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Review

Demand Prediction with Machine Learning Models; State of the Art and a Systematic Review of Advances

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Abstract: Electricity demand prediction is vital for energy production management and proper exploitation of the present resources. Recently, several novel machine learning (ML) models have been employed for electricity demand prediction to estimate the future prospects of the energy requirements. The main objective of this study is to review the various ML models applied for electricity demand prediction. Through a novel search and taxonomy, the most relevant original research articles in the field are identified and further classified according to the ML modeling technique, perdition type, and the application area. A comprehensive review of the literature identifies the major ML models, their applications and a discussion on the evaluation of their performance. This paper further makes a discussion on the trend and the performance of the ML models. As the result, this research reports an outstanding rise in the accuracy, robustness, precision and the generalization ability of the prediction models using the hybrid and ensemble ML algorithms.

Keywords: demand prediction, energy systems; machine learning; artificial neural network (ANN); support vector machines (SVM); neuro-fuzzy; ANFIS; wavelet neural network (WNN); big data; decision tree (DT); ensemble learning; hybrid models; data science; deep learning; renewable energies; energy informatics; prediction; forecasting; energy demand

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Introduction

Electrical energy is an essential element for the sustainable development of today's nations in economic, environment and social aspects. The global energy consumption has been ever increasing exponentially. Therefore, implementing energy management can be a major step in the progress of economic development and environmental security. As the electrical energy cannot be stored, managing an efficient balance between electricity demand and generation is crucial (Jebaraj and Iniyan 2006). Electricity demand forecasting aims at predicting the precise amount of this kind of energy (Suganthi and Samuel 2012; Debnath and Mourshed 2018). Both under- and over-estimating can have very costly consequences. The high operating cost of the network, excess supply and network balance problems are examples of overestimation whereas failure in delivering enough electrical energy is the most important issue of underestimation (Palensky and Dietrich 2011).

In general, electricity demand is generated as a quantity of electricity and distributed in a specific area over a given period (Engle, Mustafa et al. 1992). Electricity demand forecasting is considered as one of the most important areas in the research in the electric power industry due to its decision maker role in the management of power grid in response to changes in the consumption of subscribers. It is also attractive for companies related to the fields of energy generation, transmission, and marketing. Most importantly, the nation's gross national income,

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technological development energy price and efficiency, gross output, and population are being linked to energy demand to make the optimal decision for the future world (Suganthi, Samuel et al. 2012; Torabi, Hashemi et al. 2018). Therefore, energy demand modeling and management has become an important issue among policy-makers.

Traditional energy models for demand prediction includes Time series, Econometric, Regression, Decomposition, and ARIMA models, and Expert systems (Ghalehkhondabi, Ardjmand et al. 2017; Hosseini Imani, Zalzar et al. 2018). Over the years such models have been improved using SC techniques such as Genetic algorithm and fuzzy logic (Amasyali and El-Gohary 2018; Torabi, Mosavi et al. 2018). In addition, the integrated models e.g. Ant Colony Optimization, Particle swarm optimization, Bayesian vector auto regression (Azadeh, Ghaderi et al. 2007; Hong 2010; KıRan, ÖZceylan et al. 2012; Ahmad, Chen et al. 2018) along with Bottom-up models e.g. MARKAL, TIMES G5, and LEAP (Zonooz, Nopiah et al. 2009; Shabbir and Ahmad 2010) have become widely popular.

Recently, ML models e.g. ANNs, SVRs (Azadeh, Ghaderi et al. 2007; Ahmad, Hassan et al. 2014; Amasyali and El-Gohary 2018) have been noticed in academic and empirical proposes for overcoming the real-world problems. ML (Michalski, Bratko et al. 1998) is a subset of artificial intelligence which is inspired mainly by biological learning. ML deals with the computer programs and systems which have the capability of experiential learning. Motivation in use of ML methods in electrical energy demand estimation is that they can build and analyze more complex and large-scale models in an accurate, robust and efficient manner (Tso and Yau 2007). Building precise models with high accuracy is so important for electricity power generation since just a 1% rise in demand prediction lapse is equal with losing out of millions of dollars.

Methodology of review

The methodology of search and selection of relevant articles is described in figure 1.

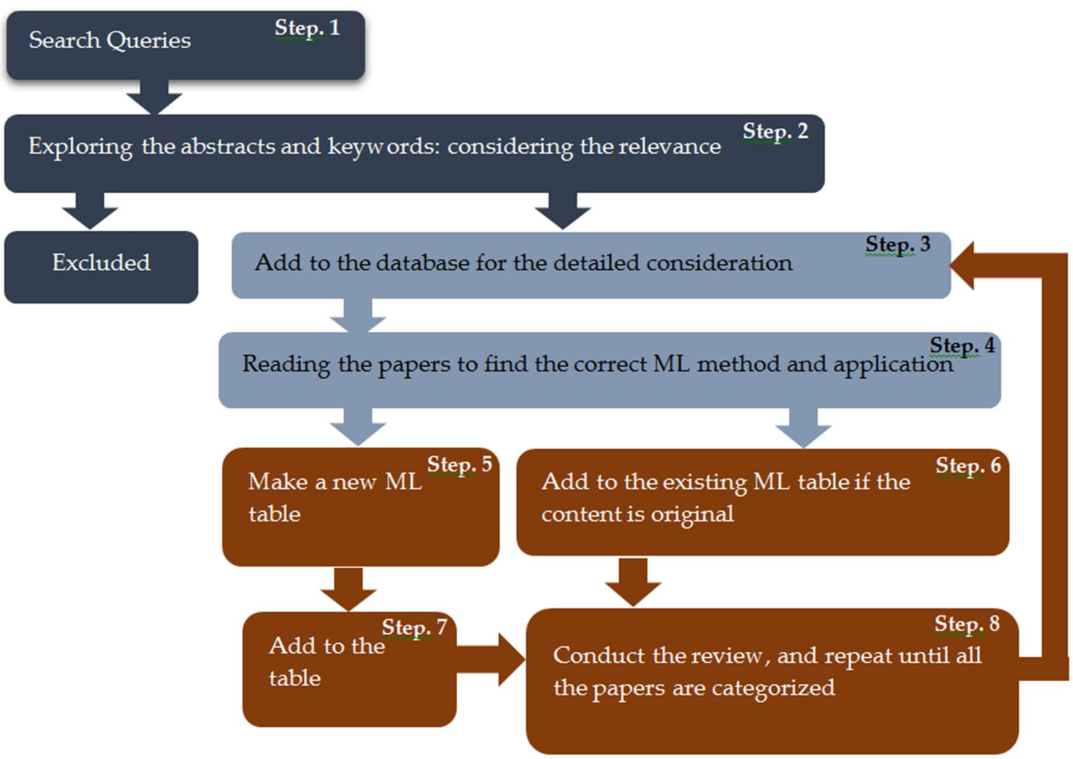

Figure 1. Taxonomy of the research.

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This research work has been investigated in the prediction of electricity demand in three different classes: single methods, hybrid methods, and ensemble methods. Single methods are … , ensemble methods are …. And the hybrid method is…

In this study, the general evaluation factors were correlation coefficient, MAPE and RMSE as the most popular evaluation factors to indicate the accuracy and precision of the developed models (Faizollahzadeh_Ardabili, Najafi et al. 2017; Najafi and Ardabili 2018) (Eq. 1, 2 and 3).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}\left(Actual_i - predicted_i\right)^2} \tag{1}$$

$$r = \left(1 - \left(\frac{\sum_{i=1}^{n}\left(Actual_i - predicted_i\right)^2}{\sum_{i=1}^{n}\left(Actual_i\right)^2}\right)\right)^{1/2} \tag{2}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{N}\left|\frac{Actual_i - predicted_i}{Actual_i}\right| \tag{3}$$

Where, Actuali represents the target values, predictedi represents the output values by the methods and n is the numbers of data.

Classification

ML employs advanced statistical techniques to able the computer systems to learn based on data, without specific programming. One of the applications of ML, these days, is predicting electricity demand. There is a number of different methods which are used for this purpose.

Single methods

Future prediction can be developed in the presence of one single ML algorithm. In the literature, some of the single methods like KNN, SVM, ANN, DT, and other ML methods have been used to overcome these problems. KNN is one of the most simple and traditional nonparametric techniques to classify sample (Tsai, Hsu et al. 2009). SVM which is proposed by Vapnik (1998), first maps the input vector into a higher dimensional feature space and then obtain the optimal separating hyperplane in the higher dimensional feature space. The ANN is information processing units which to mimic the neurons of the human brain (Haykin 1994).

Table 1 presents the latest research work has been done for electricity demand prediction with single ML methods. The first columns show the reference, while the second columns give us information about the model which is used for prediction. In some cases just a single method used for this purpose, in some others one method has been compared with some other methods to give credit for the one which outperforms the other like (Ali and Azad 2013).

Table 1. Single ML methods

Reference	Modeling Method	Year	Duration	Historical Data	Region
(Ren, Suganthan et al. 2016)	RF	2016			
(De Felice, Alessandri et al. 2015)	SVM vs. LR	2015	Mid-term	1990-2007	Italy

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(Zjavka 2015)	PNN	2015	Short-term		
(Zahedi, Azizi et al. 2013)	ANFIS	2013	monthly		Canada
(Ali and Azad 2013)	SVR vs. LR & MLP	2013	Daily		
(Kheirkhah, Azadeh et al. 2013)	ANN vs. GA & FIS & ANFIS & FR	2013	monthly	1992-2004	Iran
(Azadeh, Saberi et al. 2010)	Fuzzy Regression	2010	Seasonal and monthly	1994-2005	Iran
(Adam, Elahee et al. 2011)	ANN	2011	Monthly	2005-2008	Mauritius
(Çunkaş and Altun 2010)	ANN	2010	Long-term	2008-2014	Turkey
(Kandananond 2011)	ANN vs. ARIMA & MLR	2001		1996-2010	Thailand

When it comes to predict future electricity demand prediction, ANN is considered as one the most common methods. An ANN has a pliable structure that is for making fuzzy rule. It performs weight adjustments by connecting the layers. This characteristic of the ANN leads to be used in modeling highly complicated systems. Therefore, ANN can be used to model a system to predict future electricity demand (Çunkaş and Altun 2010; Adam, Elahee et al. 2011; Kandananond 2011; Kheirkhah, Azadeh et al. 2013). (Adam, Elahee et al. 2011) used the ANNs for predicting the monthly peak electricity demand in Mauritius. The source data, which is collected from January 2005 to December 2008, is used in this paperwork. It is reported by this paper that the proposed model predicts the monthly peak in electricity demand accurately. (Çunkaş and Altun 2010) implemented a model based on ANN for long-term prediction of electricity demand in Turkey. Data, which is gathered for this purpose, is for the years between 2008 and 2014. To conclude, it is shown that the proposed approach has the lower percent errors. (Kandananond 2011) compared the efficiency of the different prediction model, namely, ARIMA, ANN, and MLR. The data, which is tested in this work, is for Thailand for the years between 1996 and 2010. Based on results, ANN outperforms the other two models by reducing the MAPE values. In a study by (Kheirkhah, Azadeh et al. 2013)), it is shown that the performance of the ANN can be improved by some changes. (Kheirkhah, Azadeh et al. 2013) proposed a model based on ANN for estimating seasonal and monthly electricity demand. In this research work, conventional time series, ANN, PCA, DEA and data pre-processing method are integrated with each other for electricity demand prediction. It has been also shown that the proposed method outperforms the algorithms like GA, ANN, FIS, ANFIS, FR. The data, which is used in this article, presents monthly consumption in Iran from April 1992 to February 2004. (Zjavka 2015) employed a differential polynomial neural network to predict electricity demand for a short period.

SVM is considered as a modeling technique for classification. It is also useful for regression of the noisy data. The understandable mechanism and the accuracy of the prediction, has make this method to be a preferable method among the others. (Ali and

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Azad 2013; De Felice, Alessandri et al. 2015) try to compare the performance of this method with others like LR & MLP for electricity demand prediction. (De Felice, Alessandri et al. 2015) present a way to predict mid-term electricity demand prediction based on seasonal climate forecast. In order to predict, the writers use to different ML approaches, namely linear regression and SVM. The electricity data, which is used in this research, is for the time from 1990 to 2007 in Italy. By doing this research, the writers report that they could find a relationship between temperature and electricity demand and as a result, they claim that the anomaly of the electricity prediction in that region is because of heat-waves over Europe and for this purpose SVM is generally better than the linear model. In addition, (Ali and Azad 2013) use SVR for estimating daily electricity demand for a household. they compare the efficiency of this model with two other models, namely, linear regress and multilayer perception. They show that SVM is the best choice for this task. The result of their study shows that ML techniques can be used to forecast demand in a smart grid environment.

ANFIS for short, is a hybrid fuzzy-ANN method. In other word, it integrates ANN with fuzzy logic principles in order to benefit capabilities of both method. It uses some rules like IF_THEN that ability to learn to estimate nonlinear functions. So, ANFIS is considered as a general model for estimation and modelling purposes. (Zahedi, Azizi et al. 2013) estimate the electricity demand of the Ontario province of Canada by using ANFIS. To train the model it uses the data, which is collected from the year 1976- 2005. The proposed network which is based on ANFIS maps size parameter as input data to electricity demand as the output variable. The best MSE for the network is 0.0016 for the test data.

Fuzzy regression is a kind of classical regression model that has a fuzzy variation. It uses fuzzy numbers to consider the relation between the independent and dependent variables in a fuzzy dimension. (Azadeh, Saberi et al. 2010) for estimating seasonal and monthly electricity demand use fuzzy regression and time series framework for Iran and China. The user data is collected from Iran during the period March 1994 to January 2005. The paper shows that the proposed model outperforms other methods like GA and ANN.

RF algorithm is a one of the most popular and powerful supervised ML algorithm that is able to do both classification and regression tasks. As the name provides, this method creates the forest with a number of decision trees for estimation. (Ren, Suganthan et al. 2016) establish a big data-driven forecasting of electricity demand based on the RF. The model can identify the relation between factors for all users of a smart grid, which is clustered by a subspace-clustering model based on their electricity consumption model. (Ren, Suganthan et al. 2016) establish a big data-driven forecasting of electricity demand based on the RF. The model can identify the relation between factors for all users of a smart grid, which is clustered by a subspace-clustering model based on their electricity consumption model. (De Felice, Alessandri et al. 2015) present a way to predict mid-term electricity demand prediction based on seasonal climate forecast. In order to predict, the writers use to different ML mwthods, namely linear regression and SVM. The electricity data, which is used in this

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Ensemble methods

Ensemble methods are those which use a set of classifiers to classify the new data by taking a weighted vote of the prediction which is made by each classifier. These methods can be separated into two main categories: sequential and parallel. In the former, the base learners are generated sequentially, whereas, in the latter kind, they can be generated in parallel. AdaBoost and RF are two examples of these two kinds of ensemble methods respectively.

Most of the ensemble methods use a single base learner to produce homogeneous base learners. In this case, the base learners are the same and lead to homogeneous ensembles, though there are other types that different types of learner are used, leading to heterogeneous ensembles. Bagging, boosting and stacking are three different types of ensemble technique.

Table 2. Ensemble-ML methods

Reference	**Modeling Method**	**Year**	**Duration**	**Historical Data**	**Region**
(Wang, Wang et al. 2018)	Ensemble (bagging)	2018	Hourly	2014-2015	USA
(Shao, Gao et al. 2015)	Ensemble (EEMD)	2015	Mid-term	2004-2012	China

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(Hassan, Khosravi et al. 2015)	Ensemble (NN)	2015	Short-term	2011-2012	Australia/USA
(Burger and Moura 2015)	Ensemble	2015	Real-time	2 years	USA
(Xiao-Hua, Dong-Xiao et al. 2015)	Ensemble	2015	Real-time		
(Shen, Babushkin et al. 2013)	Ensemble (PSF)	2013	Daily	2007-2009	Australia
(Pezzulli, Frederic et al. 2006)	Ensemble (Bayesial Hierachical)	2006	Seasonal	1986-2003	England/ Wales
(Taylor and Buizza 2003)	Ensemble	2003	Daily	1997-2000	

(Wang, Wang et al. 2018) propose an EBT to predict hourly electricity demand prediction. The historical data for this work is for an institutional building (Rinker Hall) in the University of Florida (UF) campus from 2014 to 2015. The writers claim that the presented method can predict the electricity demand for the test building with improved accuracy. (Hassan, Khosravi et al. 2015) present an ensemble method, which is constructed by 100 NN models, then the output from NN models combined by three different aggregation algorithms. The test and train data is a dataset which is from AEMO and New York Independent System. (Shao, Gao et al. 2015) present an EEMD based framework for mid-term electricity demand prediction. The data, which is used for training and testing the proposed method, is for Suzhou city from February 2004 to January 2012. It is claimed that the proposed method outperformed the common decomposition forecast methods.

(Burger and Moura 2015) introduce a new ensemble model for predicting electricity demand. The proposed model performs model validation and selection by using a gating function in real time. The time series data, which is used in this model, is for eight building located in the Berkely campus of the University of California, which is recorded hourly for 2 years. As a conclusion, the writer claims that the proposed ensemble method is able to help in the production of accurate multivariate electricity demand forecasting for the buildings. (Xiao-Hua, Dong-Xiao et al. 2015) conduct a research on using an improved heterogeneous ensemble method for estimating electricity demand in China. The proposed method is based on the characteristics of the MLR model, WNN, GM (1, 1). The real-time data is used for this work is for electricity demand in China. The writers claim that their method overcomes the defect single assessment standard of general variable weight combination forecast model and conquer the limitations of fixed weight combination forecast models and a result it can achieve a better improvement in forecasting.

(Shen, Babushkin et al. 2013) try to solve the problem of the new-day electrical demand problem by an ensemble approach. The proposed method is based on the PSS and five model for this estimation is used. The clustering methods for this research are K-means, Self-organizing Map Model, Hierarchical clustering, K-methods, and Fuzzy C-means models. Based on results the proposed method provides better

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performance in comparison with the other five methods.

(Pezzulli, Frederic et al. 2006) present a Bayesian hierarchical model for seasonal (winter) electricity demand prediction in Central England and Wales. The daily peak demand data for training and testing is collected by NGT for 17 winters from 1986-1986 to 2002-2003. It is claimed by the writers, which their methods for this purpose are extremely flexible. (Taylor and Buizza 2003) Make a relationship between weather ensemble predictions in electricity demand estimation. The proposed method is for short-term which can predict 1 to 10 days ahead. The data that is used in this work is for 22 months, which contains daily data from 1 January 1997 to 31 October 1998 for estimating the parameters of the model and from 1 November 1998 to 30 April 2000 to test the methods. In a conclusion, the writers claim that there is a potential use for weather ensemble prediction to improve the accuracy and uncertainty assessment of electricity demand prediction.

Hybrid methods

Hybrid methods are a combination of completely different techniques to increase the performance (Tsai, 2010). This kind of methods generally consists of two functional components. The first one takes raw data as input and generates intermediate results. The second one will then take the intermediate results as the input and produce the final results. The following table also has the same structure as the previous ones. It contains information about the references which uses hybrid prediction modeling for electricity demand. They have to combine different techniques to improve the performance of the single methods.

Table 3. Hybrid ML methods(Ren, Suganthan et al. 2016)(Ren, Suganthan et al. 2016)

Reference	Modeling Method	Year	Duration	Historical Data	Region
(Anand and Suganthi 2018)	Hybrid (ANN,GA_ PSO)	2018	Annual	1991-2015	India
(Chen, Lo et al. 2017)	Hybrid (ANN,COGSA)	2017	Monthly	2006-2010	Oman
(Chen and Tan 2017)	Hybrid (SVR, MWD)	2017	Hourly		
(Günay 2016)	Hybrid (ANN, MLR)	2016	Annual	1975-2013	Turkey
(Ismail and Abdullah 2016)	Hybrid(ANN,PCR)	2016	Long-term	1995-2013	Malaysia
(Yu, Wang et al. 2015)	Hybrid (ANN, PSO, GA_RFB)	2015	Short-term	1990-2013	China
(Mostafavi, Mostafavi et al. 2013)	Hybrid (GP , SA)	2013	Long-term	1986-2009	Thailand
(Velasquez Henao, RUEDA MEJIA et al. 2013)	Hybrid (SARIMA, NN)	2013	Monthly	1995-2010	Colombia
(An, Zhao et al. 2013)	Hybrid (ANN, EMD)	2013	Short-term	2011	Australia
(Wang, Wang et al. 2010)	Hybrid (NN, IBPW)	2010	Annual	1985-2000	Taiwan

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A GA is a search method for exploring that can be applied in finding an optimal solution in different applications. On the other hand, due to the fact that PSO falls into a local optimum, it is not a good candidate for finding a solution in optimization issues. By combining this two methods, an optimized result can be achieved. (Anand and Suganthi 2018) use an ANN, which is optimized by a hybrid algorithm of GA and PSO. This hybrid algorithm is used for improving the annual electricity demand prediction in India. The historical data, which is used in this paper, is from 25 years from 1991 to 2015. COGSA is a method that helps to optimize the forecasting procedure. First, CO algorithm tries to search the global search space to find global optima, then GSA as an algorithm that search the local, tries to fine some better solutions near to the optima which has been found by COA. This process is used to reach the benefits of exploiting the space. (Chen, Lo et al. 2017) use the same procedure to solve the problem of forecasting electricity demand. They train ANNs by different heuristic algorithms like GSA and Cuckoo optimization. The resulting model is used to predict monthly electrical demand. The data, which is used for the model, was collected from the years 2006 to 2010 in Oman. The result shows that the ANN-CO is the best fit model for the historical data.

Pre-processing of data in an integral part of data mining. It is done to clear the initial data from the noise, therefore the result data is efficient for data modelling. For example Fourier transform can be used in this step. However this method has some drawbacks like phase shift. WT can overcome these disadvantageous by providing better temporal resolution for components which have low frequency. Also it provides better frequency resolution for low frequency components at the same time. MWD is a way of analysing that considers both time and frequency domain. In general, a series of wavelets are derived from a mother wavelet by displacement and scaling on time shaft and shift translations. The role of MWD is to find how and how much inevitably random sections in the dataset can be reduced. (Chen and Tan 2017) propose a hybrid model based on SVR and multi-resolution WD for predicting hourly electrical demand prediction in the building sector. In this research work, WD is used as a pre-processing step. The data, which is used in this paper, is collected from an electric consumption of a mall and a hotel in China. The writers report that introducing WD, the prediction accuracy can always be improved for the hotel, and it is not necessary for the mall.

ANN can also be combined with MLRs in order to make a hybrid method to produce better results. It this combination, a MLR is used to be applied on the whole data to specify that a specific descriptor variable is appropriate or not. In this combination, then the ANN is used to construct a prediction model on the variables which have been already specified by the MLR. The hybrid model can be used in electricity demand prediction as it is use by (Günay 2016). In this research work, the writers show that how they combine ANN and MLR to predict annual electricity demand in Turkey. The data, which is used for the work is for the years between 1975 and 2013. The writer concludes that the presented approach can be used by other countries to make a precise prediction for the future.

One of the main reason for the weakness in the accuracy of the electricity

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prediction models is the property of the input data. The multi-collinearity among the independent variables and the changing in the pattern of the input variables. In order to solve this problem, the PCR are employed which is a combination of the Principle Component analysis with linear model. The main aim for this combination is to improve the accuracy. BPNN or the Back-Propagation Neural Network model is also a suitable model for working with independent variable and get a good accuracy in estimation model. In order to tackle the issues which comes from the mixed pattern datasets, (Ismail and Abdullah 2016) use a hybrid model which a combination of linear and nonlinear approaches. They present a new Hybrid model, which a combination of PCR and BPNN in order to improve the accuracy rate for the electricity demand prediction. The dataset used for this work is for Malaysia for the duration of the years between 1995 and 2013. It is concluded by the writers that, the proposed hybrid system is more accurate than the others, and this model can be used in modelling in the other areas.

Radial Basis Function model or RBF is a function which its values only depends on the distance from the origin. So the RBF neural networks has a simple structure and their ability in approximating the nonlinear problems are better. They also convergence speed. With combining these models with PSO_GA which has been already introduced, the prediction of the future can be optimized. This model is used to forecast electricity demand by (Yu, Wang et al. 2015). The writers try to use a hybrid model, which is a combination of PSO-GA-RBF for estimating annual electrical energy demand. The paper concludes that the presented model has a simpler structure and has higher precision than ANNs. The data, which is used in this paperwork, is related to the years between 1990 and 2013 in China.One the powerful estimating model for electricity demand is GP. When this model combines with SA, the result improve the performance of the GP. (Mostafavi, Mostafavi et al. 2013) use the same idea to predict long-term electricity demand. The data is related to the total electricity demand in Thailand during the years 1986 to 2009. The writers compare the proposed model with a regression and ANN and it outperforms them with high accurate forecasting.

SARIMA methodology is able to capture the linear components in the time series, so combining it with ANN which can apply on nonlinear components, will improve the performance for of the neural networks. Therefore, (Velasquez Henao, RUEDA MEJIA et al. 2013) use a hybrid model which is a combination of SARIMA and neural network for estimating monthly electricity demand. The data is gained from the Colombian Energy Market for the time between August 1995 and April 2010. This paper shows that the proposed method provides forecasting with accuracy better than SARIMA and GSMN in isolation. Empirical Mode Decomposition or EMD is a way to breakdown a signal without leaving the time domain. So, the process which EMD uses is useful for analysing natural signals which are nonlinear. The combination of EMD with FFNN which is a feed-forward neural network can improve the accuracy of the prediction. (An, Zhao et al. 2013) combine a multi-output FFNN with EMD to propose a novel method for short-term electricity demand forecasting. The collected data from 2nd May 2011 to 26th June 2011 form Australia is used in this research work. As a result,

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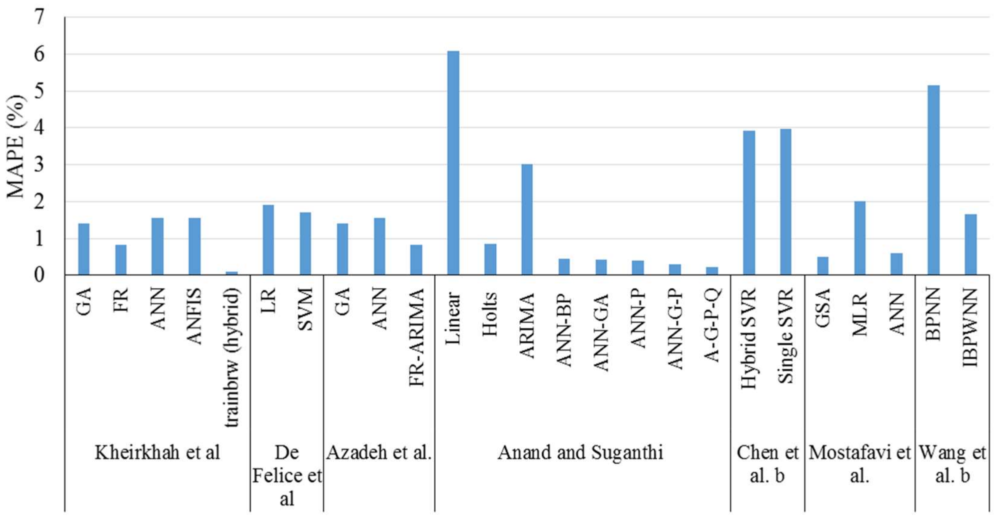
the paper reports that MFES improves the prediction of the electricity demand significantly. (Wang, Wang et al. 2010) propose an improved version of BP wavelet neural network (IBPWNN) to forecast electrical energy demand. In this study, the annual power demand of Taiwan between the years 1985 and 2000 is used. This data is divided to train and test data, which the data of the years 1985 to 1996 is used as training data and the rest as the text data. It is reported by this paper that IBPWNN has high precision and a good ability for estimating electricity demand.

Discussions

Here come the discussions on the ML methods used and on the outstanding rise in the accuracy, robustness, precision and the generalization ability of the prediction models using the hybrid and ensemble ML algorithms. This section provides the graphical results related to the studies presented in the above sections. These results provide a better comparison capability as well as a better understand about the performance of each method. Figures 1 and 2 presents the results in term of MAPE and RMSE for the highlighted studies, respectively. In this way, the method with a low MAPE provides a better performance compared with other methods.



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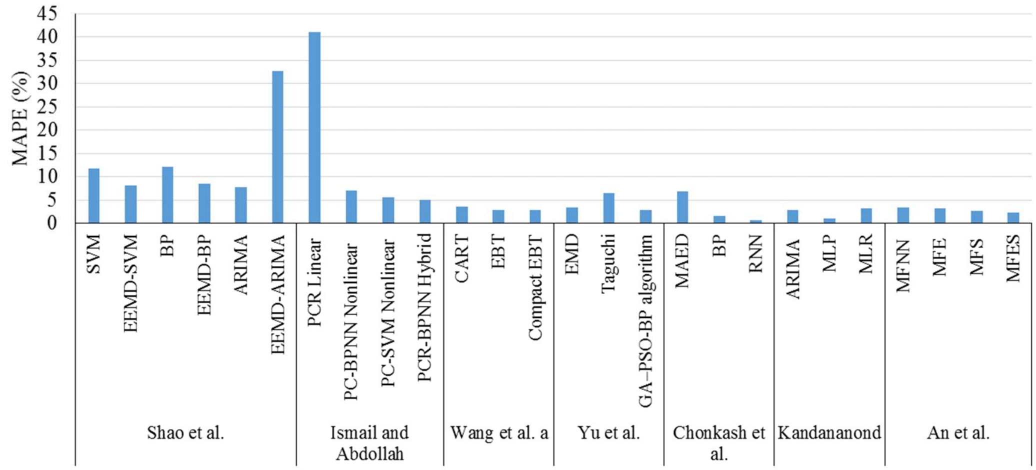

b

Figure 1. MAPE values for the highlighted studies. b continues by a

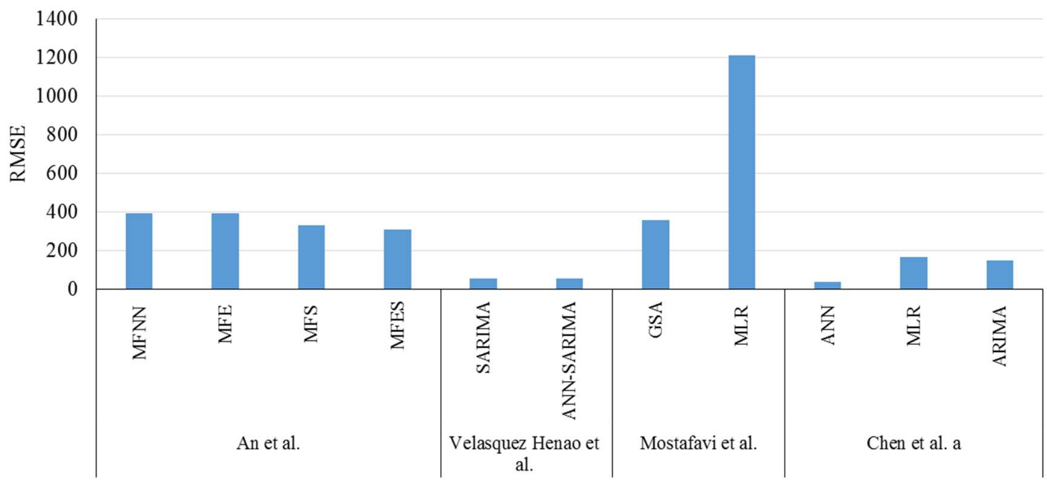

Figure 2. RMSE values for the highlighted studies

Based on results, in all cases, hybrid and ensemble methods provide a better performance compared with other techniques, significantly.

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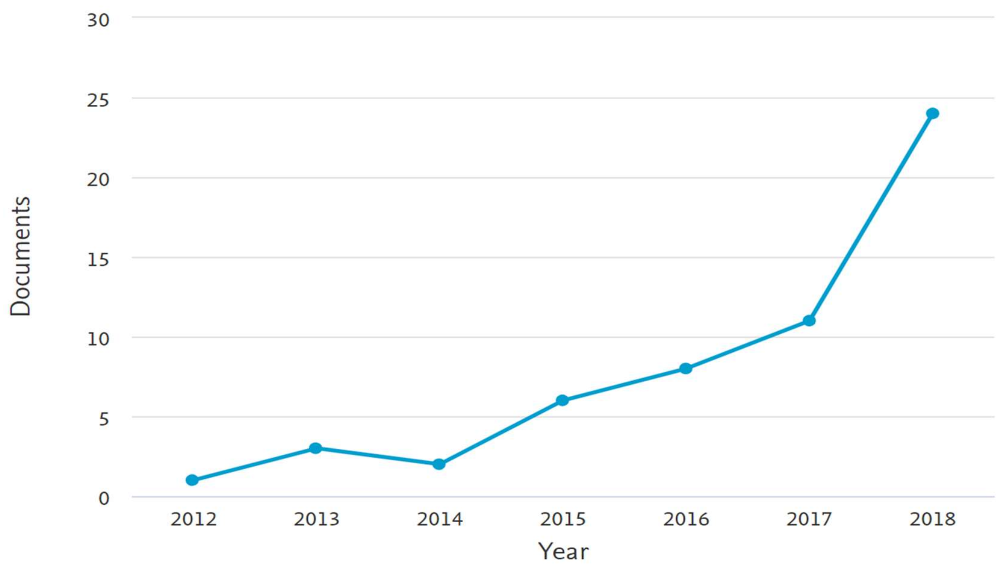

Figure 3. Number of documents on demand prediction which used machine learning models.

Fig. 3 shows the increasing number of machine learning models for demand prediction. Further reading include e.g., (Afrin, Nepal et al. ; Ahmad and Chen ; Ahmad, Chen et al. ; Ahmad, Chen et al. ; Ai, Chakravorty et al. ; Chen, Tan et al. ; Cui, Fan et al. ; Ferreira, Lee et al. ; Grolinger, L'Heureux et al. ; Guo, Wang et al. ; Jiang, Li et al. ; Kim, Song et al. ; King, Abrahams et al. ; Kumar and Singh ; López Lázaro, Barbero Jiménez et al. ; Marcek and Kotillova ; Muzi, De Lorenzo et al. ; Nguyen, Kieu et al. ; Qu, Zhang et al. ; Sala-Cardoso, Delgado-Prieto et al. ; Sánchez-Oro, Duarte et al. ; Shah, Miled et al.)

Conclusion

Energy demand prediction models using ML methods have been reviewed. It is found that today, various nations are investing in the advancement of prediction models of ML for a detailed energy planning for their sustained development. Such models are formed using hybrid and ensemble ML techniques. ANNs, SVRs, Neuro-fuzzy in an integration with SC techniques yielded better prediction performance.

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