, where the plug reading database in terms of Time stamp, User id, no of devices, and Total active load can be used. According to the given model, it contains two different types of consumers i.e. industrial user and domestic user, who is generating the data. The data generation process is discussed in the previous section.

The dataset generated by the industrial and domestic users are utilized. So, the pre-processing technique is used to make clean the data. However, the presented work is directly utilizing the data. The pre-processed data can be used for data exploration tasks. The data exploration is performed, based on which the user profiles are created. Further, neural network is used as described in previous section and the training of all configured neural network has been performed. Further, by utilizing the last 5 samples the one-hour advance prediction has been performed. Additionally, at that hour a similar predicted amount of power supply is enabled. Additionally, power supply is increasing or decreasing on demand basis. The on-demand system provides the flexibility to fulfil the demands with a smaller number of resources. In this context, the given system is configured using the python script and random variables. Additionally, based on experiments, the performance of the implemented power scheduling system has been discussed in the next section.

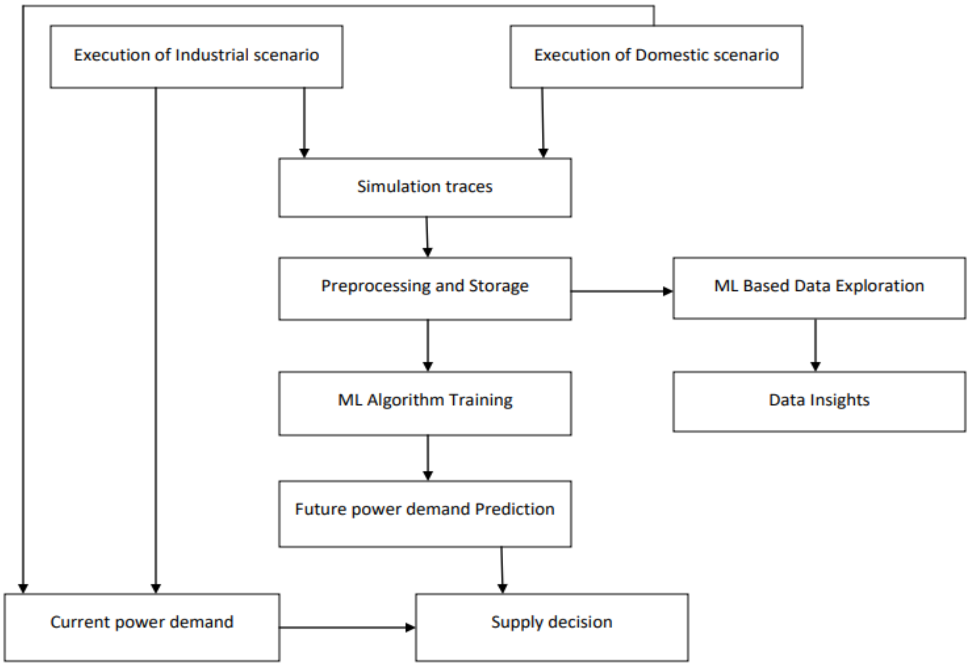

Figure 11: Proposed system demand and supply management

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4.5 Results Analysis

The configured network is trained on the profile specific power demand data. There are a total of eight instances of CNN is trained. Each CNN is learning with one type of profile. Additionally, performance in terms of Mean Square Error (MSE) has been measured. The MSE of the CNN for training and validation is given in figure 12 and figure 13, respectively. According to the results, MSE of all the models are significantly high, but, with the increasing number of epochs the MSE is reducing.

Thus, we need to train all the models for a long run before applying to the final model development. But, to simulate the utilization of the predicted power demand in fulfilling the user supply, we can utilize these trained CNN models. There are two groups of users i.e. industrial and domestic. Based on the power utilization patterns, both the user groups are subdivided into some subcategories. The industrial group of users is having three subcategories and domestic consumers has five. The model has been implemented to predict future power demand. Therefore, a set of eight neural networks has been trained on the traffic behavior of the individual user profiles. After training and validation, the MSE has been reported using figure 12 and figure 13. Next, it is also required to make power supply decisions for different user profiles. Figure 14 consists of the power supply for the industrial users. Figure 14 demonstrates the demand and supply of the medium demanding users. In this experiment, for training 135-hour data was used and for validation 33-hour data used. In this diagram, the red line shows the predicted power demand of the user group, which is calculated using the ML algorithm. Blue line shows the actual power demand and green line shows mean power demand. Similarly, in figure 15 the demand and supply of the domestic user profiles are given. In this diagram, black color line shows the supplied amount of energy based on prediction. Basically, the predicted amount of power is not actually supplied.

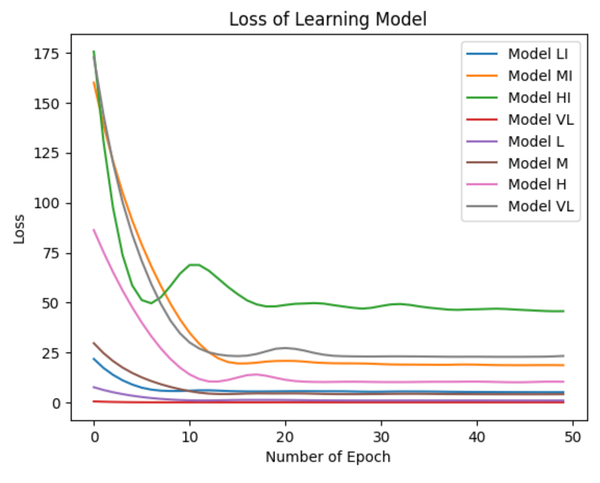

Figure 12 MSE of the CNN models for training samples

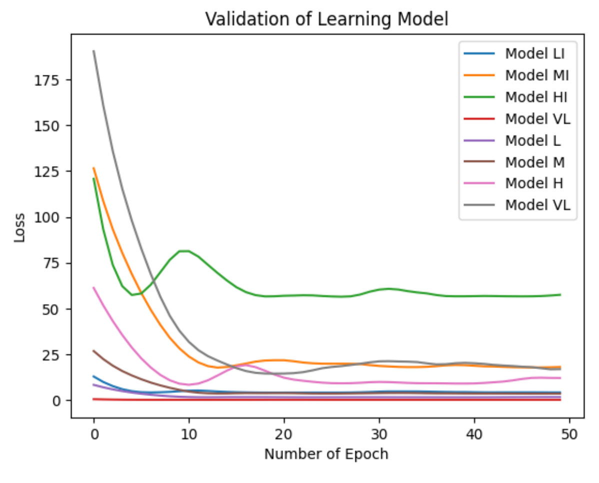

Figure 13 MSE of the CNN models for Validation samples

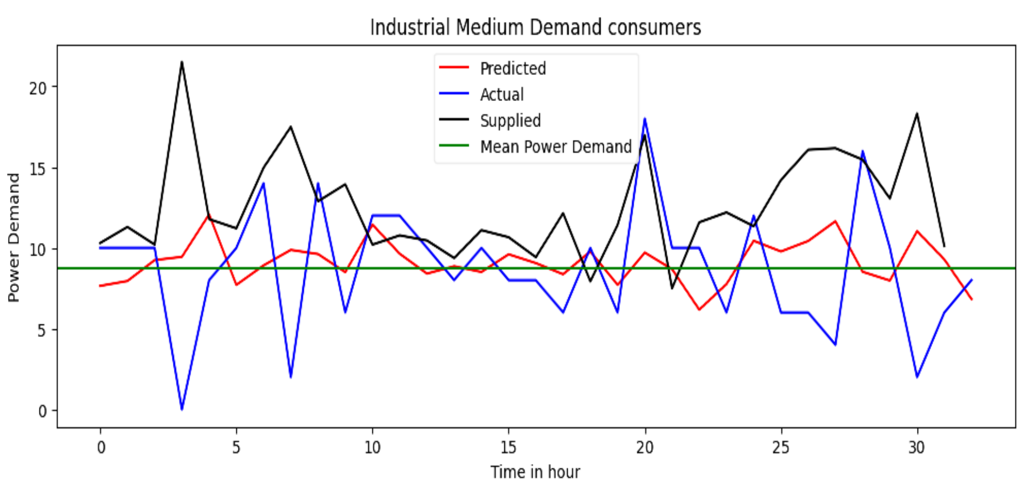

Figure 14: Power Demand and Supply for medium Industries Consumer

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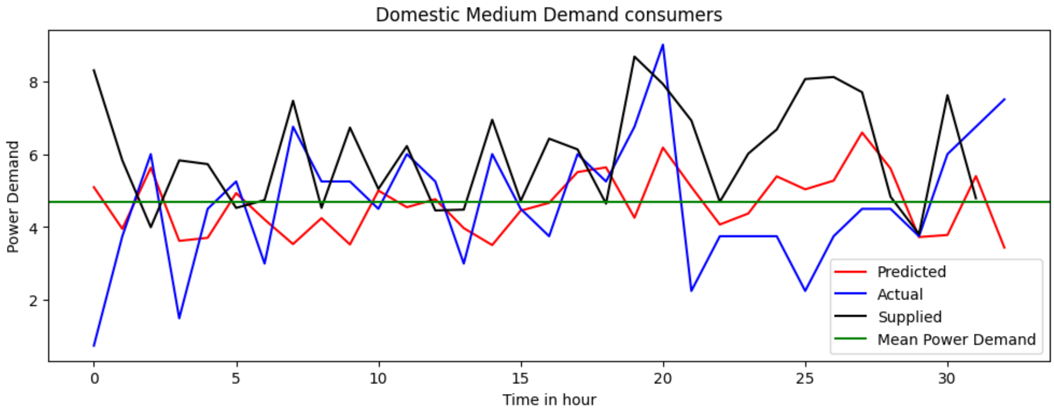

Figure 15: shows the power demand and supply for domestic consumer's group for medium

To supply the power for a user profile. Let, a specific user profile p is trained by the ML algorithm T_{model}, which predict an amount of power as demand D_t for the time t. This prediction is performed based on last five-hour actual demand D^A of user.

The last five-hour actual demand D^A can be defined as:

$$D^A = \{D_{t-5}, D_{t-4}, \dots, D_{t-1}\}$$

Currently t it is required to provide supply by adjusting the error in prediction in previous time stamp. Thus, first the error ΔE is measured in prediction using:

$$\Delta E = D_t - A_t$$

Where, A_t is the actual power demand of the user for t[th] hour.

Next, we adjust the measured error in prediction and predict the power supply S_{t+1} by using:

$$S_{t+1} = \begin{cases} D_{t+1} - \Delta E & if\ \Delta E = Negetive \\ D_{t+1} + \Delta E & if\ \Delta E = Possitive \end{cases}$$

In order to measure the quality of service of the proposed system the hit and miss has been measured. The Hit (H) shows the percentage amount of time, the algorithm successfully fulfilled the power demand (D_f) and measured using:

$$H = \frac{D_f}{T} * 100$$

Where the T is the total samples to predict. Similarly, the miss shows the number of times the algorithm fails (D_N) to satisfy the demand of the user using the following formula:

$$M = \frac{D_N}{T} * 100$$

Figure 16 includes the hit and miss of the algorithm. According to the results, algorithm shows up to 84.37% hit ratio and the minimum hit ratio is 71.87%. Similarly, the maximum miss ratio is 28.13% and minimum miss ratio is 15.63%. Thus, the proposed system can deal with the power management issues for achieving high quality of service with limited energy production.

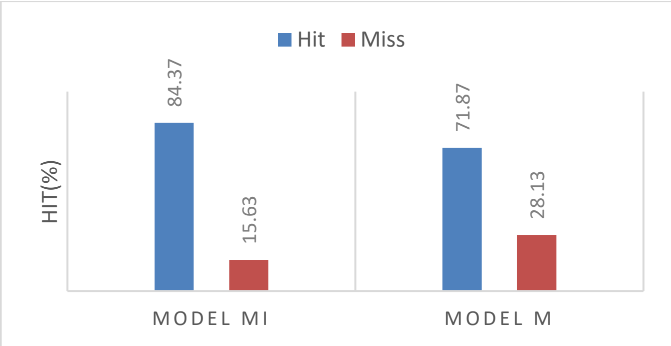

Figure 16: Hit percentage of the proposed power scheduling algorithm

5. CONCLUSION

The future of electricity supply and demand lies in smart networks. We can create a variety of cutting-edge applications to support SG by utilizing communication infrastructure and machine learning. We review the literature on smart grids in this study. We discovered via the review that proactive power scheduling is crucial for managing power supply and demand. Additionally, we have researched SVR, ANN, and LR, three machine learning algorithms. Our goal in using these algorithms is to forecast power usage. The HAN dataset [33] has been used for experiments. In this case, we discovered that the ANN outperforms the other two ML methods in terms of accuracy and time. The next step is to attempt to comprehend the power requirements of the various user types, such as residential and commercial. A sizable smart plug dataset is taken into consideration in this context. Two categories of customer patterns are also found. We conduct the visual analysis to determine the trends of hourly power consumption and daily power demand using these two types of consumer patterns. Additionally, we have experimented with ML approaches, including SNN, LSTM, and LR algorithms, to build a proactive technique. We also forecast the power need for hourly and daily demands after training. The study shows that compared to other types of demand projections, hourly trend prediction is more complicated. Furthermore, a comparative analysis reveals that LSTM outperforms ANN and LR in terms of prediction accuracy. Here, we discovered that a standard machine learning model cannot reliably forecast every kind of trend. Therefore, we need to train different machine learning models to precisely forecast each person's power need. Finally, we are simulating and discussing the electrical energy demand and supply, using the intelligent decision-making system. The proposed method can help in reducing energy wastage and can improve the quality of service by fulfilling the needs of the consumer profile. Therefore, some initial assumption has been made to configure the simulation. Additionally, the simulation has been conducted. In this experiment, eight 1D CNN has been configured in a stacked manner for learning and predicting the future power demand according to the power consumption profiles. Then prediction of the actual power supply is calculated one hour ahead. The prediction performance has been measured in terms of mean square error (MSE). Further to demonstrating the effectiveness of the proposed method the quality of service has been measured in terms of hit and miss. Based on the measured performance, the proposed method provides 85% maximum throughput. Finally, the actual power utilization or power saving of the model has also been evaluated. Additionally based on results, we can say the profiling and prediction can improve the quality of service of power distribution, reduce the power wastage, and improve better utilization of energy.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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