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ELECTRICITY CONSUMPTION FORECASTING SYSTEM OF INDIA: A REVIEW

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ABSTRACT. The paper provides a comprehensive overview of research related to machine learning models which are used in predictive analysis. A manual search of published articles in the previous 13 years (2007 to 2020) for electricity consumption forecasting utilizing the classical methods and novel neural network models was used to conduct the systematic review. In the study, it was found that alone classical model can't forecast properly. The accuracy in forecast can be improved by using a hybrid approach. The widely used method for predictive analysis is artificial neural network. ANN has been discovered to be a highly innovative and effective model when it comes to problem-solving and machine learning. Hence, for time series forecasting LSTM has proved to be best model to predict electricity consumption in India.

1. INTRODUCTION

Electricity is a need in every part of our lives. It is recognized as the basic human need. And is a necessary component of economic activity. It acts as a critical infrastructure on which the country's socio-economic development depends. The twentieth century saw significant growth in worldwide population,

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economic production, and fossil fuel use. All know that India is the world's third-largest producer of electricity as well as the third-largest user. Coal, gas, nuclear, petroleum and renewable energy are the primary sources of electricity generation. To meet the need of the growing population humans are deteriorating the natural resources. The existing energy system is heavily reliant on fossil fuels, the combustion of which accounted for 84% of worldwide greenhouse gas emissions in 2009. Global energy demand is quickly growing as a result of population and economic expansion, particularly in big emerging nations, which will account for 90 percent of energy demand increase through 2035. At the same time, over 20% of the world's population does not have access to power. The national grid in India has an installed capacity of 370.106 GW as of 31 March 2020. Renewable power plants, including large hydroelectric plants, constitute 35.86% of India's total installed capacity. During the FY 2018-19, the gross electricity generated by utilities in India was 1,372 TWh and the total electricity generation including utilities and non-utilities in the country was 1,547 TWh and the gross electricity consumption in the year 2018-19 was 1,181 kWh per capita.

In light of the recent COVID-19 situation, when everyone has been under lockdown for the months of April & May the impacts of the lockdown on economic activities have been faced by every sector positively or negatively. Demand for electricity has continuously increased in India. The boost in energy usage seen today is due to rapid expansion in the industrial and commercial sectors [1]. Development in the agricultural and housing sectors, population expansion, and a better quality of life are all factors that contribute to this increase [2]. As a result, forecasting electricity consumption is an important component of an electric utility's strategic planning. A utility firm may take several years to develop and commission a complicated distribution and transmission network, or even longer build a power production plant [3] and the forecast may give the data needed to strategically plan these activities. Improving energy use efficiency can save energy and mitigate global warming and climate change. The forecast not only predicts the amount of electricity that will be consumed but also assists in the management of reserved electricity for emergency use. As a result, electricity generation costs can be reduced and electricity tariffs can be kept under control [2]. And it will also help the corporation to generate electricity closer to consumption.

Various approaches for forecasting power usage have been proposed and evolved. Statistics, time series analysis, regression analysis, nonnegative least square method, multiple linear regression, and artificial neural networks are among them [2, 3, 4, 5]. Statistical models, time series methods, and artificial intelligence (AI) based approaches are the three types of forecasting methodologies that can be classified according to the forecasting framework [6]. AI-based forecasting systems have gained significant popularity in recent years, owing to their exceptional benefit of ensuring a certain level of estimation accuracy as compared to the high fluctuation of independent and dependent variables in the statistical model [7]. In [8], for example, ANN was widely used among many AI-based technologies to anticipate power consumption and price. However, several factors influence the accuracy and robustness of ANN-based approaches, including convergence speed, weight adaption methodology, and network design choices. [9,10] employed support vector regression (SVR) for power price forecasting because it can adapt and encapsulate intricate interactions with the input data. In contrast, AI techniques can handle nonlinearity issues in short-term electricity price forecasting because these methods can remove different discriminators in complex environments, and they can recall, learn, and store information based on previous experience, which has made them popular in the field of electricity price forecasting.

2. Second section

Various researches in the subject of energy demand response prediction have been done using various prediction objectives, prediction periods, and model approaches. Specifically, a wide range of machine learning and statistical approaches based on time series have been widely used. Previous researches on prediction models are discussed in this section. While doing research work, the main part of the topic is to go through the papers based on that topic. It will provide extensive knowledge to the researcher about their topic and they will be able to know about the benefits and consequences of the methods or techniques he would like to choose. After reading some following papers, many researchers comes out with their proposed methods, applied that method to the collected dataset, and further made comparisons with other techniques and analyze the results. Following are the papers that are reviewed for this topic.

AI. Rahman et.al. proposed a scheme in the paper in which Big Data Analytics is used to the power generation data of the U.S. collected in the past 20 years to process the power management. The Neural Network model is used, to train the system for the prediction of future power generation and it came out to be a close match between forecasted and actual power generation values [11].

Jui-Sheng Chou et.al. evaluate the value of the proposed model in predicting the 1 day- ahead electricity consumption. The ARIMA-MetaFA-LSSVR model used, which demonstrates a good agreement between projected and real values of air conditioner power usage. The results confirmed that the suggested model outperformed the others in terms of performance metrics and is an effective tool to facilitate managers in forecasting the 1-day-ahead power consumption of air conditioners. In research gaps, one can consider the effect of a national holiday and season change on the prediction model; one can also deploy an automated energy prediction system with a flexible interacting platform for the ease of use and expand the model by making the electricity consumption prediction of AC in 5 min, 15 min or 1 hr resolution [12].

Abinet Eseye et.al. has implemented and proposed a BGA-based feature selection approach which includes the use of the GPR fitness function for improved short-term electricity demand forecasting models. The proposed BGA-GPR FS was applied to 4 different datasets of electricity demand which was representing 4 different customer types. When compared to forecasting based on the original feature space without FS, the electricity demand forecasting model created utilizing the acquired FS findings improved yearly accuracy by 38.7 percent, 81.2 percent, 81.9 percent, and 83.0 percent, respectively [13].

Shu Fan et.al. presented a new statistical methodology to forecast the short-term electricity demand. The model allows non-linear and non-parametric terms within the regression framework which can record the complex non-linear relationship between electricity demand and its driver. And this model is used by AEMO to forecast the short-term loads of 2 regions with some different characteristics. And the model performs admirably on historical data as well as on real-time on-site implementation. Other than that, we can include more drivers like humidity to improve the prediction accuracy [14].

Ghulam Hafeez et.al. has proposed a framework based on HEMC and a strategy based on DA-GmEDE is presented for HEMC for performing efficient energy management of residential building under the forecasted day-ahead DR pricing signal and consumer preferences. This strategy reduced the electricity bill with some efficient value. For performance validation, simulations were run, and the outcomes of the suggested framework based on DA-GmEDE have been compared in terms of electricity bill and PAR reduction to DA-GA based strategy, DA-game-theory based strategy, and W/O scheduling. When compared to W/O scheduling, the suggested DA-GmEDE-based method lowered the power cost and PAR by 23.90% and 47.05%, respectively [15].

Prince Waqas Khan et.al. apply a genetic algorithm-based optimization feature engineering and machine learning to the energy consumption forecasting system. His study has suggested an approach that employs the machine learning models namely XGBoost, Support Vector regressor, and k-nearest neighbor regressor algorithm, and a genetic algorithm that is used to predict total load consumption for optimal feature selection. He also compared the model with the proposed hybrid model and achieved a MAPE of 3.35% by applying the proposed hybrid model. In the future, the work can be extended by adding some parameters like no. of residents, electric vehicles, and tourists coming in a different season of the year [16].

Again an approach to predict a day-ahead electricity price is proposed by Paras Mandal et.al. in presented an application of the neural network method. To propose the ANN method, data about the PJM electricity were used to explain the functioning of the method which is based on a similar day's approach. From the paper, we got to know that the suggested ANN outperforms the direct usage of a similar day's method for day-ahead price forecasting. Future work will involve the identification of more relevant input variables, along with price volatility analysis [17].

M.S. Mohamed Othman et.al. explained an artificial neural network-based technique on historical data for the forecasting of electricity consumption. The ANN model involved the creation of several feed-forward backpropagation networks in

MATLAB and selecting the best ANN model via the cross-validation method. After comparing the results, he got to know that the k fold cross-validation method produces a better result for the ANN [18].

Alireza Pourdaryaei et.al. has developed the hybrid ANN-ACS method for forecasting the day ahead of electricity price. In his work, he combined ANN and mutual information techniques forming a hybrid feature selection technique, which has been proposed for the selection optimum subset of features within a pool of features to be taken as input for the direct prediction method. The result in terms of MAPE was 4.58 percent, 1.2 percent, 2.62 percent, and 3.79 percent in winter, spring, summer, and fall, respectively, the ANN-ACS model outperforms other AI techniques in terms of predicting precision and simplicity [6].

Shan et.al., presented a study attempting to predict building electricity consumption taking linear and non-linear issues in the prediction of electricity consumption. To solve this problem, 2 outstanding base models LE_GRA and GRU are used and made a new prediction model i.e. GRA_GRU model. The extensive computational studies show that the GRA_GRU model provides higher average accuracy and variance for different types of buildings in different cities. This demonstrates that the GRA GRU model is capable of excellent prediction and generalization and is more suited for practical applications, particularly predicting short-term power use [19].

Joana Teixeira et.al. offers a forecast of power consumption based on mathematical models, with a daily resolution, including upscaling, using a hybrid model that combines multiple linear regression with artificial neural networks. A hybrid model (MLR & ANN) is used and compared with an MLR. The result came out that the hybrid model was the most precise and closest to the true values [20].

Zhang et.al. proposed a hybrid method based on support vector regression (SVR) with meteorological factors and electricity price. Then an improved adaptive genetic algorithm (IAGA) is used for optimizing input features and SVR parameters. After applying the proposed model, when compared to the ELM model, SVR model, and artificial neural networks (WNNs, BPNNs, and RBFNN) models, the suggested model outperforms them in terms of predicting performance. And it came out that GA (IAGA) surpasses GA in terms of optimizing SVR to enhance predicting accuracy [21].

Khotanzad et.al. have described an artificial neural network-based short-term load forecasting system which is also known as ANNSTLF. This approach has gained widespread industry adoption by replacing several old techniques like regression and similar day-based algorithms [22].

Mu-Chun Su et.al. have suggested a neural-network-based fuzzy model for modeling a system. In the work, the integration of the paradigm of neural networks with the fuzzy rule-based approach was done which made them more useful. And demonstrated the potential for using FHRCNN'S to solve transient stability prediction problems. The FHRCNN approach outperforms the MLP method in terms of learning time, network complexity, and, most importantly, classification performance [23].

Huiting Wang et.al. has used the Markov combined forecasting model for electricity demand forecasting in the paper. The forecasting results demonstrate that the suggested method is an excellent methodology for forecasting electricity demand because its MAPE value was less than ARIMA and combined i.e. 7.67% while other models have 9.10% and 11.06%, and it can also apply to other forecasting issues with random, trend, and periodicity [24].

Saleh Albahli et.al. has used the machine learning technique to support a dramatic spike in electricity prices to offload the data storage which will minimize the energy consumption in cloud data centers. The paper tells the performance of their cost-saving models on different standard deviation values and gave the optimized result. Considering this forecast, the optimized model has successfully reduced the electricity price cost up to 25.32% in data centers [25].

S. Anbazhagan et.al. proposed an Elman network for real-world electricity price forecasting. This approach is good based on accuracy than other forecast approaches except for the hybrid model and its average computation time was also less than a hybrid model. This approach presented a lower modeling complexity. And further research is underway to develop a better feature selection algorithm for different forecast models and power markets [26].

D. Baczynski et.al. use an artificial neural network with 3 hidden layers and quickly reach a state of deep over learning and unattained its minimal error for the network with one or 2 hidden layers making an ANN structure an essential influencer on the quality of electric energy consumption forecasts. The work validates that evolutionary algorithms are a promising direction of research in the future [27].

Debi Prasanna Acharjya et.al. have surveyed the various research challenges, issues, and tools which are used to analyze big data. The survey, explains that every big data platform has its focus and specific functionality, some are designed for real-time analytic and some are for batch processing. Different techniques are used for the analysis including statistical analysis, machine learning, data mining, cloud computing, etc [28].

Ashish Juneja et.al., has analyzed the case study of weather monitoring and used the big data gathered from multiple sources, and designed a system that is capable of forecasting weather based on the recent concerns of global warming [29].

Albahli et.al. have presented an Extreme Gradient Boosting (XGBoost) model for offloading or moving storage, predicting power prices, and lowering energy consumption expenses in data centers. The performance of this technique is tested using a real-world dataset given by the Independent Electricity System Operator (IESO) in Ontario, Canada, to optimize data storage and reduce energy usage in data centers. And the results are compared with RF and SVR benchmark algorithms in which the proposed technique was 91% accurate than the other two [25].

Chung-Chian Hsu et.al. have studied the influence of Taiwan's holiday on forecasting. He studied and compared the electricity load, forecasting models. Results demonstrated that the LSTM, a modern deep learning approach achieved the best performance. And in the future, parameters like rainfall and humidity will be taken into account to improve accuracy [30].

Taehyung Kang et.al. has investigated the effectiveness of fundamental deep learning models for electrical power forecasting, such as facility capacity, supply capacity, and power consumption, in the study. Several deep learning models, including a convolution neural network (CNN), a recurrent neural network (RNN), and a hybrid model that combines CNN and RNN are used. After applying models to the data, the results show that a convolution neural network (CNN) achieved the best performance than the other two models significantly. But it cannot forecast more than one day as it is a short-term power demand forecasting model. To build a more robust forecasting model capable of mid-to-long-term power demand forecasting, the future work is to acquire more training data from the Korea Power Exchange [31].

Tian Guo et.al., offer an adaptive gradient learning approach for recurrent neural networks (RNN) to forecast streaming time series in the presence of anomalies and change points. And investigated the local characteristics of time series to automatically weigh the gradients of the loss of newly available observations with distributional aspects of the data in real-time. To assess the performance of the proposed technique, comprehensive experimental research was conducted on both synthetic and actual datasets. And the results showed that (Weighted Gradient) WG-Learning performed better [32].

Zheng Wang et.al. proposed a hydrological time series forecast model based on wavelet de-noising and ARIMA-LSTM. And compare a model to the ARIMA model, the LSTM network, and the BP-ANN-ARIMA model using the daily average water level time series of a hydrological station in the Chuhe River Basin as the experimental data. And experiments demonstrate that the model has a good forecast effect and greater prediction accuracy than other models [33].

Musaed Alhussein et.al., provide a deep learning framework based on a convolutional neural network (CNN) and long short-term memory (LSTM). The proposed hybrid CNN-LSTM model extracts features from input data using CNN layers and sequence learning using LSTM layers. The proposed model is tested against a newly studied LSTM-based deep learning model on publicly accessible electrical load data of individual household customers from the Smart Grid Smart City (SGSC) project. When compared to other competing approaches, the hybrid model outperforms the LSTM based model [34].

Xiaorui Shao et.al. presented a unique domain fusion deep model based on convolutional neural network (CNN), long short-term memory (LSTM), and discrete wavelet transform (DWT). This suggested technique is tested on two public nature data sets relating to electricity usage using multiple metrics. And the suggested model DF-CNNLSTM predicted Short Term Power Consumption correctly [35].

Hyo-Joo Son and Changwon Kim presented a forecasting model combining social and weather-related variables using long short-term memory (LSTM), which is effective in deep learning-based time series forecasting techniques. The suggested model was validated using data collected over 22 years in South Korea. And six performance measures were used to evaluate the resulting forecasting performance. Furthermore, the performance of this model was compared to the performance of four benchmark models. And By reaching the lowest value, 0.07, LSTM surpassed greater performance for MAPE [36].

Ke Yan et.al. presented a hybrid deep learning model that combines an ensemble long short term memory (LSTM) neural network with the stationary wavelet transform (SWT) method. Furthermore, the ensemble LSTM neural network improves the proposed method's predicting performance. Experiments were performed on a dataset based on a real-world household energy consumption collected by the UK Dale project. And the output showed that the SWT-LSTM framework yields the most accurate predicting results [37].

Dedong Tang et.al. suggested a power load forecasting method based on two LSTM (long-short-term memory) neural network layers. A power load forecasting technique based on LSTM is built using real power load data given by EUNITE. Two models, a single-point forecasting model, and a multiple-point forecasting model were built to anticipate the power of the next hour and a half day. And the accuracy of a single point load forecasting model was higher than that of multiple point models [38].

From Table 1, many pieces of research have been done on this electricity forecasting system, power forecasting system, load forecasting system, energy forecasting system, and electricity consumption forecasting system. Some have taken a historic dataset; some have taken a real-time dataset. The more it takes data, the better results it would give. From reading the above papers we would get to know that the neural networks suit best for forecasting problems and hybrid models or combined models also perform outstandingly in predicting the data.

TABLE 1. A brief table of literature survey

Sr. No.	Author/ Year	Primary Objective	Dataset used	Technique/Method/ Algorithm used	Parameter Evaluated	Results/Output
1.	Alireza Khotanzad et al.(1997) [22]	ANNSTLF—A Neural-Network-Based Electric Load Forecasting System	2 to 3 Years of historical hourly load and weather data.	1. Multilayer perceptron(MLP) network 2. Error Backpropagation (BP) rule	Performance, Accuracy	ANN-based forecaster gave a 5.89% MAE value.
2.	Mu-Chun Su et al.(1999) [23]	Neural Network-Based Fuzzy Model and Its Application to transient Stability Prediction Power Systems	The linguistic information and numerical information	1. A novel 2-layer fuzzy hyper rectangular composite neural network (FHRCNN) 2. Multilayer perceptrons (MLPs)	Performance, Accuracy	The FHRCNN's method has shown the best classification accuracies of 99%.
3.	D. Baczynski and M. Parol (2004) [27]	Influence of Artificial Neural Network structure on the quality of short-term electric energy consumption forecast	Historical data of electric energy consumption, calender data, technological process data, and weather data from the period up to 48 hours previously.	1. One directional ANN structure	Accuracy	The neural network gave 2.5% MAPE.

4.	Paras Mandal et al.(2007) [17]	A Novel Approach to forecast electricity price for PJM using Neural Network and similar days method	The data(from Jan 1, 2004, to May 31, 2006) derived from the PJM electricity market Sets of data include hourly price and load data.	1. ANN model 2. Similarity Technique	Efficiency, Accuracy High adequacy	The algorithm gave a MAPE value of 9.72 with robust , efficient and accurate results for any day of a week.
5.	M.S. Mohamed Othman et al. (2010) [18]	Artificial Neural Network- Based forecast for electricity consumption in Malaysia.	Data for the electricity consumption were obtained from the Malaysian Energy Commission from the year 1996 to 2008.	1. ANN model 2. The holdout cross-validation method 3. k-fold cross-validation method	Performance, Accuracy	The k-fold cross-validation method gave results for the ANN with an R- value of 0.99899.
6.	Huiting Wang et al.(2010) [24]	An improved combined model for electricity demand forecasting	The missing data of the original series for November 2004 and May 2008 are replaced by the average between the previous one and the next one	1. Markov combined model 2. ARIMA model	Performance	Markov combined model gave the forecasting results with MAPE of 3.39% and 1.43% over ARIMA.

7.	Shu Fan, Rob J. Hyndman (2011) [14]	Short-Term Load Forecasting Based on a Semi- Parametric Additive Model	Half- Hourly demand and temperature data were obtained from the AEMO from 1997 to 2009	1. Regression methodology 2. Semi-parametric additive models 3. Bootstrap method	Performance, Accuracy	The overall MAE and MAPE values of the proposed model are 0.11 GW and 1.88%.
8.	S. Anbazhagan & N. Kumarappan (2012) [26]	Day-Ahead Deregulated electricity market price forecasting using Recurrent Neural Network	The electricity prices data taken from mainland Spain's daily trading reports, presented every month and NYISO, CAPITL Zone customized on yearly report	1. The feed-forward multilayer perceptron (MLP) network 2. Simple recurrent network (SRN)	Performance, Accuracy	The Elman recurrent network approach performed well in forecasting accuracy with MAPE close to 6.46% and 3.82%
9.	M. Naimur Rahman, A. Esmailpour (2015) [11]	An Efficient Electricity Generation forecasting system using the ANN approach with big data.	Past power generation data of all the states of the U.S. and stored in a distributed DB.	1. Big Data Tools (Hadoop) 2. Distributed Algorithm (MapReduce) 3. Artificial Neural Network(BP Algorithm)	Performance	The forecasted values closely match the actual generation.

10.	Debi Prasanna Acharjya, Kauser Ahmed P(2016) [28]	A Survey on Big Data Analytics: Challenges, Open Research Issues and tools	Big Data	1. MapReduce 2. Apache Spark 3. Storm	Performance	Every big data platform has its particular focus. Some of them are for batch processing and some are at good at real-time analytic.
11.	Tian Guo et al.(2016) [32]	Robust Online Time Series Prediction with Recurrent Neural Networks	Yahoo's S5 dataset	1. RLSTM 2. SR-LSTM 3. ELSTM 4. WG-Learning	Performance	WG-Learning performed better with an RMSE value of 9.62 over RLSTM, ELSTM.
12.	Joana Teixeira et al.(2017) [20]	A Hybrid model approach for forecasting electricity demand	The clients connected to the higher voltage levels network are remotely metered and the daily energy consumption is tracked.	1. Hybrid model 2. Multiple linear regression(MLR) models 3. Neural Network model	Accuracy	The hybrid model(MLR + ANN) was the most accurate and closer to the real values whose R^2 value is 98.8% compared to the MLR.

13.	Jui-Sheng Chou et al.(2019) [12]	Hybrid Machine Learning system to forecast electricity consumption of Smart grid-based Air conditioner	Direct access to researcher DB, collected data from the USB on the meters, direct monitoring using the smart meters, remote control, accesing the cloud DB.	1. Sliding Window 2. ARIMA model 3. MetaFA-LSSVR model	Performance improvement rate = 190% and 12% in RMSE	ARIMA-MetaFA-LSSVR model has max R value=0.62 than ARIMA (0.29) and LSSVR (0.58).
14.	Abinet Tesfaye Eseye et al.(2019) [13]	Machine Learning-Based Integrated Feature Selection Approach for Improved electricity demand forecasting in decentralized systems	The electricity consumption in decentralized energy systems such as buildings and its association with historical(prior) consumption and external agents.	1. BGA (Binary Genetic Algorithm) based feature selection approach 2. GPR(Gaussian Process Regression)	Accuracy, Time	FS results reported an annual accuracy improvement of 38.7%, 81.2% and 83.0%, respectively for residential, educational, office and mixed-use building types.
15.	Pourdaryaei et al.(2019) [6]	Hybrid ANN and Artificial Cooperative Search Algorithm to forecast Short-Term electricity price in Deregulated electricity market	Actual data sets are collected from Ontario electricity market of the year 2017	1. Artificial neural network (ANN) 2. Artificial cooperative search algorithm (ACS) 3. Hybrid support vector machine (SVM) 4. Hybrid ANN optimization methods	Performance, Accuracy	ANN-ACS model provides a higher forecasting precision and simplicity with MAPE of 4.58%, 1.2%, 2.62%,and 3.79% in winter, spring, summer and autumn.

16.	Shubing Shan et al.(2019) [19]	Forecasting the Short- Term electricity consumption of building using a Novel Ensemble Model	Hourly electricity consumption data of a 5- star hotel building in Shanghai (China) from Sept 1st,2013 to Aug 31st , 2015	1. LE_GRA 2. GRU	Accuracy, Variance	GRA_GRU model gave a MAPE of 1.8% and is more suitable for practical applications.
17.	Ashish Juneja & Nripendra Narayan Das(2019) [29]	Big Data Quality Framework: Pre-Processing data in Weather Monitoring Application	The application will capture global temperature data average for the last 5 decades. and capture fresh data for locations across the world to monitor any change in temperature above 1.5 degrees Celsius	1. Data Preprocessing 2. Techniques and rules of Auto-Discovery, Domain and User- Defined.	Accuracy	The weather application system is capable of forecasting weather based on recent global warming concerns.
18.	Zheng Wang, Yuan-sheng Lou (2019) [33]	Hydrological time series forecast model based on wavelet de-noising and ARIMA-LSTM	The daily average water level of a hydrological station in Chuhe River base.	1. LSTM 2. ARIMA 3. BP 4. ANN	Accuracy, MAPE, MSE	De-noising-ARIMA-LSTM has higher accuracy than that of others with a MAPE of 0.51%.

19.	Musaed Alhussein et al.(2020) [34]	Hybrid CNN-LSTM model for Short-term Individual Household Load Forecasting	Real- world load consumption data of various households from the smart grid smart city project (SGSC)	1. Hybrid CNN-LSTM model 2. LSTM	Performance, Efficacy, MAPE	The hybrid model outperforms the LSTM based model by giving the MAPE of 44.76%.
20.	Ke Yan et al.(2019) [37]	A Hybrid LSTM Neural Network for Energy Consumption forecasting of Individual Households	Energy consumption data is collected in 6-second intervals through remote sensors installed in 5 diff. family houses in London, UK.	1. LSTM 2. SVR 3. NN 4. CNN 5. CNN-LSTM 6. LSTM-SWT	RMSE, MAPE, MBE(mean bias error)	SWT-LSTM framework reported the most accurate forecasting results by giving RMSE (0.0577), MAPE (12.83), MBE(0.0308) values lower then other models.
21.	Dedong Tang et al.(2019) [38]	Power Load Forecasting using Refined LSTM	EUNITE competition load forecasting dataset contains load data of a plant of the Eastern Slovakia Power Company from 1997 and 1998	1. 2 layer LSTM 2. Single point forecasting model 3. Multiple - Point forecasting model	MAPE	Single Point Load forecasting model has higher accuracy than multiple point models with only 1% of error.

22.	Ghulam Hafeez et al.(2020) [15]	An Innovative Optimization Strategy for Efficient Energy Management with Day-ahead Demand Response signal and Energy Consumption Forecasting in Smart Grid Using Artificial Neural Network	The network training dataset is obtained from the report of the midwest independent system operator MISO taken from the federal energy regulatory commission (FERC)	1. DA-GmEDE algorithm - hybrid of grey wolf optimization(GWO) algorithm and modified enhanced differential evolution (mEDE) alogorithm	Performance	DA-GmEDE based strategy reduced electricity bill and PAR by 23.90% and 47.05%.
23.	Prince Waqas Khan & Yung-Cheol Byun(2020) [16]	Genetic Algorithm Based Optimized Feature Engineering and Hybrid Machine Learning for Effective Energy Consumption Prediction	The latest updated energy consumption and metrological data from jeju island have been collected from Jan 2017 until April 2020.	1. XG Boost 2. SVR 3. KNR 4. GA (Genetic Algorithm)	Performance, Accuracy	MAPE of 3.35% by applying the GA model
24.	G.Q. Zhang and J.F. Guo(2019) [21]	A Novel Method for Hourly Electricity Demand Forecasting	The 6 year recorders(gathered from state grid Heilongjiang Electric Power Co. Ltd.)of power load and weather factors of each hour in Daqing city(China).	1.Improved adaptive genetic algorithm (IAGA) 2.SVR (with novel feature input and selection method)	Performance, Accuracy MAE of SVR-GA= 7.29%	GA (IAGA) is more effective than SVR with RMSE of 20.27% and SVR GA is better than SVR with RMSE of 5.57%.

25.	Saleh Albahli et al.(2020) [25]	Electricity Price Forecasting for Cloud Computing Using an Enhanced Machine Learning Model	15 Years of historical data gathered from IESO provider.	1. Extreme Gradient Boosting (XGBoost) model 2. Random Forest 3. Support vector Machine (SVM)	Cost, Accuracy Accuracy = 91%	The model successfully reduced electricity costs up to 5.32%
26.	Saleh Albahli, Muhammad Shiraz and Nasir Ayub(2020) [25]	Electricity Price forecasting for Cloud computing using an Enhanced Machine Learning Model	Electricity data of Ontario-Canada (2003-2018) from the provider IESO.	1. XGBoost 2. Random Forest (RF) 3. SVR (Support Vector Regression)	Accuracy, MSE, MAE	XGBoost has 91% accuracy than RF (89%) and SVR(88%).
27.	Chung-Chian Hsu et al.(2020) [30]	Short-term load forecasting by machine learning	Historical data of climate from Jan 1st,2017- Sept 30th, 2019 provided by TaiPower and the CWB observation	1. ARIMA 2. SVR 3. ANN 4. CNN 5. RNN 6. LSTM	Performance, Accuracy, MAPE, RMSE	LSTM outperformed the other model with a MAPE of 1.85

28.	Taehung Kang et al.(2020) [31]	Forecasting of Power Demands Using Deep Learning	Data between 01.01.2003 to 22.05.2020 from Korea Power Exchange	1. CNN 2. RNN Hybrid CNN- RNN	Performance	CNN has a comparatively better MAE value of 0.314 MW than ANN and SVM.
29.	Xiaorui Shao et al.(2020) [35]	Domain Fusion CNN-LSTM for short-Term Power Consumption Forecasting	14 hours power consumption data is collected by Pennsylvania- New Jersey- Maryland(PJM) in the United States.	1.CNN 2.LSTM 3.DWT (Discrete Wavelet Transform)	Performance, Accuracy,RMSE, MAPE, MAE	DF-CNNLSTM accurately forecast short-term Power consumption with an improved RMSE of 6.71% compared to CNN-LSTM.
30.	Hyojoo Son and Changwan Kim (2020) [36]	A deep learning approach to Forecasting Monthly Demand for Residential- Sector Electricity	Monthly residential electricity demand data were collected from 1991 in South Korea.	1. LSTM 2. SVR 3. ANN 4. ARIMA 5. MLR	Performance, MAE, RMSE,MAPE	LSTM outperformed performance for MAPE by achieving the lowest value i.e. 0.07.

3. RESULTS

Electrical load forecasting is a critical procedure that may boost efficiency and profitability for power generation and distribution businesses. It enables them to plan their capacity and operations to dependably deliver all necessary energy to all users. Nowadays forecasting is becoming necessary as it tells the future predictions which allow people to plan the system accordingly.

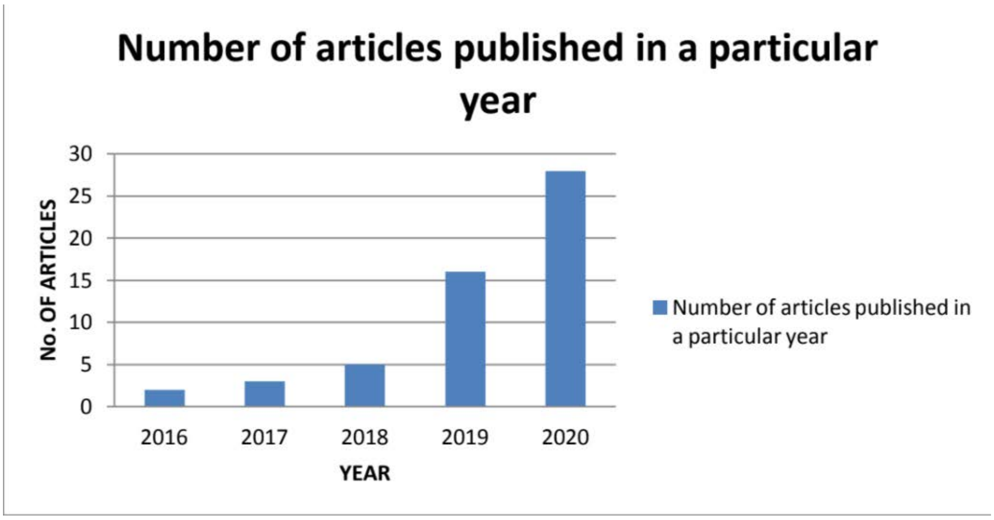

FIGURE 1. Representing several articles being published in the year 2016-2020 on electricity forecasting.

From Figure 1 , we get to know that the energy sector is important and is the main contributor to the country's economy that's why the research is increasing in this sector. Here, the x-axis represents a year, and the y-axis is representing some articles. A lot of articles were published in the year 2020 compared to other years.

According to Figure 2, the most proposed technique used in the above papers was Artificial Neural Networks (ANN). Because of its capability, it makes models easier to use and more accurate from complicated natural systems with big inputs. ANN has been discovered to be a highly innovative and effective model when it comes to problem-solving and machine learning.

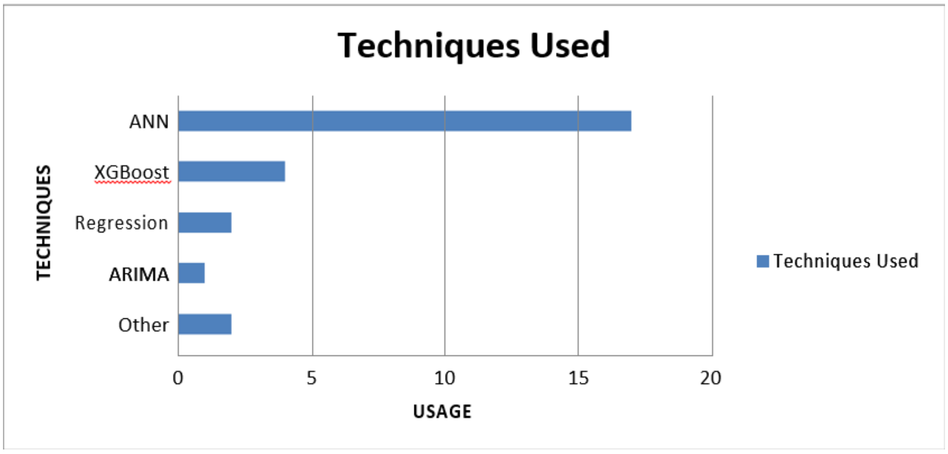

FIGURE 2. Representing mostly used technique in electricity forecasting system.

4. CONCLUSION

During the years 2007 to 2020, the most relevant published papers were taken in the literature. The survey focused on the various classical models as well as the new models based on artificial neural networks for the prediction of time-series data. The key to good forecasting is identifying patterns or hidden information in historical data. There are many methods used in electricity consumption forecasting systems like Regression, XG Boost, ARIMA, ANN, and many more. It was observed from the literature that regression, ARIMA, and other traditional methods alone can't handle non-linear relationships well. Only ARIMA gives RMSE of 1.18 KW, but when this model or other linear models is combined with non-linear models then it will give RMSE of 0.41 KW. Therefore, the only single classical technique is not very good for forecasting time series data. On the other hand, some AI technologies like SVM and traditional ANN do not count the time relationship of electricity consumption. In literature, SVM reported RMSE value as 8.32, ANN as 8.73, and LSTM as 8.13 in which ARIMA with RMSE value 18.69 performs worst which made the LSTM a better method for a time series forecasting. Therefore, it was concluded that the deep learning technique LSTM has become one of the most widely used models for predicting power demands or consumption, with smaller prediction errors.

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