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EVALUATION OF ENERGY FORECASTING IN TRENDS OF DEMAND USING MACHINE LEARNING ALGORITHMS

Akanksha Jain[1], S.C. Gupta[2]

[1]Department of Electrical Engineering, NIT, Bhopal, India.

akanksha091091@gmail.com

[2]Department of Electrical Engineering, NIT, Bhopal, India.

scg.nit.09@gmail.com

Abstract

The diversity of machine learning algorithms influences power load forecasting in energy sectors. The forecasting of power load decides the policymaking of power generation and distributions. The forecasting of power load depends on various factors of non-linear characteristics of data. Recently several single and multiple predictive models have been developed. Machine learning algorithms and the artificial neural network have played a significant in forecasting in the current decade. This paper study of machine learning algorithms such as support vector machines, LSTM, ensemble classifiers, recurrent neural networks and deep learning. The various authors suggest that the combination of RNN and LSTM outperforms forecasting of power load instead of existing machine learning algorithms. The deep learning results also surprise the accuracy of forecasting. Deep learning processing is very complex instead of RNN and LSTM networks. However, the combined task of extracting attributes and classification has several advantages over specific limitations. This paper extensively analyses short-term power load forecasting using Chandīgarh UT electricity consummation for the last five years. The accuracy of forecasting estimates as RMSE, NMSE, MAE and MI. these parameters results suggest the pros and cons of machine learning algorithms. The hyper-parameters of the algorithm decide as per data transformation of energy consumption. The experimental validation uses MATLAB 2017 software.

Keywords: Forecasting, Power Load, Machine Learning, SVM, LSTM, RNN, Deep Learning, EM

Introduction

Load forecasting is the bridge between electricity generation and distribution. Load forecasting is the process of forecasting power load for the coming years, months, and weeks. The accurate forecasting of power loads manages the scarcity of power distribution. The forecasting of power plays a decisive role in nations' industrialization and urban development [1, 2, 3, 4]. Precise forecasting aids in planning and the expansion of a country's economic development. The forecasting of power load uses archive data with a statical model for prediction. The non-linear nature of the generation of power data maximises the prediction error, and factors of power generation and distribution are compromised. Despite several mathematical models of power load forecasting, forecasting accuracy is still challenging [5, 6]. The challenge of forecasting power load in a new area of research and using machine learning algorithms advances machine learning development and its derivation for forecasting in energy sectors. The integration of sensor technology with power distribution accumulates a massive amount

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of data. The collected data created many opportunities and challenges for informed decision-making. Data-intensive tasks proceed for analysis and forecasting; however, machine learning-based algorithms and models contribute more to the forecast process. Recently, machine learning algorithms and models have become core components of predictive modelling of production, consumption, and demand analysis due to their efficiency and efficacy [7, 8]. Despite various machine learning studies and the development of memory-based algorithms, novel methods for forecasting electricity demand have been proposed. The modelling of statical function derives several forecast-predictive models, such as multiple linear regression, autoregressive moving average models, grey models, and semi-functional partial linear models, which are the most commonly employed [9, 10–11]. However, while strong predictive results can be obtained generally, statistical approaches are limited by the basic linear assumption. For example, although no statistical assumptions are required for the grey prediction model, its predicting performance is related to the degree of dispersion of the input time series [12, 13, 14]. Furthermore, due to each model's unique strengths and limitations, it is uncommon for a single forecasting model to remain superior in all circumstances. Another study area is the evolution of power demand forecasting from statistical approaches to more hybrid forecasting models based on intelligent methods that can handle more challenging and nonlinear issues [15, 16, 17, 18]. The incremental approach to algorithm design includes hybrid algorithms of machine learning and artificial neural networks [19, 20, 21, 23]. In current trends of research in data analysis, recurrent neural networks (RNN) and feedforward neural networks (FNN) are applied in several models for the accurate prediction of power load forecasting. The model's prediction is based on the nature of the data processing in the decision system. The processing of electricity data in predictive models uses various algorithms, such as sub-set data formation in time series. Data pre-processing approaches such as ensemble empirical mode decomposition, singular spectrum analysis, and enhanced complete ensemble empirical mode decomposition with adaptive noise have been frequently employed for analysing electrical data. The EMD-based modelling framework was utilised to deal with the electricity demand series. The findings indicate that the EMD framework has the potential to be used for interval forecasting of energy demand. The authors of the paper [30, 31–33] examined a date-framework technique for selecting date information from observed load series and created feature selection techniques to improve model performance. A hybrid feature selection technique for mining the fundamental knowledge of electricity time series was also developed. It demonstrates the importance of pre-processing data methods in improving predictions. Apart from the data, pre-processing power load forecasting may also suffer from weather conditions. Seasonal effects increase the computational complexity and decrease the accuracy of dedicated models. So various authors consider seasonal pattern effect models to be incorporated into predictive modelling [34, 35, 36]. This paper's main objective is to study machine learning and artificial neural network-based power load forecasting. Another objective is the transformation of energy sensor data for classification and accuracy. Finally, through experimental analysis of datasets using machine learning algorithms, the conclusion of the research determines the concept of model formation in load power forecasting. The remaining segments of this study are as follows: Section II focuses on recent work in power load forecasting. In Section III, we describe the machine learning approach for forecasting. In Section IV, we describe the experimental analysis of algorithms. Finally, Section V concludes the study and the future direction of work.

II. Related Work

The author [1] provides In the field of renewable energy forecasts, a survey and evaluation of machine-learning algorithms have been conducted. Furthermore, the strategies used in machine-learning models for renewable-energy forecasts are described in this work, including data pre-processing procedures, attribute selection methods, and prediction performance metrics. Finally, scientists investigated renewable sources of energy, mean absolute error percentage levels, and coefficients of determination. The authors [2] provide a thorough examination of existing DL-based solar modules and wind turbine power forecasting approaches and a significant amount of data on electric power forecasting. It also contains the datasets that were used to train and validate the various DL-based predictive models, making it easier for new researchers to choose the right datasets for their projects. The author [3] achieves a new short-term load prediction algorithm with higher accuracy by using the weighted k-nearest neighbour technique. To compare prediction errors, the back-propagation neural network model and the moving average (ARMA model) are utilised. The correlation values reveal that the proposed forecasting model can capture flexible benefits and is suitable for forecasting short-term demand. The author [4] presents the present state of energy machine learning models, as well as a new edition and application taxonomy. A novel methodology is used to identify and categorise ML models based on the method of ML simulations, the type of energy, and the application sector. As a result of using hybrid ML models, the efficiency, resilience, reliability, and generalisation performance of ML models in energy systems have all improved dramatically. The author [5] investigates ANN, SVM, GBM, and Gaussian process regression as examples of data-driven predictive models for natural GPR. To train the model, we use quarterly Henry Hub natural gas market pricing data and a pass approach. These two machine learning algorithms, according to the data, function differently in predicting natural gas prices. However, ANN outperforms SVM, GBM, and GPR in prediction accuracy. The author [6] presented machine learning techniques used to construct a hybrid power forecasting model. Extreme boosting, subcategory boosting, and the randomised forest technique are the four machine learning algorithms used. Our hybrid model improves forecasting by using feature extraction to preprocess data. ML algorithms are frequently good at accurately predicting high energy, but our hybrid version improves forecasts by using feature engineering to preprocess data. The author [7] proposes using a groundbreaking deep learning-based technique to forecast electrical load. A three-step model is also developed, with a hybrid feature selector for feature selection, an extracting features technique to reduce redundancy, and improved SVM and ELM for classification and forecasting. The numerical simulations are graphed, and the statistics are presented, suggesting that our upgraded methods are more accurate and perform better than SOTA approaches. The author [8] used a seven-year dataset of charging events collected from public charging stations in Nebraska, the United States. The

XG Boost regression model exceeds the other techniques in predicting charging needs, with an RMSE of 6.7 kWh and an R2 of 52 percent. The author [9] proposes using a variety of data mining approaches, such as pre-processing past demand data and analysing the properties of the load time series, to examine patterns in energy usage from renewable and non-renewable energy sources. The author [10] presents two approaches to improving district energy management. A heater set point temperature is used to directly regulate building demand, in addition to improving district heat generation via a multi-vector energy centre. These findings show the potential advantages of managing energy holistically, taking into consideration a variety of energy vectors as well as supply and demand. The author [11] examines recent advancements in the smart energy sector, with an emphasis on methodology in key application areas and important implemented examples, as well as highlighting some of the sector's significant challenges and charting future prospects. The goal of this study is to present an overview of computational intelligence's current condition in the subject of smart energy management as well as insight into how current limits might be overcome. The author [12] proposes Smoother diesel generator performance can be combined with peak shaving using renewable energy, reducing demand variability that must be met by conventional units. This operation tries to limit the maximum capacity of diesel engines while also increasing the renewable energy supply to the grid. The author [13] proposes to acquire season-based segmentation data and develop a deep learning method for projecting electricity usage while accounting for long-term historical dependency. The monthly electricity use data is used to do the cluster analysis first. The load trend characterization is then performed to gain a better understanding of the metadata that falls into each of the clusters. The author [14] provides intervals of prediction that more accurately represent the underlying complexity of complex power system design and operation. The findings reveal that the proposed model can yield promising projections when compared to alternative combination schemata, and it can be valuable for policymakers and public agencies in preserving the security and control of the energy system. The author [15] applies a one-of-a-kind data set that contains considerable strength and tenant time-use data from UK homes, as well as a groundbreaking clustering approach for capturing the entire structure. Discuss how such an approach can result in a customised strategy for residential peak demand reductions and response measures, as well as a better understanding of the constraints and opportunities for requirement flexibility in the domestic segment. According to the author [16], a useful integration model stacking structure has been designed to meet the growing energy demand. To ensure that the final model can observe datasets from a range of spatial and structural angles, the stacking model leverages the advantages of numerous base prediction algorithms and converts them into "meta-features." With accuracy gains of 9.5 percent (31.6 percent) for Case A and 16.2 percent (49.4 percent) for Case B, the stacking method outperforms earlier models. The author [17] demonstrates a variety of perspectives and the rising interest in and quick response of machine learning technologies to successfully tackle the technological problems of the smart grid. High-performance data collection and analysis for intelligent decision-making in large-scale, complex multi-energy systems, lightweight machine learning-based approaches, and other difficulties are yet unsolved. The author [18] proposes a novel and precise integrated model for short-term load and pricing forecasting. This package includes the gravitational search strategy, variational mode decomposition, mix data modelling, feature selection, generalised regression neural network, and generalised regression neural network. According to the findings, the suggested model exceeds the existing benchmark prediction model in terms of accuracy and stability. The author [19] presents in-depth information on the utilisation of previous innovations in ITS, computer hackers, energy-efficient SG use, effective use of UAVs to ensure the best 5G and beyond 5G communications services, and smart medical systems in a smart city. The author [20] proposes LR, SVM, GBM, and RF as four alternative classification algorithms that are compared to our methodology. An MLP-based system for calculating a building's energy consumption based on data from a WSN, such as light energy, day of the week, humidity, temperature, and so on They provide state-of-the-art results in the testing set, with 64 percent of the coefficient of determination R2, 59.9 percent RMSE, 27.3 percent mean absolute error MAE, and 28.04 percent MAPE. The author [21] reports on energy, peak electricity usage, air pollution, mortality and morbidity, and urban susceptibility. It also examines new data on the characteristics and magnitude of urban overheating, as well as analyses of recent research on the relationship between urban heat islands and rising temperatures. The author [22] used, in order to estimate electricity demand in hourly intervals, a range of machine learning algorithms at the individual building and aggregated levels. When processing time and error accuracy were factored in, the results showed that boosted-tree, random forest, and ANN produced the best hourly granularity prediction results. The author [23] provides a comprehensive analysis of building energy prediction, encompassing feature engineering, prospective data-driven models, and predicted outputs, which covers the full data-driven process. The author [24] provides a thorough examination of deep learning-based renewable energy forecasting systems in order to determine their efficacy, efficiency, and relevance. To improve forecasting accuracy, we also look at various data preparation strategies and mistake post-correction processes. Several deep learning-based forecasting algorithms are thoroughly investigated and discussed. The author [25] provides A classification study is being carried out using AI algorithms and current solar power prediction models. Taxonomy is a system for classifying solar energy forecasting methods, optimizers, and frameworks based on similarities and differences. This research can assist scientists and engineers in conceptually analysing a variety of solar forecast models, allowing them to select the optimum model for any usage scenario. In energy economics publications, the author [26] proposes that SVM, ANN, and GAs are among the most commonly used methodologies. They explore the literature's successes and limitations. The author [27] conducted a study of short-term energy demand forecasts at the district level using two deep learning models; the DL models had higher predicting accuracy at distinct hidden neurons due to the suggested network layout. The author [28] describes a weather prediction method based on previous days' weather conditions that is used for optimal weather conditions. According to a study of predictive accuracy between new methods and known algorithms, the RMSE accuracy of a predicting approach that is based on LSTM networks can reach 4.62 percent for optimal weather circumstances.

The author [29] proposes the ability to forecast the best weather conditions using a method based on the past day's climatic data. The RMSE accuracy of LSTM infrastructure prediction approaches can reach 4.62 percent under favourable climatic circumstances, according to research comparing the projected accuracy of innovative approaches and known algorithms. The author [30] used a fresh augmented optimization model that was constructed and refined using a differential evolution methodology based on the bagged echo state network. Bagging is a network generalisation technique that improves network generalisation while lowering forecasting error. Due to its great accuracy and stability, the proposed model can be a useful tool for estimating energy use. Among the techniques used by the author [31] are an auto-gressive integrated moving average, an ANN, a fuzzy inference system model, an adaptive neurofuzzy inference system, support vector regression, an ELM, and a genetic algorithm. When compared to the top artificial intelligence and econometric models, the proposed approach reduced mean squared error by 22.3 percent and mean absolute percentage error by 33.1 percent in a sample inquiry. The author [32] proposes Utility businesses require a stable and robust algorithm for accurate energy demand prediction in a variety of applications, including electricity dispatching, market participation, and infrastructure planning. The forecasting outcome supports the enhancement and automation of the predictive modelling process by resolving knowledge gaps between machine learning and traditional forecasting models. The author [33] proposes the whole wavelet neural network methodology, which is an ensemble method that uses the overall wavelet packet transform and neural networks. The proposed method can assist utilities and system operators in precisely forecasting electricity consumption, which is important for power generation, demand-side management, and voltage stability operations. According to the author [34], an SVM and an upgraded Dragonfly algorithm are used to generate short-term wind energy. To increase the performance of the standard dragonfly approach, an adaptive learning multiplier and a convex optimization strategy are proposed. The suggested model outperformed existing methods such as multilayer perceptron networks and Gaussian process models in terms of prediction accuracy. The author [35] proposes a hybrid technique that combines the lion swarm optimizer with the genetic algorithm to improve the standard least-squares support vector machine model. When the new algorithm's forecasting results are compared to the previous eight methods, it is clear that the hybrid algorithm has a better global optimization capability, a faster convergence rate, higher accuracy, and a medium calculation speed. The author [36] demonstrates that total GHG emissions from the energy-generating industry can be predicted using DL, SVM, and ANN approaches using CO2, CH4, N2O, and F-gases. All of the algorithms tested in the study, according to the findings, gave individually satisfying results for forecasting GHG emissions. The greatest R2 value for emissions, according to the expected data, ranges from 0.861 to 0.998, and all conclusions are considered "excellent" in terms of RRMSE. The author [37] provides a thorough analysis and evaluation of previous DPTs, but it also identifies adequate application scenarios for each prediction model and summarises ways to accommodate for dealing with prediction inaccuracies, all of which will assist prospective designers in selecting appropriate DPTs for various applications and contribute to further improvements in the performance of PEMS for hybrid and plug-in hybrid electric vehicles. The author [38] proposes that in a smart grid with high renewable penetration, an ISEMS is employed to meet energy demand. For exact energy estimations, the proposed method compares a variety of prediction models with hourly and daily planning. In terms of performance accuracy, the PSO-based SVM regression model outperforms other prediction models. The author [39] proposes the DE clustering technique, which is based on theoretical morphology's basic processes and is used to select days in the proposed approach that have similar NWP information to the projected day. The innovative GRNN prediction framework based on the recommended DE clustering methodology outperforms the DPK-medoids clustering-GRNN, the K-means clustering-GRNN, and the AM-GRNN in terms of day-ahead wind power forecast. The author [40] discovered that artificial neural network ensembles are the best for generating short-term solar power forecasts, that asynchronous sequential extreme learning machines are the best for adaptive networks, and that the Bootstrap procedure is the best for assessing uncertainty. When paired with hybrid artificial neural networks and evolutionary algorithms, the findings bring up new possibilities for photovoltaic power forecasting. The author [41] provides a look at how AI is employed in disaster recovery applications. The research is divided into categories according to the AI/ML algorithm used and the energy DR application area. The paper concludes with a review of the advantages and disadvantages of the AI algorithms studied for various DR tasks as well as suggestions for future research in this rapidly expanding subject. The author [42] investigated the effects of climate change on the fuel efficiency of urban buildings using machine learning techniques and future weather simulations. Because there is no universal measure capable of providing such a worldwide comparison, there is no optimal combination of criteria for generating the most reliable machine-learning-based projection. The author [43] proposes that KCNN-exact LSTM's energy demand forecast is a potential deep learning model for energy consumption forecast problems because it can find spatiotemporal connections in the data. Using well-known quality criteria, the reliability of KCNN-LSTM was compared to the k-means variation of state-of-the-art electricity consumption forecast models. The author [44] examines Using actual pollution and sustainable consumption data, the NARM, LMSR, and LS Boost approaches were used to anticipate the energy usage requirements of large-scale city-wide utilities, utility companies, and industrial clients. In the summer, fall, winter, and spring seasons, the coefficient of variation of the LS Boost model is 5.019 percent, 3.159 percent, 3.292 percent, and 3.184 percent, respectively. The author [45] contains a thorough assessment and comparison of several simulations in order to select the best forecasting model for reaching the required result in a number of situations. With coefficients of correlation of 0.972 and 0.971, respectively, the BRBNN and the LMBNN provide better forecasting accuracy and performance. The author [46] examines renewable energy and electricity projection models, which are used as a critical and systematic tool for energy planning. The forecasting intervals are divided into three categories: short-term, medium-term, and long-term. The outcomes of this study will aid practitioners and researchers in recognising prediction methodologies and selecting relevant methods for achieving their desired goals and forecasting criteria. The author [47] presents PACPA, a revolutionary

PACPA that improves CPU and bandwidth usage. It's based on a side-by-side comparison of the most widely used prediction models. Our empirical findings demonstrate that the proposed methodology saves 18% of energy while lowering service violations by over 34% when compared with some of the most commonly used placement algorithms. The author's [48] impact on energy production, demand, and greenhouse gas emissions Climate scenarios RCPs are used to project changes in weather elements because of this. Under RCP2.6, RCP4.5, and RCP8.5, hydropower generation will increase by around 2.765 MW, 1.892 MW, and 1.219 MW in the near future, correspondingly, and by around 3.430 MW, 2.475 MW, and 1.827 MW in the long term. The author [49] discovered distinct characteristics in neural networks and support vector machines whose incorrect modification will cause mistakes to rise. The algorithms can be adjusted to match a variety of situations thanks to the many parameters. A developing trend is the use of machine learning to digitise wind power estimations. The author [50] creates In response to the recent power demand patterns, a new unique power demand forecasting system based on the LSTM deep-learning approach has been developed. They conducted tests to determine the inaccuracy rates of the forecasting module as well as the unanticipated shift in energy patterns in the actual power demand surveillance system. The author [51] proposes that residential management systems use an hour-ahead load management algorithm. A steady price methodology based on artificial neural networks is proposed to deal with the complexities of future pricing. Calculations with non-shiftable, shiftable, and guided loads are used to validate the suggested energy management method's performance. The author [52] proposes Under the machine learning structure and logic, machine learning approaches are used to provide load prediction, which is to fulfil tasks T using performance measures P and based on learning from experience E. They conclude with a list of well-studied and under-explored sectors that could be further investigated.

III. Machine Learning Algorithms

Forecasting power load is a big challenge in the energy sector in the current decade. Machine learning algorithms provide frameworks for analysing production, consumption, and distribution. With the coupling of supervised learning and unsupervised learning, machine learning derives thousands of algorithms in the form of single and multiple predictive models for forecasting. The development of machine learning algorithms focuses on the accuracy and effectiveness of algorithms. This paper studies several machine learning models but focuses on support vector machines, LSTM, deep learning, ensemble-based classifiers, and recurrent neural networks (RNN). The accuracy of algorithms varies according to the sampling of energy data and modelling of models. The basic concept of the machine learning algorithm is to select the power load of the past period as training samples, design a suitable network structure, and use training and learning algorithms to meet the accuracy requirements of energy sectors. The processing of machine learning models in power load data is shown in figure 1.

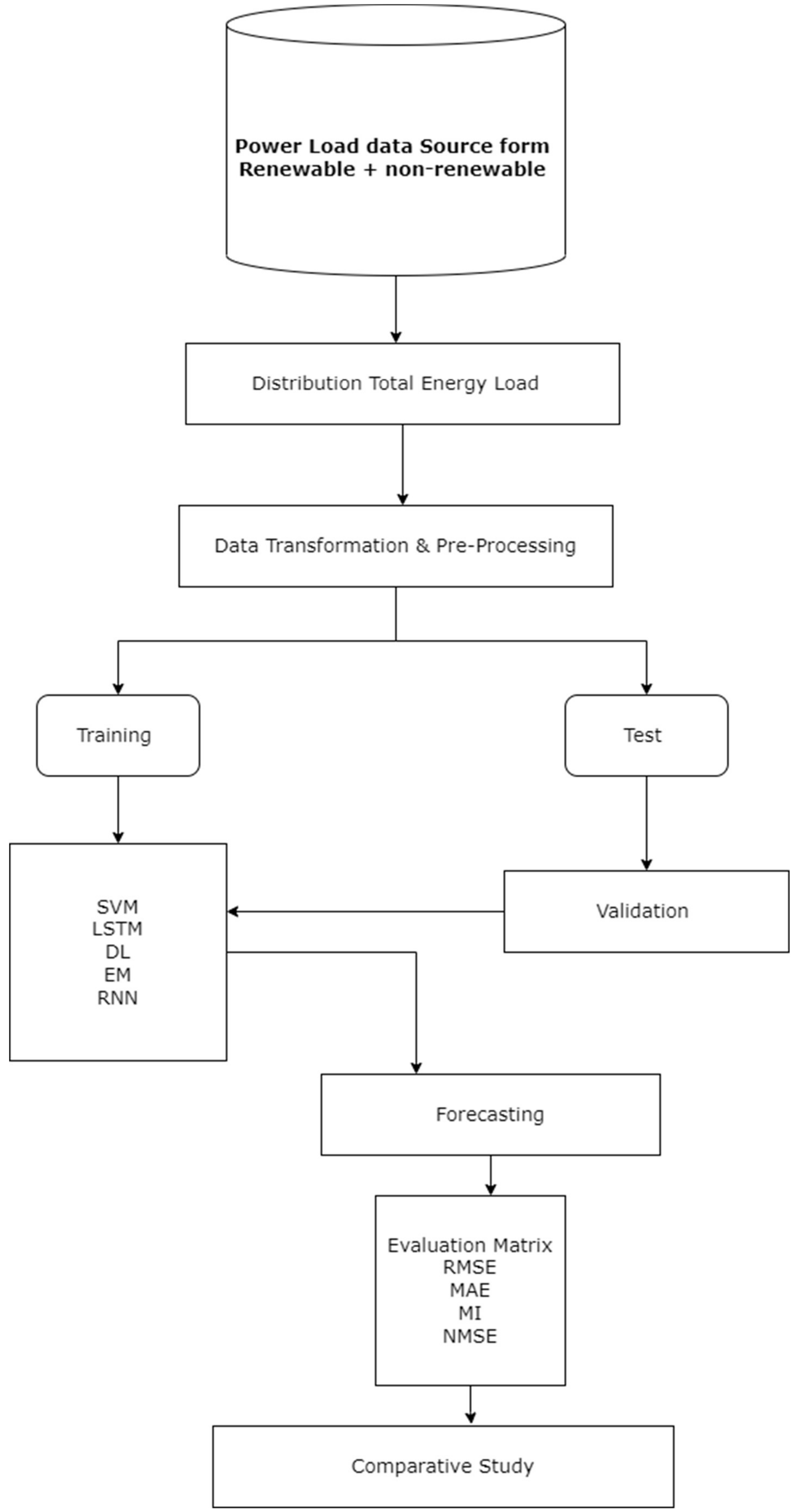
Power Load data Source form
Renewable + non-renewable
Distribution Total Energy Load
Data Transformation & Pre-Processing
Training
Test
SVM
LSTM
DL
EM
RNN
Validation
Forecasting
Evaluation Matrix
RMSE
MAE
MI
NMSE
Comparative Study

Figure 1 process block diagram of machine learning algorithms-based forecasting of power load

Support Vector Machine (SVM)

Vipin developed the SVM (Support vector machine) machine learning technique in 1990. The support vector machine is used in forecasting and pattern identification. Support vector machines can be linear, non-linear, or sigmoid in nature. The non-linear support vector machine maps the feature data from one plane to another. The data plan separation is non-linear, and the decision factor correlates with the margin function of the support vector. The equation's hyperplane is deduced as[14,15,16,17]

$$WD.xi + b \geq 1 \; if \; yi = 1$$

(1)

$$WD.xi + b \leq \; -1 \; if \; yi = -1$$

Here W is weight vector, x is input vector yi label o class and b is bias.

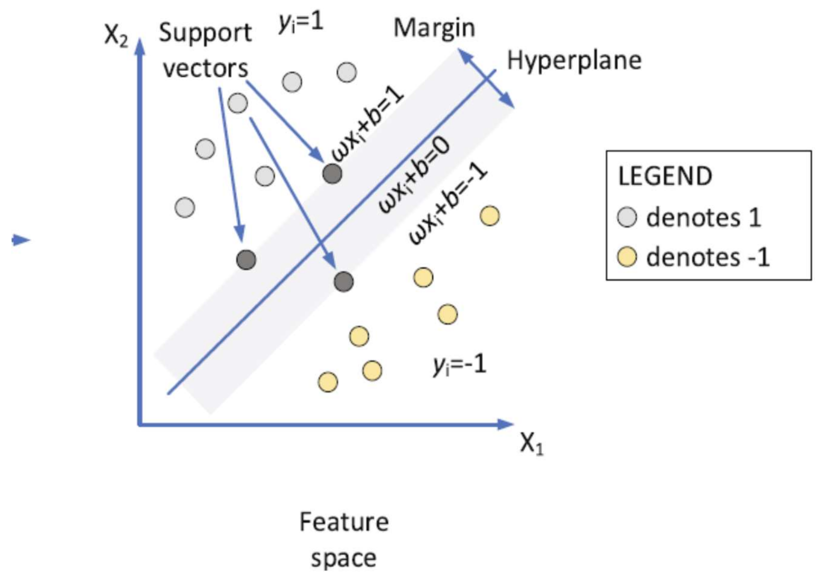

Figure 2 process block diagram of support vector machine.

The minimization formulation of support vector

$$Minimize \; \frac{1}{2}||w||2 + C\sum_{i=1}^{n} \varepsilon i \;, i = 1,2, \dots \dots, n$$

$$subject \; to \; y_i(w^T D.x1 + b) \geq 1 - \varepsilon 1$$

$$\varepsilon_i \geq 0 \; i = 1,2, \dots \dots, n \dots \dots \dots \dots \dots \dots \dots \dots . (2)$$

Here C is constant, n is number of observation and $\varepsilon 1$ is slack variable.

The rule of decision function is

$$f(x) = \sum_{i=1}^{n} yi\alpha iK(xi, xj) + b \dots \dots \dots \dots \dots \dots . (3)$$

Recurrent Neural Network (RNN)

Recurrent neural network (RNN) is special case of artificial neural network and design for the sequential time series data analysis. The major advantage of RNN networks is transversal of signals in forward and backward. They create network loops and allow internal connections between concealed components. RNNs are more suited for using information from previous data to estimate future data when they have such internal connections. RNNs, in particular, enable the exploration of temporal correlations among disparate data sets [24,25,26]. Figure 3 show the processing of RNN. The processing of input x={x1,x2,………………xT}, the RNN estimates hidden state sequence h={h1,h2,……………..,hT} and output of sequence is y={y1,y2,y3,………yT}

$$h_t = f(Whxxt + Whhht - 1 + bh) \dots\dots\dots\dots\dots\dots (4)$$
$$yt = g(Wyhht + by) \dots\dots\dots\dots\dots\dots\dots. (5)$$

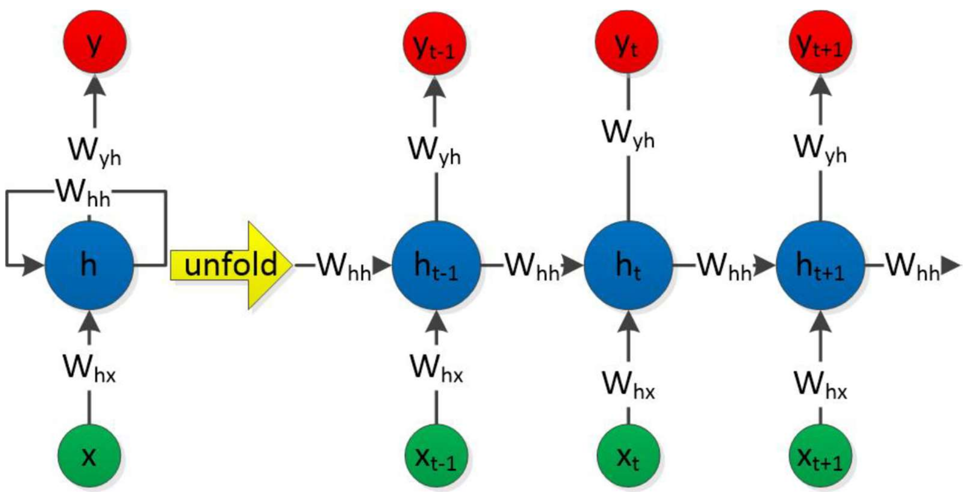

Figure 3 processing of recurrent neural network in set of input, hidden and output sequence

In equation (4) and (5) Whx, Whh and Wyh represent the input hidden weight matrix. the hidden-hidden weight matrix, and the hidden-output weight matrix, respectively. The vectors bh and by represent the bias of the hidden layer and the output layer, respectively. In addition, f(·) and g(·) are the activation functions for the hidden layer and the output layer, respectively. The RNN uses the hidden state ht at time step t to memorize the network. The hidden state captures all the information included in the previous time steps.

Long Short-Term Memory (LSTM)

Hochreiter and Schmid Huber first the LSTM design in 1997 [16], and it has been developed by numerous individuals since then [29]. When dealing with long-term dependencies, LSTM was primarily driven and built to address the traditional RNN's vanishing gradients problem. The overall neural network of a conventional RNN is a chain of repeated modules created as a succession of basic hidden networks, such as a single sigmoid layer. The hidden layers of LSTM have a more intricate structure than the normal RNN, which includes a sequence of repeating modules with a relatively straightforward structure. Specifically, at each hidden layer, LSTM introduces the notions of gate and memory cells. A memory block is made up of four components: an input gate I a forget gate f, an output gate o, and self-connected memory cells C. The input gate regulates the activation of the memory cell. The output gate learns when to send activations to the subsequent network. The forget gate assists the network in forgetting the previous input data and resetting the memory cells. Furthermore, multiplicative gates are carefully used to allow memory cells to access and retain information over lengthy time intervals. A structure like this can substantially alleviate the vanishing gradient problem [30,35].

Deep Learning (DL)

A Deep Learning great potential to influence the methods of power load forecasting. The processing of forecasting data influences the acceptability of deep neural network in case of energy sector. It is feed-forwarded artificial neural network with multiple layers between output and input[40]. The processing of hidden unit j, a nonlinear action function f(.) is applied to map all inputs form the lower layer, Xj, to scale state Yj. Which then transfer to upper layer,

$Y_j = f(x_j) \dots\dots\dots\dots\dots\dots\dots (6)$

Were

$$x_{j=b_j+\sum_i yiwij} \dots\dots\dots\dots (7)$$

And bj is the bias of unit j; I is the unit index of lower layer; Wij is the weight of connection between unit j and unit i in the layer. Most of time chose the activation function f(.) to be a sigmoid function

$$f(xi) = \frac{1}{1+e^{-xj}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (8)$$

Ensemble Classifier (EM)

Ensemble learning strategy based on ANNs to improve load forecasting performance. An ensemble is made up of two parts: a method for producing individual ANNs and a way for mixing the individual ANNs [32]. Both strategies should be implemented in such a way that overall performance improves. Bagging generates Nbag ANN models for the ensemble by training these ANNs separately on Nbag distinct training data sets created by creating bootstrap clones of the original training data. Boosting employs a Nboost number of progressively learned ANN models. Bagging and boosting have both been used to solve load forecasting concerns. We suggest combining bagging and boosting to take use of their variance and bias reduction features[40,41].

IV. Experimental Analysis

To evaluate the performance of machine learning algorithms for power load forecasting, use MATLAB software 2017R. The forecasting analysis uses the electricity demand of UT Chandigarh, India, for the last five years. The data accumulates different demand variants such as weekly, monthly and yearly. It also contains seasonal collections such as summer, rainy, and winter. The mode of data variance is measured in terms of average and peak. The data transformation and pre-processing of data minimize the impact of noise and missing data. The missing data of attributes fulfil by the average value of data. The forecasting accuracy varies for different parameters such as RMSE, NMSE, MAE and MI. the process of evaluation measures these parameters. The formulation of parameters describes here[50,51,52,53].

A. Normalized Mean Squared Error, NMSE

The predictive model set values are, $\{r_{t+1}^{n}, r^{\wedge n}_{t+1}\}_{n=1}^{N}$, NMSE is derived as

$$NSME = \frac{1}{N}\frac{\sum_{n=1}^{N}(r_{t+1}^{n} - r^{\wedge n}_{t+1})^2}{var(r_{t+1}^{n})}$$

where $var(\cdot)$ denotes variance. Recall that $var(r_{t+1}^{n}) = min_c \frac{1}{n=1}(r_{t+1}^{n} - C)^2$; NMSE is a mean squared error (MSE) normalized by the least MSE obtained from a constant prediction.

B. Root Mean Squared Error, RMSE

RMSE is the square root of MSE, defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(r_{t+1}^{n} - r^{\wedge n}_{t+1})^2}$$

C. Mean Absolute Error, MAE

$$MAE = \frac{1}{N}\sum_{n=1}^{N}|r_{t+1}^{n} - r^{\wedge n}_{t+1}|$$

Note that inequality holds for the last two measures, $MAE \leq RMSE \leq \sqrt{N}\, MAE$; both error measures are known to informative,

Mutual Information, MI

MI measures dependency between r_{t+1} and u_t, and is defined as follows:

$$MI(r_{t+1}; u_t) = \sum_{r_{t+1}; u_t} p(r_{t+1}, u_t)\, log\frac{p(r_{t+1}, u_t)}{p(r_{t+1})P(u_t)} \approx \frac{1}{N}\sum_{n=1}^{N}\log\frac{p(r_{t+1}^{n} \mathrm{l}\, u_t^{n})}{p(r_{t+1}^{n})}$$

$MI(r_{t+1}; u_t)$ is zero when the two variables are independent, and bounded to the information entropy, $H(r_{t+1}) = -\sum_{r_{t+1}} p(r_{t+1})\ log\, p(r_{t+1})$, when the two variables are fully dependent. From the assumption made earlier, we have $r_{t+1}\, \mathrm{l}\, u_t \sim N(r^{\wedge}{}_{t+1}, \beta)$. With an additional assumption, $r_{t+1} \sim N(\mu,\ \sigma)$ timate the parameters $\beta, \mu\ and\ \sigma$

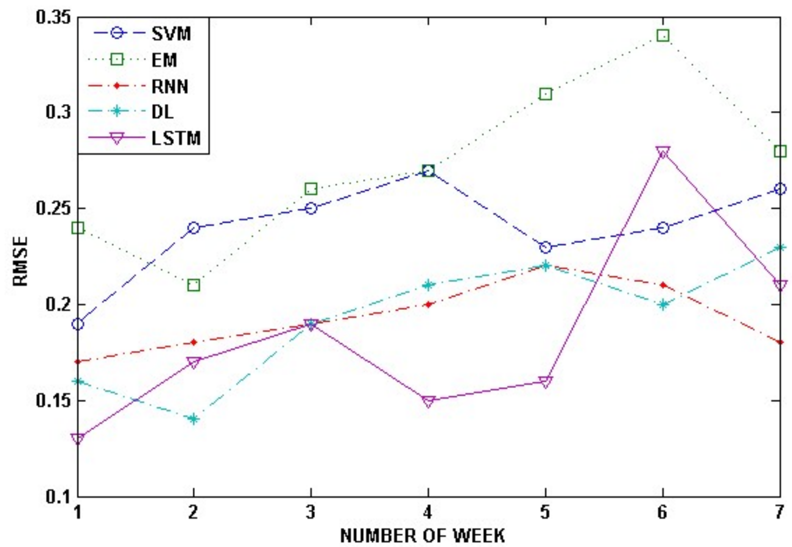

Figure 4: performance of weekly load of power demand and estimates RMSE.

In this graph indicates the variation of RMSE between SVM, EM, RNN, DL and LSTM method for the energy demand dataset of UT Chandigarh. The result of the variation, which is scattered across a number of weeks, demonstrates that the RMSE value has been optimised as a result of the optimization process and better LSTM prediction.

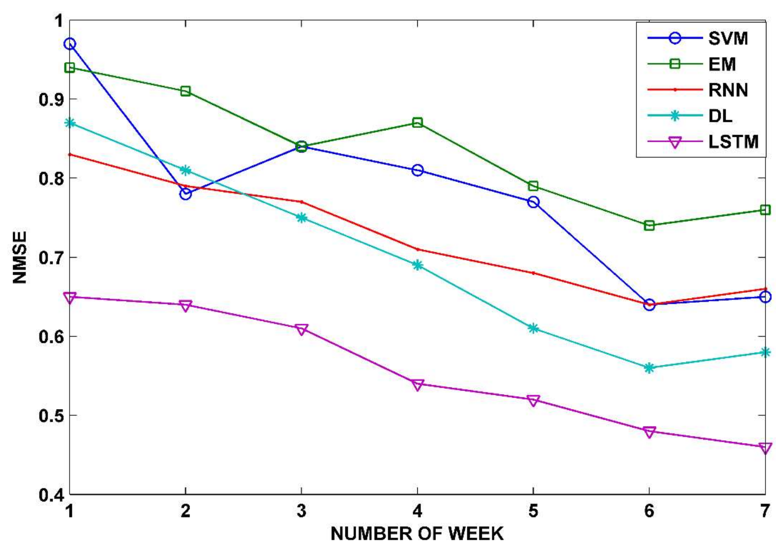

Figure 5: performance of weekly load of power demand and estimates NMSE.

In this graph indicates the variation of NMSE between SVM, EM, RNN, DL and LSTM method for the energy demand dataset of UT Chandigarh. The result of the variation, which is scattered across a number of weeks, demonstrates that the NMSE value has been optimised as a result of the optimization process and better LSTM prediction.

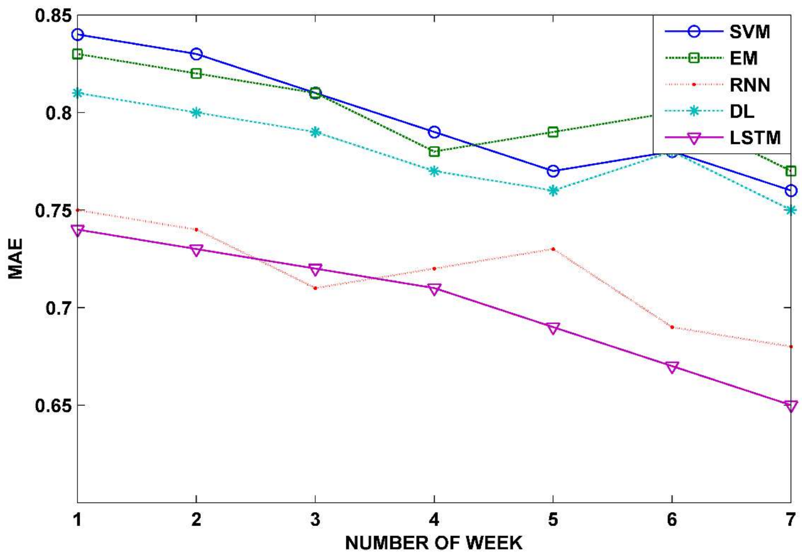

Figure 6: performance of weekly load of power demand and estimates MAE.

In this graph indicates the variation of MAE between SVM, EM, RNN, DL and LSTM method for the energy demand dataset of UT Chandigarh. The result of the variation, which is scattered across a number of weeks, demonstrates that the MSE value has been optimised as a result of the optimization process and better LSTM prediction.

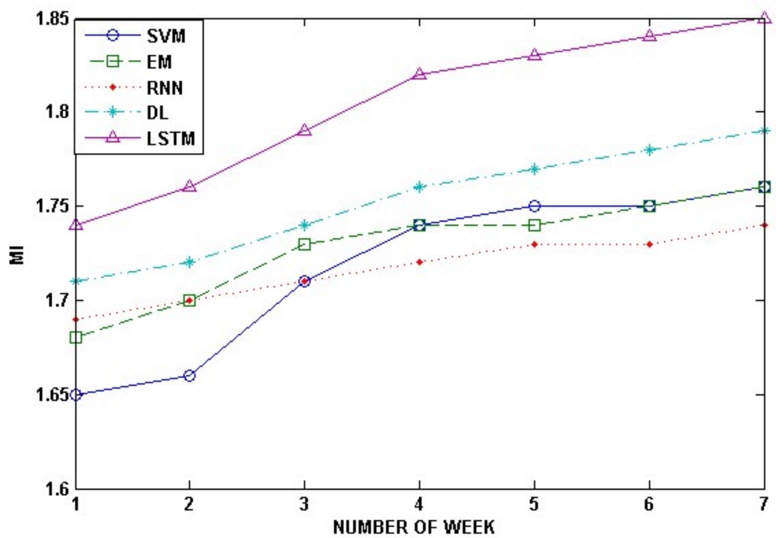

Figure 7: performance of weekly load of power demand and estimates MI.

In this graph indicates the variation of MI between SVM, EM, RNN, DL and LSTM method for the energy demand dataset of UT Chandigarh. The result of the variation, which is scattered across a number of weeks, demonstrates that the MI value has been optimised as a result of the optimization process and better LSTM prediction.

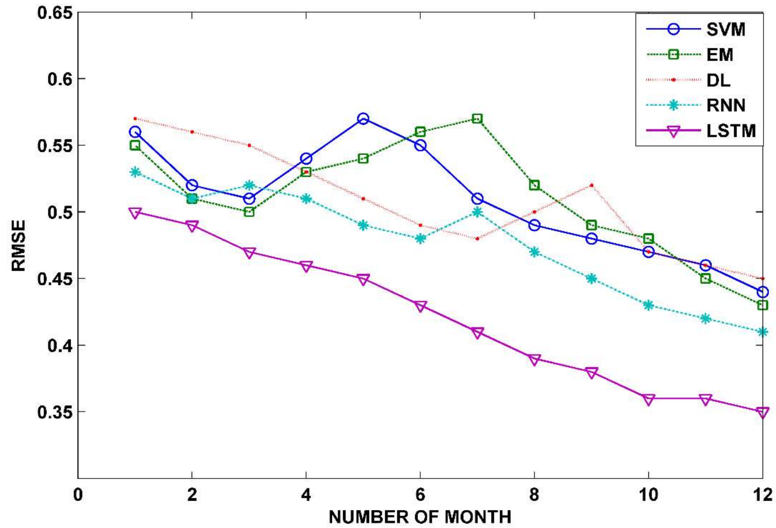

Figure 8: performance of monthly load of power demand and estimates RMSE.

In this graph indicates the variation of RMSE between SVM, EM, RNN, DL and LSTM method for the energy demand dataset of UT Chandigarh. The result of the variation, which is scattered across a number of weeks, demonstrates that the RMSE value has been optimised as a result of the optimization process and better LSTM prediction.

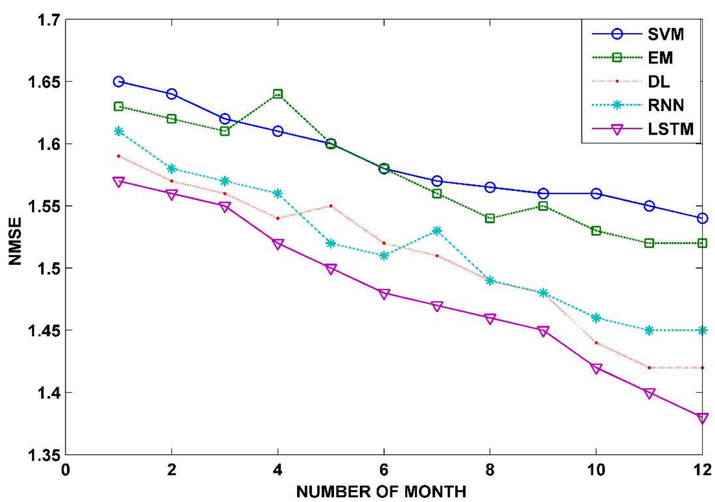

Figure 9: performance of monthly load of power demand and estimates NMSE.

In this graph indicates the variation of NMSE between SVM, EM, RNN, DL and LSTM method for the energy demand dataset of UT Chandigarh. The result of the variation, which is scattered across a number of weeks, demonstrates that the NMSE value has been optimised as a result of the optimization process and better LSTM prediction.

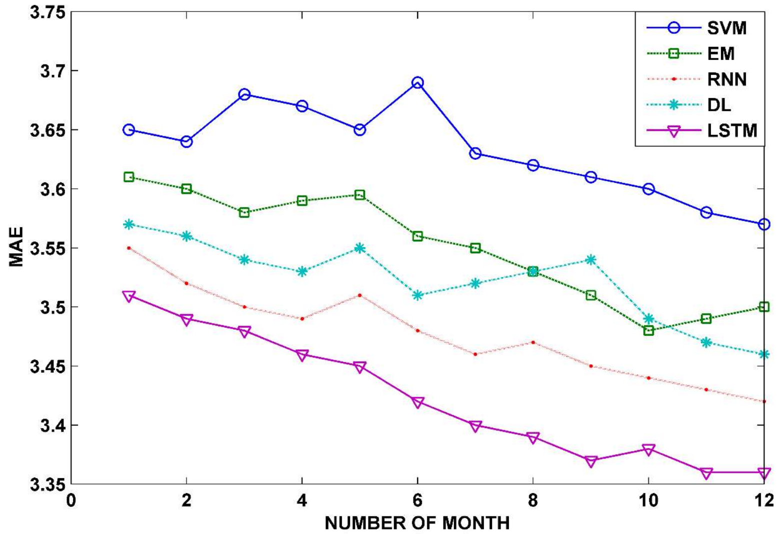

Figure 10: performance of monthly load of power demand and estimates MAE.

In this graph indicates the variation of MAE between SVM, EM, RNN, DL and LSTM method for the energy demand dataset of UT Chandigarh. The result of the variation, which is scattered across a number of weeks, demonstrates that the MAE value has been optimised as a result of the optimization process and better LSTM prediction..

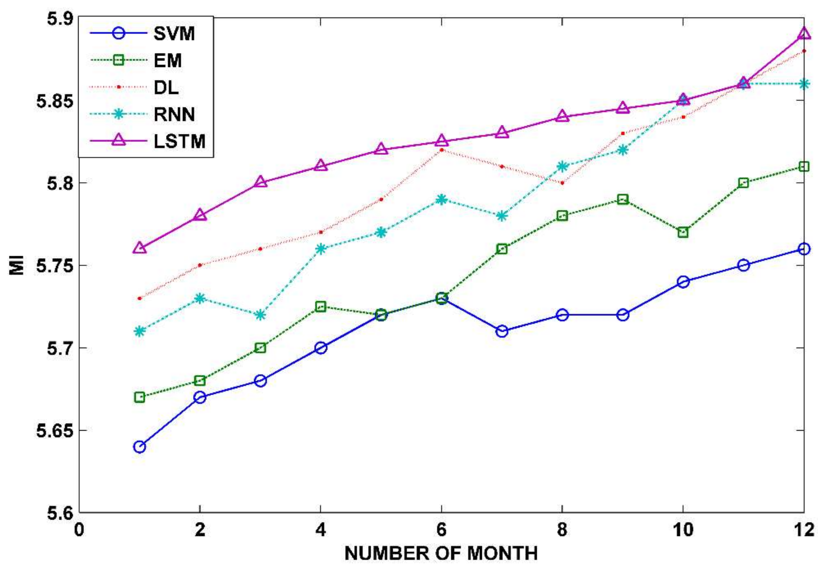

Figure 11: performance of monthly load of power demand and estimates MI.

In this graph indicates the variation of MI between SVM, EM, RNN, DL and LSTM method for the energy demand dataset of UT Chandigarh. The result of the variation, which is scattered across a number of weeks, demonstrates that the MI value has been optimised as a result of the optimization process and better LSTM prediction.

V. Conclusion & Future Scope

The reliability of power demand forecasting has great potential for energy industries. The incremental development of machine learning algorithms and hybrid models using artificial neural networks improves the performance of power load forecasting. We evaluate machine learning forecasting accuracy for forecasting power consumption in this research. The method is based on a moving window-based LSTM network methodology and can be used to predict demand for the time interval specified by the user. Furthermore, the EM, RNN, SVM, and DL models are all compared in performance. Figures 4,5,6,7, and 8 show that the suggested approach using RNN outperforms SVM, DL, and RNN regression models in predicting electricity consumption. Despite statical forecasting models, the machine learning algorithms have several advantages, such as effectively managing non-linear complexities and forecasting short- and long-term dependencies of power load time series data. The experimental analysis of the results suggests that the RNN model and the LSTM model outperform support vector machines and other existing algorithms. Some factors are related to weather, and others influence forecasting accuracy. In the future, adjust the different influencing factors of power load forecasting for the growth of energy sectors.

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