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SYSTEMATIC REVIEW

A Comprehensive Review of Various Machine Learning Techniques used in Load Forecasting

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Abstract: ***Background***: Load forecasting is a crucial element in power utility business load forecasting and has influenced key decision-makers in the industry to predict future energy demand with a low error percentage to supply consumers with load-shedding-free and uninterruptible power. By applying the right technique, utility companies may save millions of dollars by using load prediction with a lower proportion of inaccuracy.

Aims: This study paper aims to analyse the recently published papers (using the New York Independent System Operator's database) on load forecasting and find the most optimised forecasting method for electric load forecasting.

Methods: An overview of existing electric load forecasting technology with a complete examination of multiple load forecasting models and an in-depth analysis of their MAPE benefits, challenges, and influencing factors is presented. The paper reviews hybrid models created by combining two or more predictive models, each offering better performance due to their algorithm's merits. Hybrid models outperform other machine learning (ML) approaches in accurately forecasting power demand.

Results: Through the study, it is understood that hybrid methods show promising features. Deep learning algorithms were also studied for long-term forecasting.

Conclusion: In the future, we can extend the study by extensively studying deep learning methods.

Keywords: Artificial neural networks, deep learning, load forecasting, machine learning, computational modeling, NYISO dataset.

1. INTRODUCTION

Forecasting is vital in many aspects of human activity, including energy. Due to the rising usage of renewable energy sources and the integration of innovative grid technologies, it is necessary to utilise more efficient forecasting approaches to accomplish optimal planning, management, and operation of electric power systems [1]. Electric load forecasting is challenging due to seasonal, meteorological, socio-economic, and random aspects [2]. Forecasting models are used in many industries, including finance, business, health care, and meteorology [3]. A power plant's regulation and exchange estimates are also required. In order to make better decisions, energy planners employ forecasting [4]. This review paper focuses on identifying the best machine learning algorithm for optimized forecasting.

Many variables make calculating the electric load complicated. The season, weekday, and time of day all have an effect on how people respond to and react to events [5].

There are four kinds of load forecasting studies based on the time needed [6]:

- Long term: a forecasting window more significant than a year
- Mid-term: forecasting from a week to a year
- Short-term: forecasting loads for the next few hours

Fig. (**1**) shows the different methods of forecasting. In 2011, Cai *et al.* came up with statistical models, fuzzy approaches, and machine learning algorithms that can be used to predict the STLF.

2. MATERIALS AND METHODS

Experts use a variety of factors to anticipate future electricity usage. Along with weather and time information, this list may include economic data such as unemployment rates and power costs [7-9]. In addition, the deregulation of the energy market has increased the importance of electrical load forecasting [10]. Due to the difficulties of storing energy, accurate load forecasting is required to maximise market interactions, ensure supply continuity, and reduce waste [11, 12].

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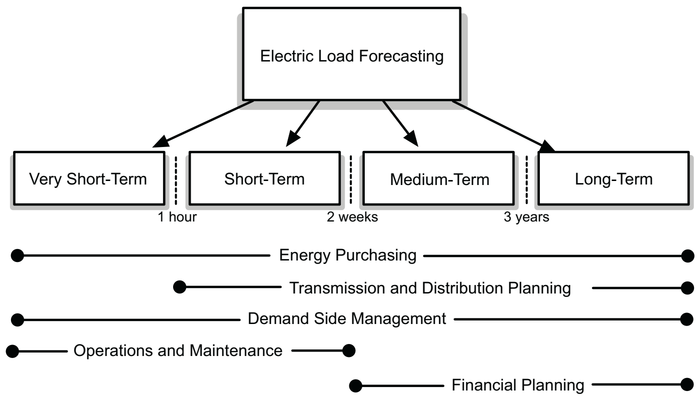

Fig. (1). Electric load forecasting applications and classification (Zor, 2017).

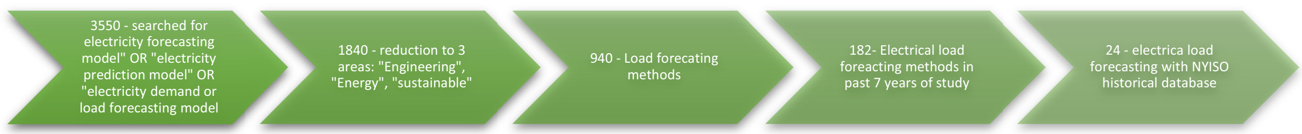

Fig. (2). Selection of study papers. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

STLF is the process of figuring out how much demand there will be every hour, week, or month [13-15].

The methodology used here is a systematic review of past studies. This research focuses on finding an optimised algorithm for the NYISO database, so the study concentrates on the past research published with the mentioned database. For reference and comparative discussion, the summary of past studies includes a few studies outside the NYISO database. The paper begins with an introduction to load forecasting, factors influencing the forecasting algorithms, challenges faced, and benefits gained. The third part includes past studies based on the NYISO database, followed by other databases. The study then has a discussion part that argues for the optimised algorithm to be used for long-term forecasting. It is understood that feed-forward deep learning algorithms (or hybridised deep learning algorithms) are the best-optimized algorithms for long-term forecasting. The conclusion part summarises the entire research paper.

2.1. Data Collection

The proposed study was initiated through online data collection on various platforms that are repositories for peer-reviewed journals. Various keywords were used in the data collection process to narrow down the available data to the scope of the study. Some of the keywords that were used in the study are listed below:

- Load forecasting using AI
- Electricity load prediction (EP) algorithms
- Energy Forecasting (EF) using NYISO
- Machine Learning (ML) algorithm
- Hybrid AI and EP
- Hybrid AI and EF
- Hybrid ML and EP
- Hybrid ML and EF
- Review of load forecasting
- Load forecasting using the NYISO database

A plethora of results popped up for the search keywords, and only relevant articles from peer-reviewed journals and conferences were downloaded. After downloading the articles, a careful review was conducted to categorise the articles based on the study method. Our focus was on the machine learning algorithms used in load forecasting that were successfully tested using the NYISO database.

The IEEE Xplore search console, when searched for the keyword "load forecasting using machine learning," displayed a result of 808 research papers. Collectively, when using Google Scholar, Science Direct, and IEEE Xplore paper collections, a total of 3550 papers were generated. Of the 10550 papers selected for the review, the study papers were narrowed down, as shown in Fig. (**2**).

The common overfitting issues in the dataset are overcome by the Holdout method. Instead of using all of our data to train, we may divide our dataset into training and testing sets. A usual split ratio is eighty percent training and twenty percent testing. Our model is trained until it performs well on both the training set and the testing set. This implies a high capacity for generalization since the testing set contains data not utilized for training. However, even after splitting, this method requires a suitably big training dataset.

2.2. Factors Influencing Load Forecasting

Load forecasting is vital for utility planning and operations. It requires accurate forecasting of electric load magnitudes and locations (often hours). The hourly total system load is essential in load forecasting [16-18]. Electrical engineering load forecasting has risen in importance. Power forecasts are required from both a production and budgetary standpoint. Predicting daily and hourly peak loads are vital [19, 20].

Even parametric nonlinear models struggle to describe the complex interplay of the electrical load and its influencing factors [21]. Short-term changes in the power network's architecture affect electrical loads. Weather, time, economics, and random disturbances are all important factors in determining system load [22-25]. The elapsed time is critical in load forecasting, and it is essential to add the time of day, week, month, and season to the load curve [26, 27].

Weather impacts household and agricultural consumers significantly because it is an independent element in load forecasting. The weather influences consumer behaviour [28-30]. THI and WCI measure how hot and cold it is in the summer and winter [31, 32]. Economic factors, including electricity prices, load management, and industrialization, impact average system load and maximum demand. Factors like customer behaviour, tariff changes, and employment levels affect the accuracy of a projection [33-35]. These parameters are optimized using the grid searching method. Grid search is a technique for tuning hyperparameters that builds and evaluates a model for each combination of algorithm parameters supplied in a grid.

2.3. Benefits of Load Forecasting

Since the origin of energy generation, electric utilities have attempted to forecast energy demand for hours, days, or even a year [36]. Renewable energy sources have aided in resource management, but energy harvesting remains expensive and time-consuming [37]. If load demand can be projected, it is used to determine optimal power distribution [38-40]. This is where the term "load forecasting" originated. Apart from economic and environmental benefits, load forecasting has several other advantages [41]. Electric utilities may be better equipped by projecting future load demand, making more cost-effective decisions, and mitigating risk [42]. This helps plan for the costs of future power generation and transmission.

Load forecasting enables the planning of future resources such as fuel for the generation and other resources necessary to guarantee that consumers get uninterrupted electricity, demonstrating that power can be generated efficiently and dependably [43-46]. Power generation plant load forecasting is critical for determining the size, location, capacity, and type of future generating facilities [47]. Finally, load forecasting ensures peak power plant performance by avoiding under-generation and over-generation, hence lowering fossil fuel consumption and greenhouse gas emissions [48, 49].

2.4. Challenges Faced in Forecasting

Researchers have worked on an accurate forecasting model for electric power generating and distribution companies for a decade [50]. As a consequence, innovative approaches have emerged. Researchers have been attempting to improve these models' accuracy for years, but they have hit several barriers. Sadly, these impediments prevent the development of the most realistic model [51]. Developing the best forecasting model has certain obstacles. The model's developers focused on numerous parts: acquiring random data, parameterizing algorithms, and choosing the most reliable model for load forecasting [52]. This section looks at the literature to address the six points stated below.

- The drivers of the macro-economic environment
- Deployment and development of new technologies; deployment of learning curves
- Demand for electricity is broken down into its parts
- Variations that last just a short time
- Granularity of time

3. LITERATURE REVIEW

3.1. Applications of ML in Past Studies using the NYISO Database

Temporal predictions include short-term and long-term estimates, such as power supply balancing and income analyses [53]. Various forecasting approaches have been utilised throughout the years, including multivariate and multiple regression, SVM, and time series (including ARIMA and ARMA) [54]. ANNs (artificial neural networks) are also extensively employed for prediction. For example, ANNs have been used to predict microgrid load, building optimization scenarios, and long-term horizon scenarios to anticipate a region's yearly energy consumption [55-58]. However, personal taste often prevails in the absence of a generally accepted forecasting methodology [59].

According to recent research, "basic procedures devised by experienced forecasters perform as well, if not better, than elaborate ones" [60]. So far, there is no indication that complex models outperform simple ones. Thus, knowing which model to use in which case is crucial [61, 62].

Precise load forecasting may allow electric companies to operate at the lowest possible cost. These predictions are used to plan generate capacity and fuel purchases [63]. Deregulation has made a lot of structural changes in the utility business over the last decade, which makes our predictions more important [64-66].

Many power and energy utilities use ML-based algorithms to predict how much power or energy they will need to balance production and demand. Demand and supply management includes load forecasting [67, 68].

A load forecasting model uses previous data to predict future load demands. Therefore, the model must initially understand the electrical load data use patterns [69]. Next, prepare the load data for training. Then the incorrect and missing values are replaced. Finally, they link this electrical data with historical information such as weather or historical occurrences. These factors substantially influence forecast accuracy [70-72].

Anomalies in instances, missing values (more than 5%), and lost data points are some of the reasons for troubles in the data collection process. It is challenging to tackle these problems without understanding how to apply the model [73, 74]. If any of these is present, the value will be less accurate. As a result, researchers are proposing solutions to these issues. Electric utilities, for example, may save money by better predicting their load [75-77].

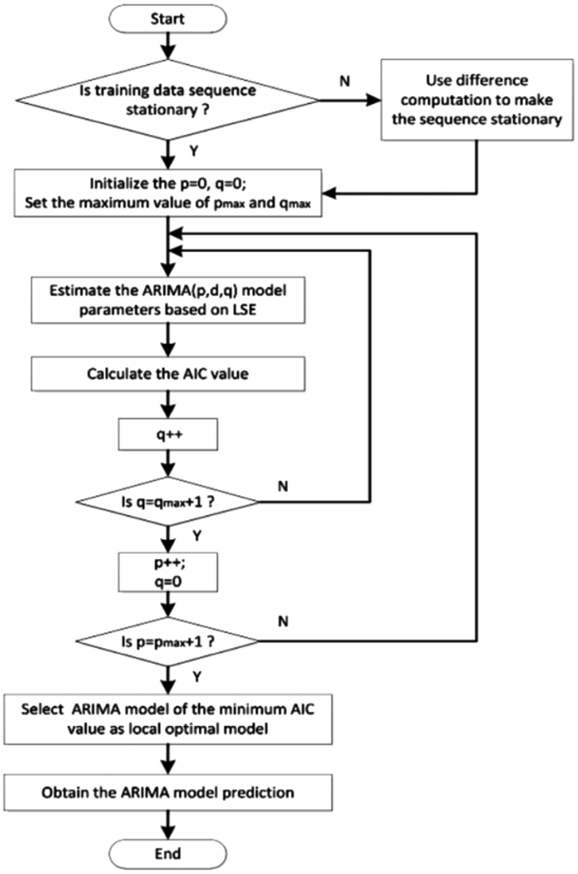

Fig. (3). Flowchart of Autoregressive Integrated Moving Average (ARIMA).

Accidental mistakes may cause significant financial and infrastructural damage. Predicting mistakes may increase energy generation costs, claim Haida and Muto *et al.* The mean absolute percentage error (MAPE) should be reduced by 1% and improve load forecasting accuracy to save 3-5% on research production costs. Renewable energy has lately caught the interest of both the government and electric utilities [78, 79].

Extrapolation of EEX, Nasdaq, or other power market exchange load profiles is often used to forecast future electricity demand. The annual growth in power consumption is often utilized [80]. However, the current profile uses the hourly pattern. Most techniques use temperature as an explanatory variable and a function indicating repeating daily and weekly load patterns [81-84]. Table **1** tabulates the remarkable research that has been published in the past using the NYISO database.

3.2 Hybrid Models of ML Methods used in Forecasting

3.2.1. Autoregressive Integrated Moving Average (ARIMA)

AutoRegressive Integrated Moving Average (ARIMA) is an abbreviation that stands for AutoRegressive Integrated Moving Average. It adds the concept of integration to the more straightforward AutoRegressive Moving Average. This abbreviation is descriptive, summarising the model's essential features. In summary, they are:

AR: Autoregression. A model that uses the dependent connection between an observation and a certain number of lagging observations.

I: Incorporation. Utilization of raw observation differencing (*e.g.*, subtraction of observation from an observation at the previous time step) to render a time series stable.

MA: Moving Average. A model that utilises the dependence between an observation and a residual error derived from a moving average model applied to lagging observations.

Each of these components is defined explicitly as a model parameter. ARIMA (p,d,q) is a standard notation where the parameters are replaced by integer values to reflect the particular ARIMA model being utilised.

The ARIMA model parameters are specified as follows:

p is the number of lag observations included in the model, which is also known as the lag order.

d: The number of times the raw observations are differentiated, also known as the differencing degree.

q: The size of the moving average window, also known as the moving average order.

A linear regression model is developed with the necessary number and kind of variables, and the data is differentiated to make it stationary, *i.e.*, to eliminate trend and seasonal patterns that adversely impact the regression model. A parameter may be assigned the value 0 to indicate that the model element is not to be utilised. Thus, the ARIMA model may be constructed to serve the same purpose as an ARMA

Table 1. MAPE of past studies using NYISO database.

Author	Year	Method	MAPE
Peng *et al.* [91]	2017	Autoregressive Integrated Moving Average (ARIMA)	60.65
		Back Propagation Neural Network (BPNN)	42.5
		Genetic Algorithm-Artificial Neural Network (GA-ANN)	33.12
		Hybrid Autoregressive (AR)-EMD-SVR	11.29
		Empirical Mode Decomposition (DEMD) -SVR-AR	5.37
		Empirical Mode Decomposition (DEMD) -QPSO-SVR-AR	4.62
Li *et al.* [69]	2016	Ensemble method	3.43
Fang *et al.* [138]	2016	Seasonal autoregressive integrated moving average	8.4
Idowu *et al.* [15]	2016	Support vector machine	4.78
Lee *et al.* [15]	2015	Fuzzy time series	2.61
Lou *et al.* [15]	2015	Fuzzy neural network	2.3
Vaghefi *et al.* [15]	2015	Linear regression model	4.56
Xu *et al.* [113]	2014	Optimistic optimization	3.1
Amini *et al.* [140]	2015	Autoregressive integrated moving average	2.59
Lahouar *et al.* [90]	2014	Random forest	1.44
Fan *et al.* [34]	2017	Original SVR	12.88
		SVR-PSO	13.5
		SVR-GA	14.31
		AFCM	11.1
		EMD-PSO-GA-SVR	3.92

model or even a basic AR, I, or MA model. Adopting an ARIMA model for a time series presupposes that the process underlying the data is an ARIMA process. This may seem apparent, but it helps justify the necessity to check the model's assumptions in the raw data and in the residual errors of the model's projections. Fig. (**3**) shows the flowchart of Autoregressive Integrated Moving Average (ARIMA).

3.2.2. Empirical Mode Decomposition (DEMD)-SVR-AR

Following is a summary of the suggested DEMD-SVR-AR model's comprehensive method, as shown in Fig. (**4**).

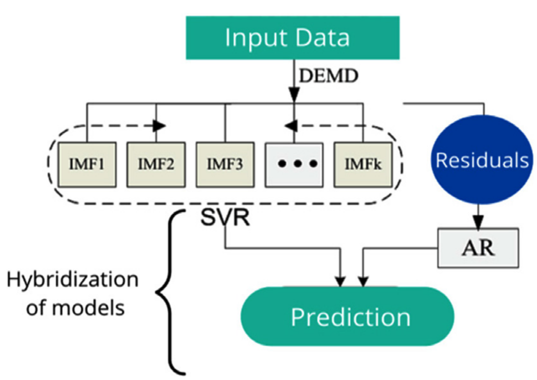

Fig. (4). Flowchart of Empirical Mode Decomposition (DEMD) - SVR-AR. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

Step 1 Separate the input data using DEMD: Each electric load data (input data) might be split into a number of intrinsic mode functions (IMFs), *i.e.*, a high frequency item and residuals.

Step 2 SVR modelling: Various sizes of fed-in/fed-out subsets will be established at this step in order to determine the optimal parameters for the SVR model used to anticipate high-frequency items.

Step 3 AR modelling: The AR model predicts residuals because they are monotonous and stable. Similarly, if the new parameters have a lower MAPE value or if the maximum number of iterations has been achieved, the new three parameters and their related objective value represent the solution at this stage.

Step 4 DEMD-SVR-AR forecasting: After obtaining the forecasting values of the high frequency item and the residual items from the SVR model and the AR model, respectively, the high frequency item and the residuals would be used to generate the final forecasting results.

3.2.3. Genetic Algorithm-Artificial Neural Network (GA-ANN)

Local minima and network paralysis are examples of ANN's downsides. The inability of the network to modify the weights towards local minima paralyses the network, diminishing the precision of the system. On the other hand, we cannot always get optimum solutions using just the genetic

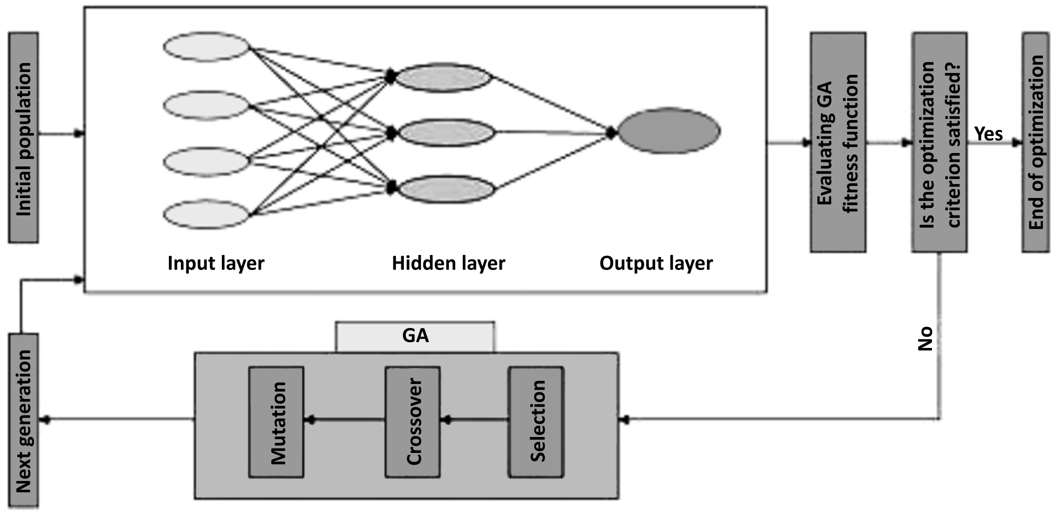

Fig. (5). Flowchart of Genetic Algorithm-Artificial Neural Network (GA-ANN). (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

algorithm. To construct a new forecasting model that addresses these issues, it will be necessary to combine ANN with GA (Fig. **5**).

3.3. Applications of ML in Past Studies using other Databases

3.3.1. Genetic Algorithm

Genetic search algorithms are influenced by Charles Darwin's theory of natural selection. They can address both constrained and unconstrained optimisation issues. For bio-inspired optimisation and search tasks, GAs are often used. Holland discovered this approach at the University of Michigan [85].

A genetic algorithm applies three rules to produce the next generation from the current population. First, pick the parents who contribute to the next generation's population. Next, children are exposed to random mutation rules [86, 87]. Finally, an assessment procedure is used to build a dataset or population, which involves choosing subsets of the datasets for crossover. People then bring in the new population and keep testing it until they achieve what they want [88-90].

3.3.2. Ant Colony Optimization

With the ACO algorithm, we may find food sources distant from the colony. Real ants use pheromones to find the fastest routes from the colony to food. The "system's" interests have all joined together to discover one answer; hence, there is only one solution [91, 92]. Ants use a pheromone to find food.

The amount of pheromone laid depends on the food source's distance, quantity, and quality [93]. On the other hand, a lone ant would likely follow the pheromone trail if it smelled it. Therefore, this ant maintains the pheromone trail along that route since it is responsible for it. Consequently, the route with the highest amount of traffic is the most likely to be chosen [94-96]. Alternatively, the chance of an ant choosing a route rises with the number of ants that have already chosen it. Thus, this mechanism has a positive feedback loop [97].

3.3.3. Cuckoo Search Algorithm

The CS algorithm is inspired by cuckoo bird behaviour. Its capacity to switch between global and local random walks is critical for global optimisation [98]. Simulated annealing is used in algorithms like SA, PSO, and DE, but CS outperforms them all. Moreover, the CS algorithm is quicker than the DE approach in achieving the ideal answer. CS is also faster than PSO in calculation [99, 100].

3.3.4. Quantum PSO

The efficiencies of the PSO have been improved over time. The quantum-behaved PSO (QPSO) method is a global search approach created by PSO researchers to guarantee that outstanding optimal solutions are identified in the search space [101]. Since it lacks particle velocity vectors, QPSO has fewer parameters to adjust than PSO. In investigations utilising typical benchmark functions, QPSO outperformed PSO [102].

3.3.5. Artificial Neural Networks

McCulloch and Pitts explained the neuron's mechanical structure in 1943, while Frank Rosenblatt used mathematical analysis, digital computer modelling, and parallel analogue experimentation with neural networks to classify spatial patterns. Since Rosenblatt's time, ANNs have gained popularity as AI tools, particularly for predicting electric load [103-105]. The artificial neuron is the most straightforward ANN unit, handling complex behaviours through connections between processing neurons and weight variables. They are simple to build-MLPs with a single hidden layer [106]. Nonlinear MLPs approximate a regular function with arbitrary accuracy. Large ANNs with plenty of neurons and weights are known to be easy to train. This may also lead to overtraining. The ANN's power rises with depth, but training gets difficult owing to the vanishing gradient issue. Shallow ANN topologies are avoided with just one hidden layer [107-109].

3.3.6. Regression Trees

Many features in the data interact in complicated and nonlinear ways, making regression trees a better machine

Table 2. MAPE of past studies using other databases.

Authors	Year	Method	MAPE
Khwaja *et al.* [64]	2020	Bag-Boost NN	1.43
Laouafi *et al.* [17]	2017	Hampel filter-based Forecast Combination Method	0.86
Wu *et al.* [20]	2019	Cuckoo search hybrid model	3.04
Bouktif *et al.* [11]	2018	LSTM	0.78
Ramos *et al.* [115]	2021	KNN	3.95
heikhan *et al.* [120]	2011	GA, ACO and MLP	1.46
Peng *et al.* [135]	2016	Quantum PSO with SVR	4.62
Ghasemi *et al.* [128]	2016	TV-SABC	6.98

learning approach than linear regression models. Regression trees assign places to their nodes (leaves) where interactions are more controlled [110-112]. This is because linear regression models use a global prediction formula. Using regression trees, decisions are regressed from the root node to the leaf node, where the solution is. The leaf node has the solution [113]

3.3.7. Regression Models based on Historical Data

We build regression models utilising historical data for electrical demand and other affecting factors like weather variables (temperature, humidity, solar radiation, and wind). Some say that load forecasting algorithms should use accurate data whenever possible to avoid making energy consumption predictions that are very different from each other [114, 115].

3.3.8. Fuzzy Sets

In the latest forecasting models, intuitionistic fuzzy sets are examined by calculating the anticipated outcomes due to the employment of the max-min composition in the forecasting technique. The researchers proposed a forecasting model based on intuitionistic fuzzy sets and a basic arithmetic algorithm. The suggested model partitioned the universe of discourse using a frequency density-based strategy and employed a simple arithmetic formula to calculate the predicted outputs [116].

Pritpal Singh introduced a novel time series forecasting model based on neutrosophic set (NS) theory and the particle swarm optimization (PSO) method. The suggested model began with the description of a time series dataset utilising three distinct memberships of NS, namely, truth-membership, indeterminacy-membership, and falsity-membership. This neutrosophic depiction of time series was known as the neutrosophic time series (NTS). It was shown that the predicting performance of the suggested model was greatly dependent on the ideal selection of the universe of time series datasets. This issue was handled using the PSO method in this research. Three distinct datasets, including the Alabama university enrollments dataset, the TAIFEX index, and the TSEC weighted index, were used to verify and validate the suggested model. Experimental findings of the proposed model outperformed current benchmark models with an average predicted error rate of 0.80% for university enrollments, 0.015% for TAIFEX, and 0.90% for TSEC [117].

Pritpal *et al.* proposed a new hybrid time series forecasting model using neutrosophic set (NS), ANN, and gradient descent. This study examines the representation of time series datasets using network structures (NS), three degrees of NS membership, and predicts outcomes. This study advocated a neutrosophic-neuro-gradient technique to solve these challenges. Neutrophic time series datasets use NS theory to convey uncertainty (NTS). In NTS, IF-THEN rules called neutrosophic entropy decision rules (NEDRs) were created. ANN-based architecture with projected results from NEDRs, to improve ANN's performance and produce optimal forecasting results. The gradient descent approach was to eliminate simulation output discrepancies. The TAIFEX index, the Alabama university enrollment dataset, and the Taiwan Stock Exchange Corporation (TSEC) weighted index were utilised to validate the proposed model. The suggested model beat existing benchmark models with average error rates of 1.02 percent for TAIFEX, 0.74 percent for university enrollment, and 1.27 percent for TSEC [118].

Pritpal *et al.* introduce a novel technique for forecasting time series datasets using a neutrosophic-quantum optimization strategy. This work uses neutrosophic set (NS) theory to describe the inherited uncertainty of time series datasets with three distinct memberships, namely, truth, indeterminacy, and false. Such representations of time series datasets are referred to as neutrosophic time series (NTS). This NTS is also used to model and predict time series datasets. The efficacy of the NTS modelling technique is significantly reliant on the ideal selection of the discourse universe and its accompanying intervals, according to a study. This work chooses the quantum optimization algorithm (QOA) and ensembles using the NTS modelling strategy to address this problem. QOA enhances the efficacy of the NTS modelling strategy by picking the optimum universe of discourse and its accompanying intervals from the collection of local optimal solutions. The suggested hybrid model (*i.e.*, the NTS-QOA model) is confirmed and validated using datasets of Alabama (USA) university enrolment, Taiwan futures exchange (TAIFEX) index, and Taiwan Stock Exchange Corporation (TSEC) weighted index. Diverse experimental findings demonstrate that the proposed NTS-QOA model is superior to current benchmark models in terms of average forecasting error rates (AFERs) of 0.44 percent for university enrolment, 0.066 percent for the TAIFEX index, and 1.27 percent for the TSEC weighted index [119, 120].

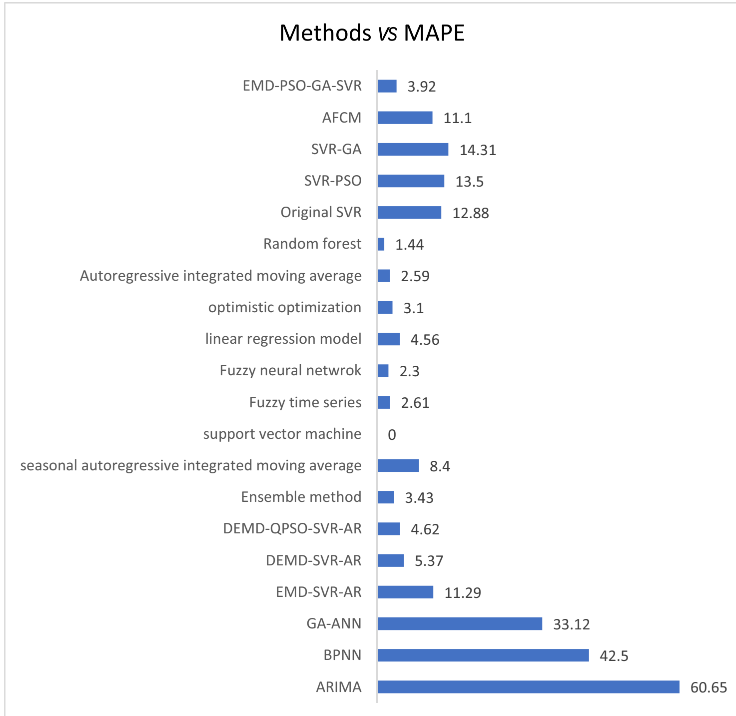

Fig. (6). Models *vs*. MAPE of past studies using the NYISO database. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

Table **2** shows the different studies other than the NYISO database with their respective MAPE.

4. RESULTS AND DISCUSSION

The discussion is based on the difference in errors in each study. The MAPE of each study is analysed to find the most optimised method for long-term forecasting. 80% of the past studies were focused on short-term load forecasting, and only 5% of the past studies included long-term forecasting. The other 15% of studies were price forecasting for medium-term forecasting. Various factors influence the electric load in a particular geographical area. The main factors are holidays, weather, lifestyle, average annual income in the particular location, and cultural background. For example, a city like Coimbatore in Tamil Nadu, India, comes to rest at 9 pm, while the considered database has a city like New York, which has more demand at night.

The study revealed that only a few studies had been published on optimising load forecasting algorithms for long-term forecasting. The Mean Average Percentage Error (MAPE) is calculated using the formula involving y', the predicted value of the model and y being the actual desired value applied to several data available.

$$\boldsymbol{MAPE} = \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\mathbf{1}}^{\boldsymbol{n}} \frac{\boldsymbol{y}' - \boldsymbol{y}}{\boldsymbol{y}}$$

Fig. (**6**). Shows the different MAPES of past studies that included the NYISO database.

MAPE does not rely on size and may be used simply for both large and low volume items. However, frequently, the differential penalty might lead to biased forecasting. The drawbacks of MAPE, such as difficulty managing small and zero denominators, are not highly significant for conventional load forecasting issues since the load at the aggregated level is seldom 0 or approaching a minimal value. Also, the value of these measures is variable for various datasets and factors.

Therefore, it is challenging to compare the outcomes of various procedures. Also, no approaches are explored in a single dataset to determine their comparison. In this study effort, the most remarkable accuracy of each described approach is tallied in the coming parts by diverse forecasting methodologies. By looking at (Fig. **7**), the MAPE of past studies that are drawn upon other databases is plotted.

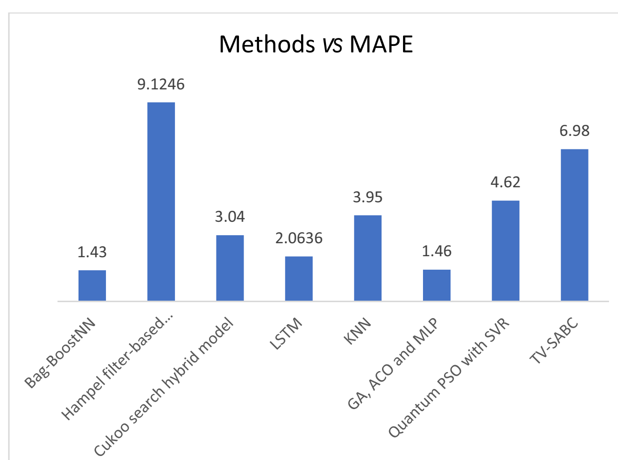

Fig. (7). Models *vs*. MAPE of past studies using other databases. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

By analysing the studies, only a few concentrate on deep learning methods, although these methods show promising outcomes while optimising the algorithms for long-term forecasting. The next section briefly talks about deep learning methods that can be used to make long-term forecasts.

4.1. Deep Learning Methods used in Forecasting

An autoencoder is a feed-forward neural network that employs hidden layers to duplicate input neurons into output neurons [121].

Because the RNN model fails on diminishing gradient descent, the LSTM model is applied. LSTM has long-term storage memory. The LSTM model uses internal self-loops to store data. The LSTM's computational graph consists of five parts: I/O has five gates: 1, 2, 3, 4, and 5. LSTM computational model at the cell layer, fused with other cells to produce an RNN model. Gate actions, like reading, writing, and deleting, happen when cells are in the memory state [122].

Like human neurons, CNNs transmit information back to themselves [123]. This level of training from CNN has been used in visual and audio processing, video recognition, and natural language processing. In addition, convolutional neural networks are often used to handle grid data (CNN) [124]. Images, for example, use a 2D pixel grid, but time series data uses a 1D grid. At least one CNN layer uses the convolutional mathematical technique [125-129].

There are several deep probabilistic models, but RBM is one of the most well-known. RBM has two primary layers: visual input and hidden variables. RBM is typically stacked to add depth [130-133].

The Deep Belief Network (DBN) architecture uses stacked RBMs to train hidden layers [134]. The DBN architecture's connection units link units from one tier to the next; no connections exist inside a layer. A DBN is an RBM with hidden layers, while an RBM has just one [135, 136].

The Deep Boltzmann Machine (DBM) is built like an RBM but with concealed variables and layers. There are also undirected relationships between variables at all levels, both visible and hidden, in DBM. This is unlike DBN, which does not have these kinds of relationships [137].

The dispersion of power transformers at a great distance from electrical plants constitutes the greatest obstacle in transformer state detection. Elsisi *et al.* presented a novel combination of an Internet of Things (IoT) architecture with deep learning against cyberattacks for online monitoring of the condition of power transformers. For failure diagnostics of power transformers and cyberattacks, a built one-dimensional convolutional neural network (1D-CNN) that was resistant to uncertainty was presented. In addition, experimental scenarios are conducted to demonstrate the efficacy of the suggested IoT architecture. Compared to other techniques, the deep 1D-CNN has an accuracy of 94.36 percent in the typical case, 92.58 percent when cyberattacks are included, and 5 percent uncertainty. The connection between the IoT platform and the 1D-CNN effectively identified cyberattacks and offered safe online monitoring of transformer status *via* the internet [138].

Elssi *et al.* presented an integrated IoT architecture to combat cyber assaults based on a created deep neural network (DNN) with a rectified linear unit to offer dependable and secure online monitoring for autonomous guided vehicles (AGVs). In place of the standard cyber attack detection strategies in the literature, the created IoT architecture based on a DNN presented a novel method for the online monitoring of AGVs against cyber assaults that was inexpensive and simple to deploy. The DNN was trained using experimental AGV data that reflect the actual state of the AGV and several sorts of cyber assaults, including a random attack, ramp attack, pulse attack, and sinusoidal attack that are fed into the internet network by the attacker.

For further validation, the proposed DNN was compared to other deep learning and machine learning techniques, including a one-dimensional convolutional neural network (1D-CNN), a supported vector machine model (SVM), a random forest, extreme gradient boosting (XGBoost), and a decision tree. In addition, the IoT architecture based on a DNN can effectively identify the state of an AGV with a 96.77 percent accuracy, which is much higher than the accuracy of the standard schemes. An enhanced IoT platform known as CONTACT Elements for IoT displays the AGV's status based on the proposed IoT architecture with a DNN. To highlight the performance of the IoT architecture based on a DNN, several test scenarios using a realistic IoT-equipped AGV system are executed. The findings validate the use of the IoT to offer effective cybersecurity for data visualisation and monitoring of the AGV's state, hence improving decision-making and industrial efficiency [139].

Elssi *et al.* presented a model predictive controller (MPC) for operating an automated voltage regulator (AVR). The design technique generally addresses the AVR parameter uncertainty problem. Hermite–Biehler theorem criteria are given to preserve the system's stability in the frequency domain. A novel evolutionary technique known as arithmetic optimization algorithm (AOA) is used to tune the MPC parameters, while expert designers rely on trial-and-error approaches to accomplish this goal. The stability restrictions are addressed throughout the process of tuning. By concurrently decreasing the voltage maximum overshoot and the response settling time, an effective time-domain target is developed in order to ensure the AVR's performance. The findings of the AOA-based robust MPC are compared to those of other approaches described in the literature. In comparison to existing strategies, the system response illustrates the efficacy and resilience of the strategy with minimum control effort against voltage changes and parameter uncertainty [140].

Elssi *et al.* presented a novel intelligent integration between an Internet of Things (IoT) platform and a deep learning neural network (DNN) algorithm for the online monitoring of computer numerical control (CNC) devices. The suggested infrastructure is used to monitor the cutting process while preserving the cutting stability of CNC machines to guarantee efficient cutting operations that improve product quality. To evaluate the vibration conditions, a force sensor is mounted in the milling CNC machine centre. Consequently, an IoT architecture is built to link the sensor node to the cloud server using the message queue telemetry transport (MQTT) protocol to collect the real-time machine status. In order to preserve the health of the CNC machine, an enhanced model of DNN is developed to categorize the various cutting circumstances (*i.e.*, stable cutting and unstable cutting). Consequently, the created deep learning can properly determine whether the sent data of the smart sensor through the internet is genuine cutting data or false data generated by cyberattacks or the inefficient reading of the sensor owing to the environment's temperature, humidity, and noise signals. The suggested technique yields exceptional results, demonstrating that deep learning may beat other conventional machine learning approaches for vibration control. Contact components for IoT are used to show cutting data on a graphical dashboard and monitor the cutting process in real-time. During the implementation of the proposed deep machine learning and IoT-based monitoring system, multiple cutting conditions for slot milling are experimentally verified. Diverse scenarios are shown to validate the efficacy of the built system, which may disconnect instantly to safeguard the system automatically upon detecting a cyberattack and switch to the backup broker to continue running operations [140].

CONCLUSION

This paper discusses the unique deep learning methods used in load forecasting. In terms of prediction, most of these new learning algorithms outperform AI and neural networks. Forecasting concerns include load, time of day, weather, seasons, consumer behaviour, and vacations. Residential load consumption projections, for example, vary based on the occupants' appliances. In load forecasting, neural networks are commonly used. However, training time, NN upgrading, and technology integration are difficulties for power systems. This article examines a single key technique and describes the state-of-the-art for developing hybrid models. Several load forecasting approaches and time frames were offered due to the study's extensive literature evaluation. These have been used to build many prediction models.

In recent decades, artificial intelligence has been developed to automate processes and make intelligent decisions. Several machine learning techniques have been used to solve AI problems in computer vision, neurology, biomedicine, and power systems. Researchers have created multiple ML models to account for continually changing elements and increase prediction accuracy. As future work, we want to delve more into the descriptions shown by the selected articles. Future studies may include deep learning forecasting methods to forecast long-term load in the NYISO database.

LIST OF ABBREVIATIONS

AOA	=	Arithmetic Optimization Algorithm
DNN	=	Deep Learning Neural Network
IoT	=	Internet of Things
MPC	=	Model Predictive Controller
MQTT	=	Message Queue Telemetry Transport

CONSENT FOR PUBLICATION

Not applicable.

STANDARDS OF REPORTING

PRISMA guidelines and methodology were followed.

AVAILABILITY OF DATA AND MATERIALS

The data supporting the findings of the article is available within the article.

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CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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SUPPLEMENTARY MATERIAL

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