State of the Art of Machine Learning Models in Energy Systems, a Systematic Review

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Abstract: Machine learning (ML) models have been widely used in diverse applications of energy systems such as design, modeling, complex mappings, system identification, performance prediction, and load forecasting. In particular, the last two decades has seen a dramatic increase in the development and application of various types of ML models for energy systems. This paper presents the state of the art of ML models used in energy systems along with a taxonomy of applications and methods. Through a novel search methodology, ML models are identified and further classified according to the ML modeling technique, energy type, and the application area. Furthermore, a comprehensive review of the literature represents an assessment and performance evaluation of the ML models, their applications and a discussion on the major challenges and opportunities for prospective research. This paper further concludes that there is an outstanding rise in the accuracy, robustness, precision and the generalization ability of the ML models in energy systems using the hybrid and ensemble ML algorithms. ML models are widely used in solar energy and wind energy prediction so that these sustainable energy sources will become more practical and more economic. Energy demand prediction by ML models will also improve our communities' sustainability.

Keywords: energy systems, machine learning, artificial neural network, support vector, neuro-fuzzy, wavelet neural network, decision tree, ensemble, hybrid models, deep learning.

acronyms used frequently in this work

GHG	Greenhouse Gas	RF	Random Forests
DL	Deep Learning	ELM	Extreme Learning Machine
WNN	Wavelet Neural Network	GANN	Neural Networks by Genetic Algorithm
SVR	Support vector regression	ARMA	Autoregressive Moving Average
RMSE	Root Mean Squared Error	CRO	Coral Reefs Optimization

RBF	Radial Basis Function	CGP	Cartesian Genetic Programming
SVM	Support Vector Machine	NDP	Neuro Dynamic Programming
ANFIS	Adaptive Neuro Fuzzy Inference System	IDSS	Intelligent Decision Support System
ANNs	Artificial Neural Networks	PSO	Particle Swarm Optimization
PV	Photo voltaic	FIS	Fuzzy inference system
MLP	Multi Layered Perceptron	NARX	Nonlinear Auto-Regressive with eXternal input
PR	Persistence model	EEMD	Ensemble Empirical Mode Decomposition
r	Correlation coefficient	KELM	kernel-based extreme learning machine
ML	Machine Learning	SAPSO	Self-Adaptive Particle Swarm Optimization
GRNN	Generalized Regression Neural Networks	BP	Back Propagation
EEMD	Ensemble Empirical Mode Decomposition	FOARBF	Fruit Fly Optimization Algorithm Radial Basis Function
FOASVR	Fruit Fly Optimization Algorithm Support Vector Regression	FOAGRNN	Fruit Fly Optimization Algorithm Generalized Regression Neural Networks
SOC	State of Charge	EMD	Empirical Mode Decomposition
WPRE	Wind Power Ramp Events	RBFNN	Radial Basis Function Neural Networks
CWNN	Convolutional-Wavelet Neural Networks	MRWNN	Multi-Resolution Wavelet Neural Network
RNN	Recurrent Neural Network	NDP	Near-Data Processing
MR		OG	
MTL	Multi-Task Learning	FEAT	
OLR		SARIMA	Seasonal Autoregressive Integrated Moving Average
SCADA	Supervisory Control and Data Acquisition	GA	
DOPH	Direct Optimum Parallel Hybrid	NWP	Numerical Weather Prediction
FDN		KNN	K-Nearest Neighbours
SANN	Subsequent Artificial Neural Networks	BANN	
EANN	Evolutionary Artificial neural networks	GARCH	Generalized Autoregressive Conditional Heteroskedasticity

MA	Moving Average	MLR	
MARS	Multivariate Adaptive Regression Splines	AR	Autoregressive
NN	Neural Networks	GP	
DT		M5P	M5-Pruned
GFF		SOFM	
MCESN		FFNN	Feed Forward Neural Network
SCG		SP	
CFS	Correlation based Feature Selection	LM	
CRBM	Conditional Restricted Boltzmann Machines	FCRBM	Factored Conditional Restricted Boltzmann Machine
ERA		GPR	Gaussian Processes Regression

1. Introduction

An energy system is referred to a group of united elements used for the purpose of producing energy [1]. Energy systems are not straightforward, yet incorporating combinations of mechanical, thermal, electrical and other energies, which are utilized to power generation or transportation vehicles propulsion or other similar phenomena. Energy systems engineers should make decisions based on physical, financial and environmental goals [2].

The growing utilization of data collectors in energy systems has resulted in huge amount of data accumulated from different energy systems. Machine learning scientists have found unlimited chances in implementation of big data methods in energy systems [3]. Since prediction methods based on machine learning algorithm extract functional dependencies from observations, these methods are known as data-driven [4, 5].

Sensors and data collectors is extensively used in the energy related industry. It leads to huge amounts of data about energy production and energy consumption [6, 7]. This amount of data can be incorporated in understanding, modeling and forecasting of physical behaviors of energy system and human influences on energy demand. Machine learning has a huge potential for applications to the energy systems. Renewable energy resources and energy demand are attractive fields for utilization of data-driven forecasting [8, 9]. Therefore, comprehensive review about different machine learning methods is essential. Consequently the contribution of this paper is to review and present the state of the art and the future trend of using ML methods in energy systems.

Wind and solar energies are site-dependent, non-exhaustible, weather-dependent and alternative for fossil fuel energies. However, the main disadvantage of wind and solar energies is their unpredictability. Independent photovoltaic or wind energy systems cannot generate usable energy for significant part of the year. The main reasons are solar energy reliance on sunshine hours and large cut-in wind speeds for starting turbines to rotate. At present, fossil fuel power plants, are utilized to manage renewable power shortages instead of expensive storage solutions. Therefore, prediction of energy and electricity demand, weather and power generation can decrease requirement for back up mechanisms such as fossil fuel power plants and energy storage systems. The use of forecasting machine learning methods, help the end-user to have preparedness over energy profile. This will reshape the consumer and supplier relationship. This will make it possible for consumers to become small scale energy producers.

In section two the methodology of the research is presented. In the section three state of the art of ML methods in energy systems is presented with an initial analysis of the databased search. Section three also includes an overview of ML methods in to energy systems, e.g. solar energy, wind energy and energy demand. In each reviewed paper, utilized machine learning method and its main application is highlighted. In forth section different methods of machine learning has been categorized and important papers has been reviewed. Each section contains a brief conclusion and outlook about the results related to each subject. Finally in fifth section an overall discussion and conclusions are presented.

2. Methodology of survey

The purpose of the research methodology is to identify, classify and review the notable ML and Deep Learning (DL) models used in energy systems. In our comprehensive review using the Thomson Reuters Web-of-Science and Elsevier Scopus for implementation of the search queries would assure that any paper in database would meet the essential quality measures, originality, high impact and high h-index. Furthermore, to present an in-depth review and understanding of each modeling technique and its progress we aimed at having four different categories for the models used in energy systems i.e. single ML models, hybrid models, ensemble models, and DL.

Figure 1 demonstrate the methodology of this review. In the step1 of the methodology the initial database of the relevant articles is identified based on the search queries of: “energy system” and "machine learning" or "neural network" or "support vector" or "ANFIS" or "wavelet neural network" or "decision tree" or "multilayer perceptron" or "extreme learning machine" or "ensemble" or "deep learning". However, for every ML method we applied a new search query to well suit that search. These queries will identify the relevant articles yet the queries are uncertain whether the ML model belong to either ensemble or hybrids. In addition a number of articles in the initial data based might not be relevant at all. For instance a hybrid or ensemble model of ML may include single model(s). For that matter the step2, and step3 of the methodology are designed in the way to classify the ML models in the right categories for the review. In the step4 the models are all classified in the four categories and arranged in separate tables to be individually reviewed.

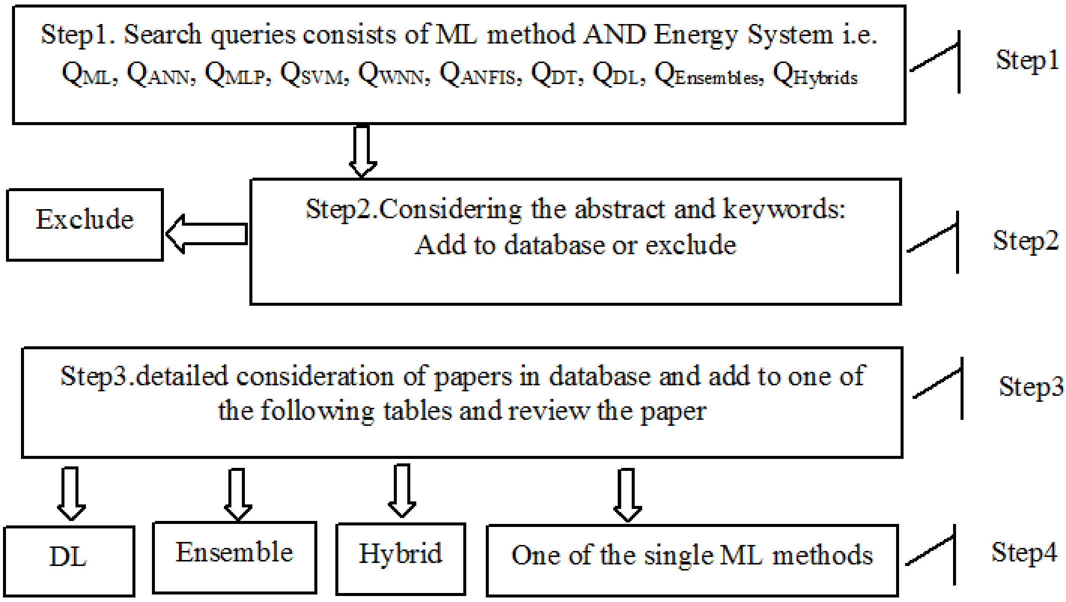


Figure 1. Methodology of research

Figure 2 and Figure 3 respectively demonstrate the growth in number of paper during past two decades in energy systems that utilized ML and different subject area of using ML in energy systems. The increase in the number of documents in Energy systems is due to future implementation trend of smart grid.

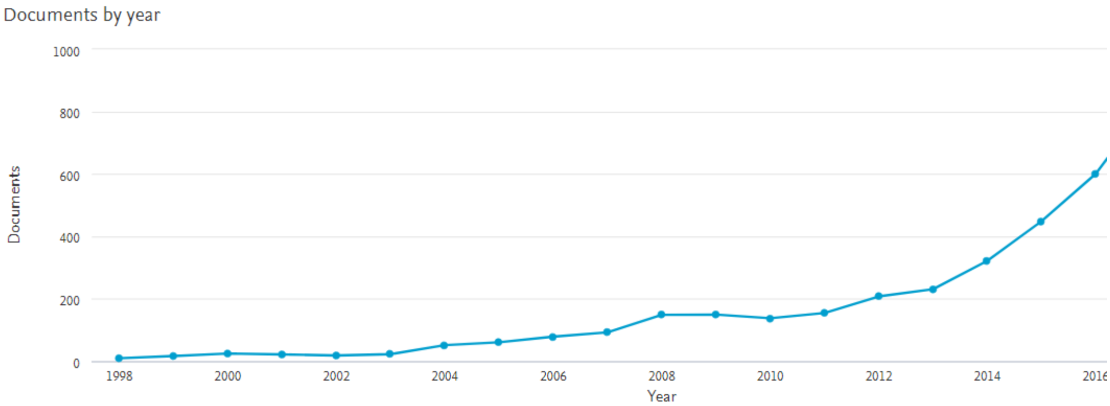


Figure 2. The growth in number of articles during past two decades with the search terms of "energy system" and "machine learning". Source Scopus

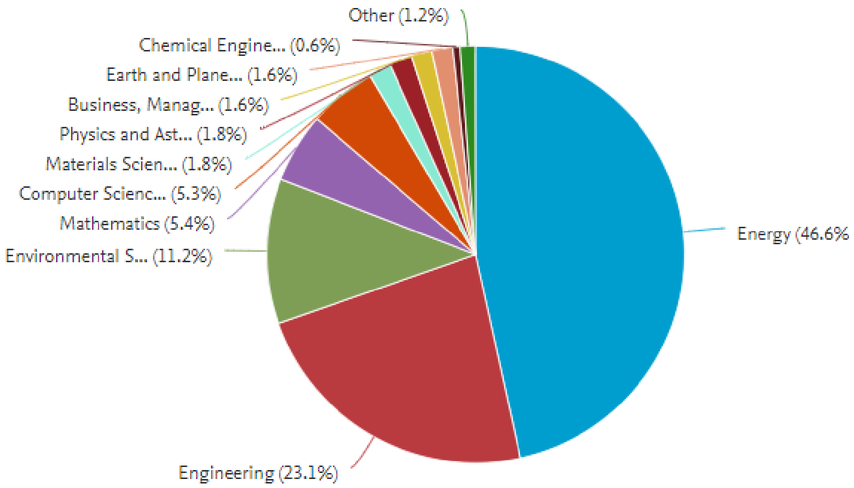


Figure 3. different subject area of using ML in energy systems

3. State of the art of ML methods

The initial consideration of the database of identified articles shows an exponential increase in the quantity of literature on the usage of machine learning in energy systems. In fact, machine learning has been extensively used in different fields of energy systems, especially in the field of energy demand, solar energy, wind energy, energy markets and etc. Therefore, machine learning techniques have a huge potential for industrial applications and management of energy systems.

Since different machine learning methods are available, choosing and demonstrating the superiority of the methods requires comparing their performance. Hence, a number of comparative performance parameters are required. The most popular comparative performance parameters are root mean square error (RMSE) and correlation coefficient (r) which are used to indicate the error and precision of the methods [10, 11], and Eq. (1) and Eq. (2) represent these parameters.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}\left(x_{ti} - x_{pi}\right)^2} \qquad (1)$$

$$r = \left(1 - \left(\frac{\sum_{i=1}^{n}\left(x_{ti} - x_{pi}\right)^2}{\sum_{i=1}^{n}\left(x_{ti}\right)^2}\right)\right)^{1/2} \qquad (2)$$

Where, x_{ti} represents the target value, x_{pi} represents the predicted value and n is the numbers of data.

3.1. Solar Energy

Machine learning methods have been recently utilized to rise solar radiation forecasting to increase energy production by solar power plants. The economic and environmental aspects of solar photovoltaic as a renewable energy source has caused significant rise in the number PV panels in recent years. High level of computational power and data have empowered machine learning methods for more precise predictions. Due to significance of prediction in solar photovoltaic power output for decision makers in energy industry, machine learning methods is employed extensively. Table 1, illustrates some important papers in this field.

Table 1. important papers in the field of Solar Energy

Year	Reference	Journal	ML method	Application
2016	David et al. [12]	Solar Energy	Hybrid ARMA-GARCH model	Forecasting of the solar irradiance
2017	Feng et al [13]	International Journal of Hydrogen Energy	generalized regression neural networks (GRNN), random forests (RF), extreme learning machine (ELM) and optimized back propagation neural networks by genetic algorithm (GANN)	Estimating daily Hd
2017	Hassan et al[14]	Applied Energy	Gradient boosting, random forest (RF) and bagging	Modeling solar radiation
2018	Salcedo-Sanz et al [15]	Applied Energy	A hybrid Coral Reefs Optimization (CRO) - Extreme Learning Machine (ELM) model.	Estimation of daily global solar radiation in Queensland, Australia.
2017	Salcedo-Sanz et al [16]	Renewable Energy	A hybrid Coral Reefs Optimization (CRO) - Extreme Learning Machine (ELM) model.	Global solar radiation prediction at a given point
2017	Touati et al [17]	Renewable Energy	Moving Average (MA), Autoregressive (AR) and Autoregressive Moving Average (ARMA) modeling	Forecasting the output power of PV panels in environmental conditions.

2017	Voyant et al [18]	Energy	linear quadratic estimation	Prediction of solar yields
2017	Voyant et al [19]	Energy	multilayer perceptron	Forecasting of global radiation time series

David et al. (2016) [12] evaluated performances of combination of ARMA and GARCH models in econometrics to establish solar irradiance probabilistic forecasts. A testing procedure has been utilized to evaluate probabilistic forecasts and point forecasts. Results have been presented in Table 2 and Figure 4.

Table 2. Results related to the study by David et al. (2016) [12]

Method/s	r	RMSE
Recursive ARMA	-	20.8%
SVR	-	20.8%
NN	-	20.6%
AR	-	21.3%

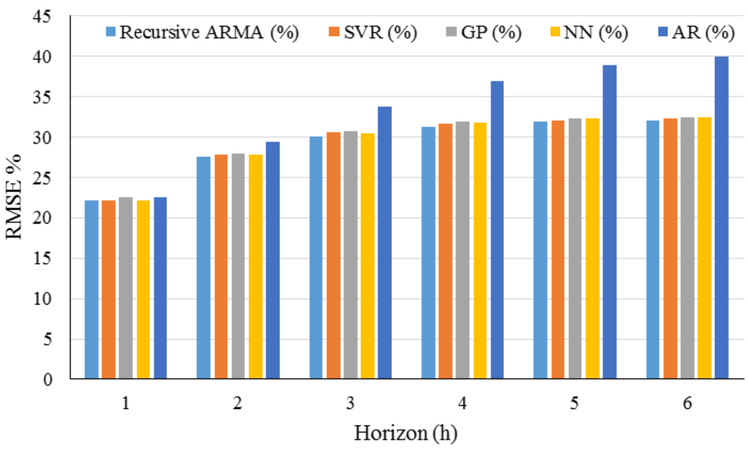


Figure 4. RMSE values for study by David et al. (2016) [12]

As is clear from Table 1 and Figure 4, Recursive ARMA has a low value for RMSE compared with other methods. Therefore it can be claimed that, the presented model can carry out point forecasts as accurately as other models established on machine learning techniques and also the accuracy of the proposed model is same as the other machine learning techniques for both point and probabilistic forecasts.

Feng et al. (2017) [13] incorporated generalized regression neural networks (GRNN), random forests (RF), extreme learning machine (ELM) and optimized back propagation neural networks by genetic algorithm (GANN) to estimate daily solar radiation (Hd) for two stations in northern china. All presented artificial models were compared with empirical model (Table 3 and Figure 5).

Table 3. Results related to the study by Feng et al. (2017) [13]

station		RMSE	r
Beijing	ELM	17.3	0.9196
	GANN	17.1	0.9209

	RF	18.3	0.9102
	GRNN	19.2	0.8902
	Iqbal	32.9	0.8865
Zhengzhou	ELM	13.8	0.947
	GANN	13.4	0.9515
	RE	15	0.9408
	GRNN	16.5	0.9072
	Iqbal	35.8	0.929

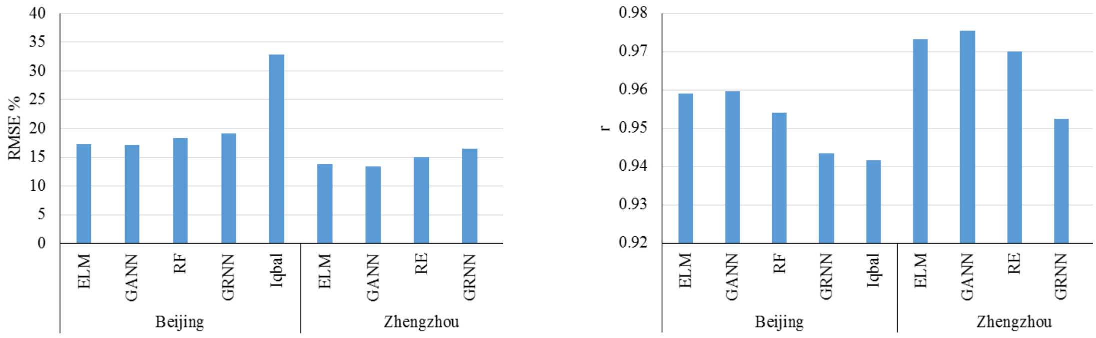
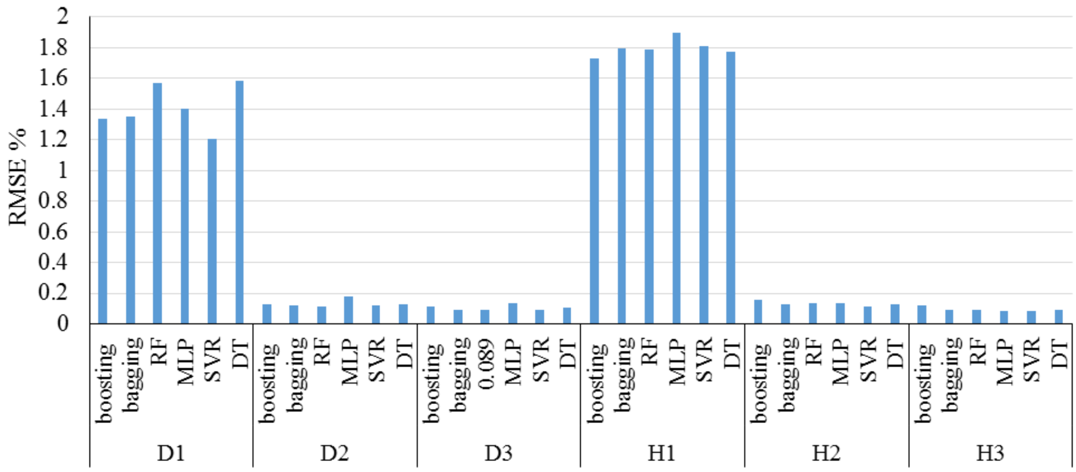


Figure 5. (a) RMSE and (b) r values for study by Feng et al. (2017) [13]

Based on Figure 5 and Table 2, GANN model presents a best accuracy due to its lowest RMSE and highest r values compared with those for others for both Beijing and Zhengzhou stations.

Hassan et al. (2017) [14] presented ensemble methods for solar radiation modeling. Gradient boosting, random forest (RF) and bagging were developed to estimate radiation in hourly and daily time scales. These novel ensemble methods were developed to generate synthetic radiation data to be utilized to simulate the performance of solar energy systems with different configurations. Figure 6 presents results of study in detail.



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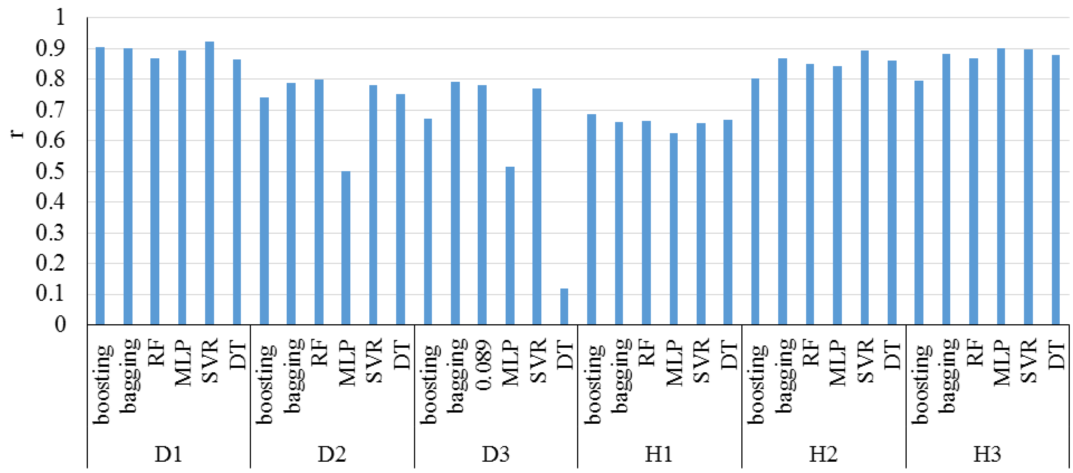

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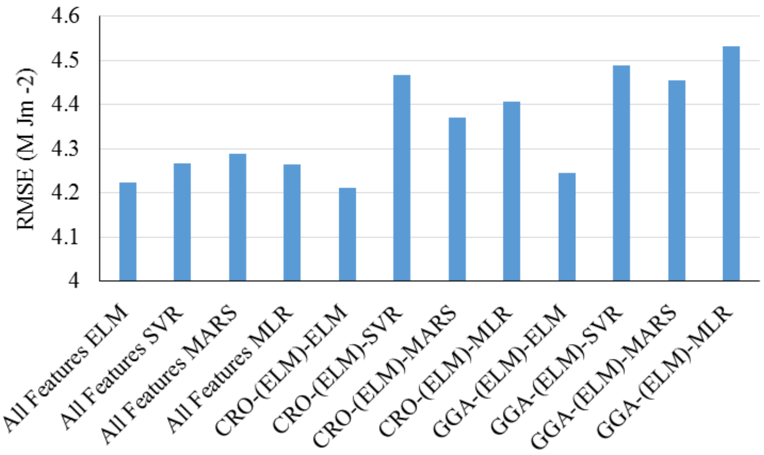
Figure 6. (a) RMSE and (b) r values for study by Hassan et al. (2017) [14]

Based on Figure 6, generally, SVR has the best prediction ability compared with other techniques. Because it has a high correlation coefficient and a low average RMSE compared with other methods employed by Hassan et al. [14].

Salcedo-Sanz et al. (2018) [15] integrated the Coral Reefs Optimization (CRO) with Extreme Learning Machine (ELM) model in their study. The presented algorithm were applied in two stage. An ELM algorithm were used for feature selection process and solar radiation were estimated using the optimally screened variables by CRO-ELM method (Figure 7).



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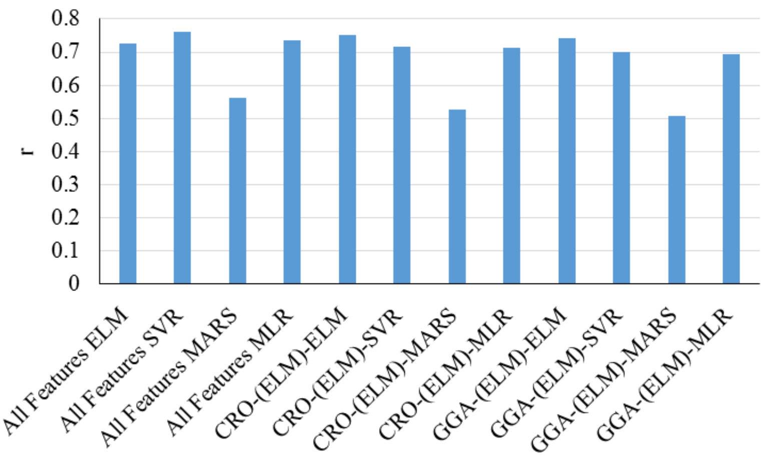

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Figure 7. (a) RMSE and (b) r values for study by Salcedo-Sanz et al. (2018) [15]

Based on Figure 7, the hybrid CRO-(ELM)-ELM method has the highest accuracy compared with that for hybrid CRO-(ELM)-MLR, CRO-(ELM)-MARS, and CRO-(ELM)-SVR and the GGA models. Generally, the CRO-based hybrid system are carefully screened through a wrapper-based modelling system. Hybrid CRO-(ELM)-ELM method presents more clear advantages compared with the alternative machine learning approaches.

Salcedo-Sanz et al. (2017) [16] studied prediction of global solar radiation at a given point incorporating a Multilayer Perceptron trained with Extreme Learning Machines. A Coral Reefs Optimization algorithm with species were used to reduce number of significant predictive variables. Based on results (Figure 8), the proposed model (CRO-SP) has been tested by Toledo (Spain) data. The average best results of RMSE was equal to 69.19 (W/m^2) which was able to do prediction more with a high accuracy compared with other machine learning techniques. This claim is clear in Figure 8 which presents the average values of RMSE for four developed techniques.

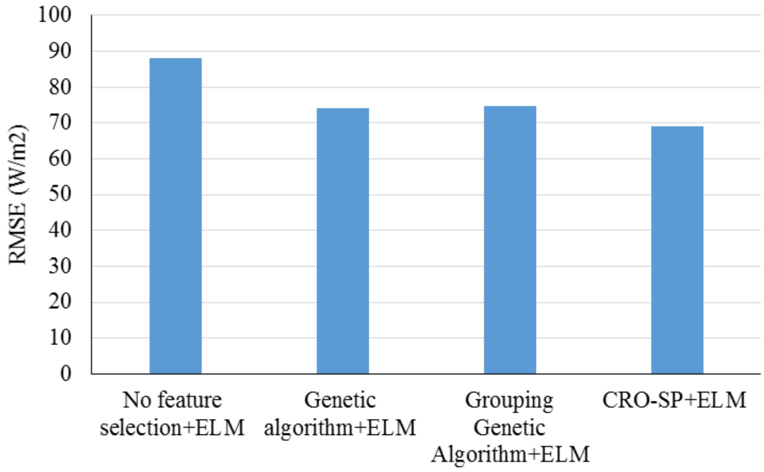


Figure 8. RMSE values for study by Salcedo-Sanz et al. (2017) [16]

Touati et al. (2017) [17] used to predict output power from photovoltaic panels under dissimilar atmospheric conditions. This study's goal was to investigate photovoltaic performance in the harsh environmental conditions of Qatar. The machine learning methods were used to relate various environmental factors such as Irradiance, PV surface temperature, wind speed, temperature, relative humidity, dust and cumulative dust to power production. Figure 9 presents the results of analyzing with correlation coefficient.

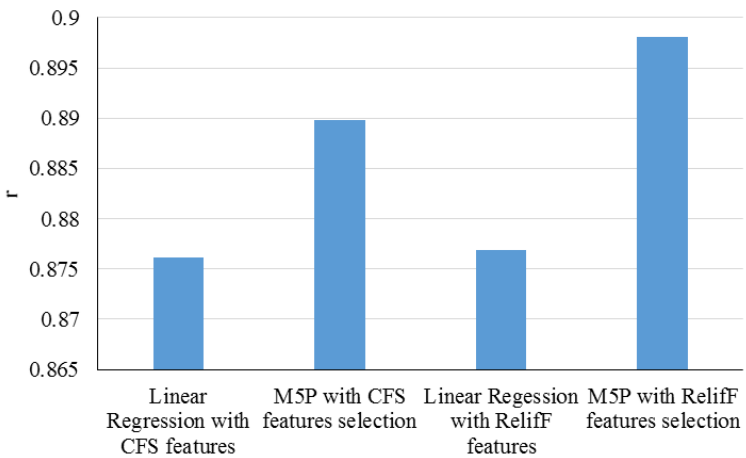


Figure 9. Correlation coefficient values for study by Touati et al. (2017) [17]

As is clear from Figure 9, Linear Regression and M5P tree decision algorithms have been developed for prediction proposes equipped with CFS and RelifF to select subsets of relevant and high quality features. Based on results, M5P model equipped with RelifF prepares more accurate prediction due to its high correlation coefficient value, on the other hand, the developed models are relatively simple and can be easily equipped to predict PV power output.
Voyant et al. (2017) [18] proposed methods based on the Kalman filter use to forecast global radiation time series without utilizing historical data. These methodologies were compared with other data driven methods with different time steps using RMSE values. Results claimed that the proposed method improved the prediction purposes. Voyant et al. (2017) [19] presented a method to better understand propagation of uncertainty in the global radiation time series. In this study, reliability index has been defined to evaluate validity of predictions. The presented method has been applied for several meteorological stations. The comparisons were performed using RMSE factor. Results were promising for successfully applying in these stations in Mediterranean area.

3.2. Wind Energy

In order to integrate highly volatile wind power to power grid, a precise forecasting of wind speed is crucial. This would results in lower need for controlling of energy provided by wind, having battery loading strategies and planning reserve plants. Machine learning methods can predict a time interval from seconds to hours and as a result are important for energy grid balancing. Table 4, shows some important papers in this field.

Table 4. Important paper about ML method utilization for wind energy

Year	Reference	Journal	ML method	Application
2017	Cornejo-Bueno et al [20]	Energies	support vector regression, multi-layer perceptrons and extreme learning machines, Gaussian processes, ERA-Interim reanalysis	Accurate prediction of Wind Power Ramp Events
2018	Khosravi et al [21]	Applied Energy	multilayer feed-forward neural network, support vector regression, fuzzy inference system, adaptive neuro-fuzzy inference system, group method of data handling type neural network, ANFIS optimized with particle swarm optimization algorithm and ANFIS optimized with genetic algorithm	Prediction of wind speed data for Osorio wind farm
2017	Burlando et al [22]	International Journal of Renewable Energy Research	Artificial Neural Networks	Accurate wind power forecast
2018	Pandit et al [23]	Energies	Gaussian Process algorithm	Predictive condition monitoring

2018	Sharifian et al [24]	Renewable Energy	particle swarm optimization, the Type-2 fuzzy neural network	The wind power accurate forecasting

The estimation of total power collected from wind turbines in wind farm depends on several factors such as its location, hub height and season. Accurate forecasting of Wind Power Ramp Events (WPREs) is necessary in efficient integration of wind farm into electric system [25]. Cornejo-Bueno et al. (2017) [20] applied different machine learning regression techniques to predict WPREs. Variables from atmospheric reanalysis data were used as predictive inputs for the learning machine. RMSE was employed as the comparison factor among the developed methods. The results have been presented in Figure 10. As is clear from Figure 10, in general, GPR followed by MLP have the lowest RMSE compared with SVR and ELM for each farm. This shows the high prediction capability of GPR and MLP methods in line with the purpose of the study.

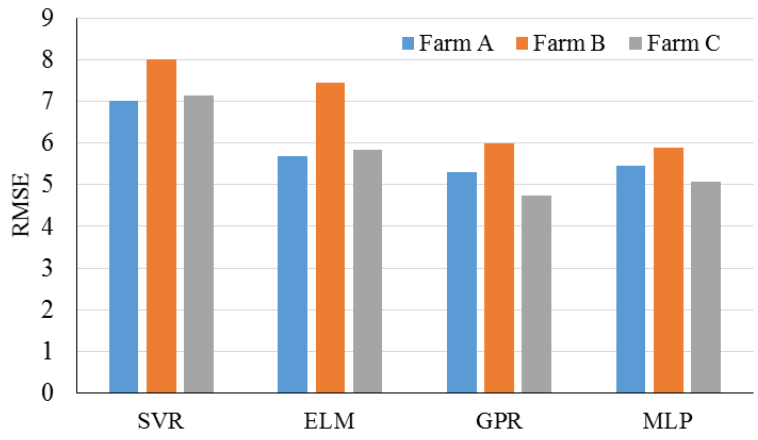
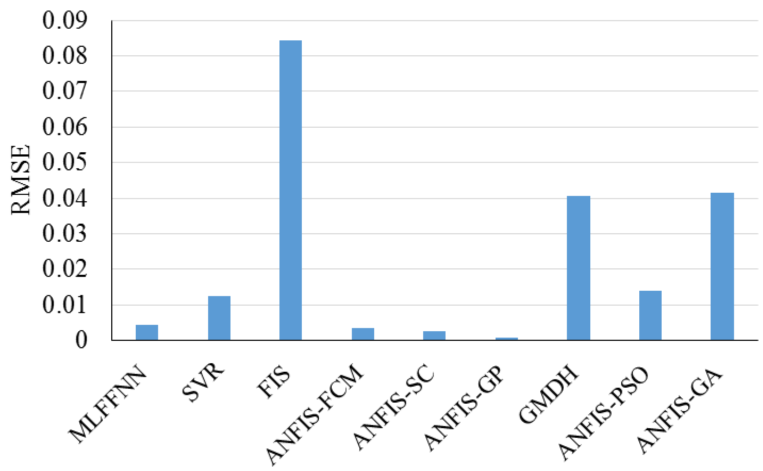


Figure 10. RMSE values for study by Cornejo-Bueno et al. (2017) [20]

Khosravi et al. (2018) [21] developed models based on group method of data handling type neural network, adaptive neuro-fuzzy inference system, ANFIS optimized with ant colony, ANFIS optimized with particle swarm optimization algorithm, ANFIS optimized with genetic algorithm and multilayer feed-forward neural network. Day, month, average air temperature, minimum and maximum air temperature, air pressure, wind speed, relative humidity, latitude, longitude and top of atmosphere insolation. Group method of data handling type neural network was the best developed model. Figure 11 demonstrates the RMSE and correlation coefficient for each method for doing a best comparison.



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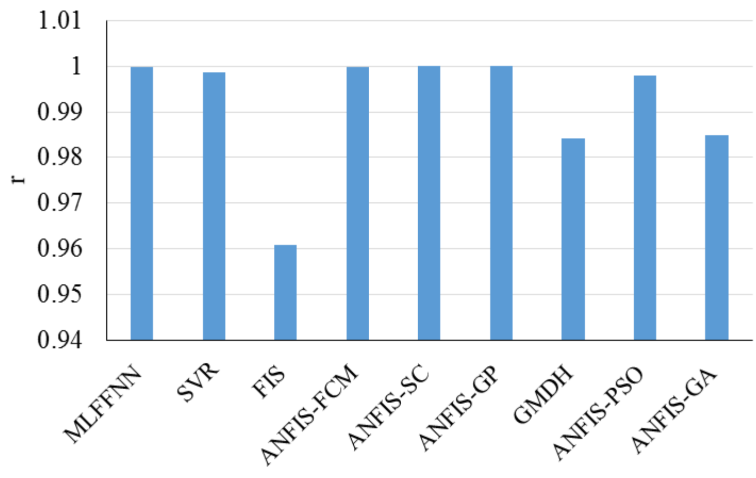

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Figure 11. (a) RMSE and (b) r values for study by Khosravi et al. (2018) [21]

Burlando et al. (2017) [22] compared a pure ANN method against a hybrid method. Both methods have almost similar performances. Both methods were validated against the wind farm SCADA data. But, the hybrid method predicts better during high and low ranges of wind speed and ANN predicts better medium wind speed ranges. The results were compared using the normalized root mean square error and the normalized mean absolute error. The best results (the lowest value of comparison factors) were calculated for NWP height of 100 and 200 meters for both layout 1 and 2.

Pandit and Infield (2018) [23] performed a study to reduce the costs of operation and maintenance wind turbine. Predictive condition monitoring based on SCADA was applied to identify early failures, boost production, limit downtime and decline the energy cost. A Gaussian Process algorithm was presented to roughly calculate operational curves which can be utilized as a reference model to recognize critical failures of wind turbine and enhance its power performance. Figure 12 presents the correlation coefficient for the prediction results of four variables using Gaussian process compared with the target values. Based on Figure 12, this method was successfully estimated the power curve compared with other variables.

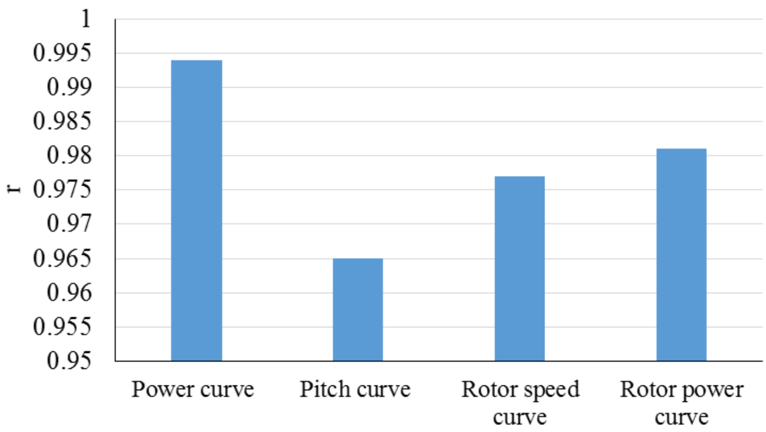


Figure 12. Correlation coefficient values for study by Pandit and Infield (2018) [23]

Sharifian et al. (2018) [24] presented a new method based on fuzzy neural network to forecast wind power under uncertain data. The proposed method was established on particle swarm optimization algorithm. This method was based on neural network's learning and expert knowledge of fuzzy system. The presented method was validated against a real wind farm. The results have been presented in Figure 13 using RMSE values for each case studies. As is clear, RMSE for the first case study has the lowest value and for the fifth case study has the highest value. Therefore it can be claimed that the precision of the employed method for the first case study is more than that for other case studies.

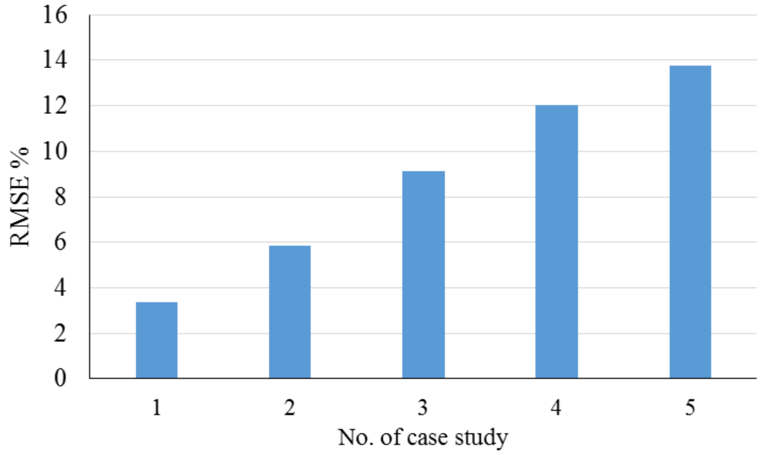


Figure 13. RMSE values for study by Sharifian et al. (2018) [24]

3.3. Energy Demand

Accurate energy consumption prediction can be provided by machine learning models and it can be used in the managerial levels such as building commissioning projects managing, utility companies and facilities managers to introduce energy saving policies. Table 5, demonstrates some important papers in this field.

Table 5. Important paper about ML method utilization for solar energy

Year	Reference	Journal	ML method	Application
2016	Albert & Maasoumy [26]	Applied Energy	predictive segmentation technique	Predictive segmentation technique for energy utility companies customers
2018	Alobaidi et al [27]	Applied Energy	ensemble method	Predicting the average daily energy consumption on a household level
2016	Benedetti et al [28]	Applied Energy	Artificial Neural Networks	Control of energy consumption in energy intensive industries
2018	Chen et al [29]	Energy	ensemble learning technique (feed forward deep networks and extreme gradient boosting forest)	Prediction of the household electricity consumption
2018	Kuroha et al [30]	Energy and Buildings	Support Vector Regression, Particle Swarm Optimization, Predicted Mean Vote	Improving thermal comfort and reduction of electricity costs
2018	Torabi et al [31], [6]	Sustainable Energy	Hybrid ML methods	Solar radiation forecasting

Albert and Maasoumy (2016) [26] presented a predictive segmentation technique to create targeting process and highly-interpretable segmentation for energy utility companies customers. The presented method utilized demographics, consumption and program enrollment data to take out predictive patterns. This method can display homogeneous segments which were 2 to 3 times more productive for targeting. Alobaidi et al. (2018) [27] proposed an ensemble learning framework for household energy consumption forecasting. In this paper, a prediction framework was presented to predict individual household average daily energy consumption. The results showed robustness of proposed ensemble model to provide prediction performance using limited data. Figure14 presents the results of RMSE for each method separately.

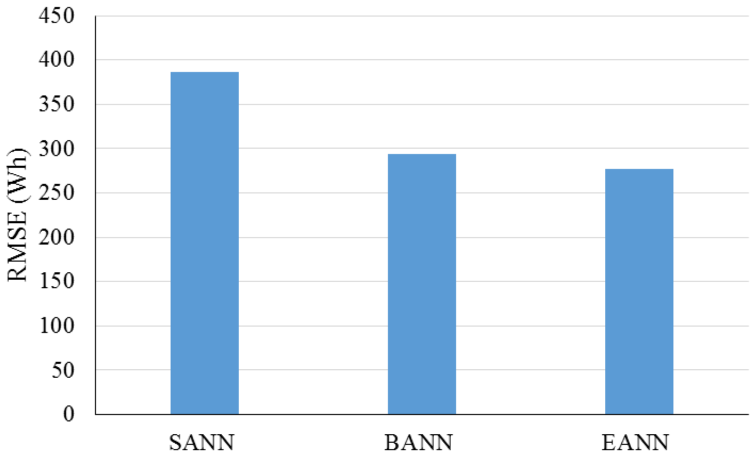


Figure 14. RMSE values for study by Alobaidi et al. (2018) [27]

Benedetti et al. (2016) [28] introduced a new methodology for control automation of energy consumption utilizing adaptive algorithms and Artificial Neural Networks. Three neural network structures was presented and trained utilizing an enormous amount of data. Three indicator was used to identify the best structure for creating control tool of energy consumption. The accuracy of the model was investigated using a method. Finally, the whole presented method was applied for a case study of a building in Rome (Italy).

Chen et al. (2018) [29] worked on a novel approach for predicting residential electricity consumption using ensemble learning. In this study, a data-driven framework was introduced to forecast the annual electricity consumption of household utilizing ensemble learning method. Ridge regression was used to combine feed-forward deep networks and extreme gradient boosting forest. Figure 15 presents the results of study in comparison with those for the other methods. As is clear from Figure 15, the proposed methods have the highest accuracy with the lowest RMSE in comparison with the other methods.

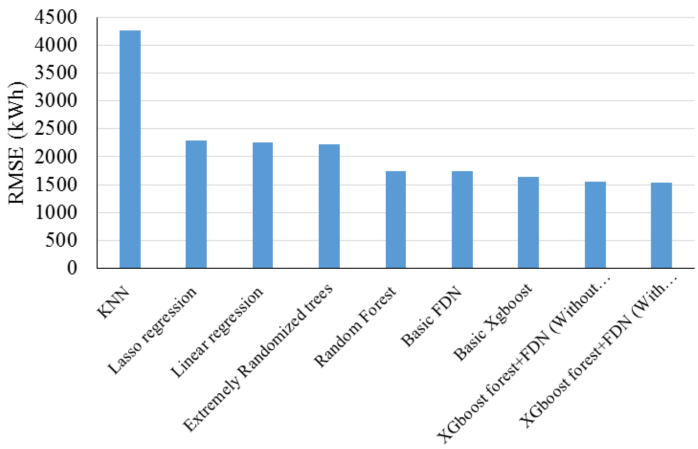


Figure 15. RMSE values for study by Chen et al. (2018) [29]

Kuroha et al. (2018) [30] presented an operational planning method for residential air conditioners. In this study, the focus was on automatic air-conditioners for thermal comfort improvement and electricity costs reduction. An energy management methodology was introduced to provide air-conditioner operation plan by learning the installation environment characteristics from result data of the historical operation. Based on results, the proposed method could reduce the electricity cost about 39.7% compared with that for the Benchmark method.

4. Different Methods of ML

4.1. ANN

Artificial neural networks are frameworks for different machine learning algorithms to process complex data inputs. ANN can be utilized for several purposes such as forecasting, regression and curve fitting. An artificial neural network fundamental unit is a neuron which utilizes a transfer function for the output formulation. The main advantage of ANN methods are their lesser complexity for multi-variable problems. Table 6, demonstrates some important papers in this field. Instead of complicated rules, ANN can learn patterns of key information within an intricate information domain [4]. Also, due to noise immune and fault tolerant characteristics of ANN, It can be successfully used for inherently noisy data from energy systems.

Table 6. Important paper about ANN method utilization for solar energy

Year	Reference	Journal	Application
2018	Abbas et al [32]	Electronics (Switzerland)	Optimization of renewable energy generation capacities
2017	Anwar et al [33]	IEEE Transactions on Power Systems	Mitigation of wind power fluctuation and scheduling strategies for power generation
2017	Boukelia et al [34]	Renewable Energy	Prediction of levelized cost of electricity
2016	Chatziagorakis et al [35]	Neural Computing and Applications	Forecasting model for wind speed and hourly and daily solar radiation
2018	Gallagher et al [36]	Energy and Buildings	Measurement and verification of energy savings in industrial buildings

Abbas et al. (2018) [32] used genetic algorithms to optimize generation capacities renewable energy systems integrated with storage systems. This study evaluated the economic feasibility of introduction of energy storage systems in the electric grid. The Artificial Neural Network was used to validate the predicted load model. The uncertainties related with the renewable energy systems was dealt with a chance constrained model. Then, the problem was solved by genetic algorithms. The robustness of proposed model was verified by its application for a case in western China. Figure 16 reports the results of the proposed method in comparison with the base case in terms of total expenditure (billion $), fuel cost (billion $), clean energy contribution (%), average cost of electricity (cents $/kWh) and CO_2 emission (million Tons). Based on Figure 16, there is about a doubled increase in the use of clean energy which leads to a reduction in CO_2 emissions from about 109 million tons to 38 million tons. Therefore the proposed case has an effective role compared with the base case.

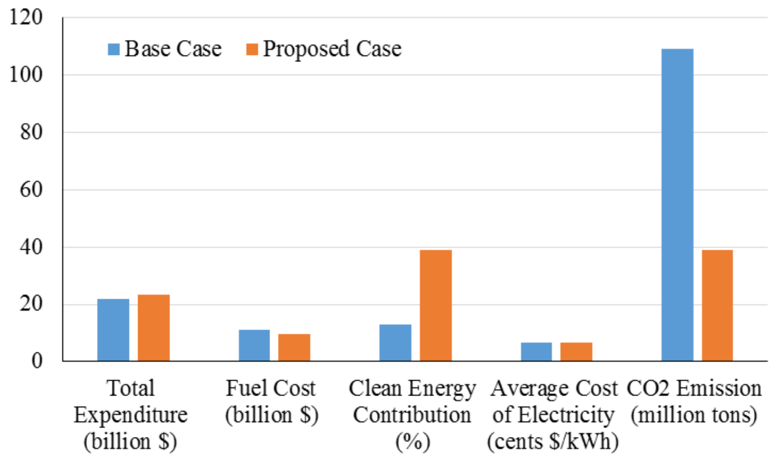


Figure 16. Results for study by Abbas et al. (2018) [32]

Anwar et al. (2017) [33] presented a novel strategies for generation schedualing and power smoothing for hybrid system of marin current and wind turbines. In this study, innovative strategies was proposed to mitgate wind intermittency effects. Contrary to randomness of wind, marine currents are highly predictable. The presented methodologies incorporate optimal strategy for sizing for this hybrid system. Bootstrapped Artificial Neural Networks were developed to predict intervals for wind speed. Speeds of marine currentis modeled utilizing the Harmonic Analysis Method. The results of the model show the robustness of the presented methodlogy to successfully decrease power fluctuations, considarable cost savings and reliable distch schedualing for power generation. Boukelia et al. (2017) [34] used artificial neural network (ANN) - based approach to assess a parabolic trough solar power plant. In this study, an ANN model was developed to predict levelized electricity cost of two parabolic trough solar thermal power plants coupled with fuel backup system and thermal energy storage. The techno-economic study was performed comparing molten salt and thermic oil usage for to optimized thermal plants for annual and hourly performance.

Chatziagorakis et al. (2016) [35] studied control of hybrid renewable energy systems using recurrent neural networks to forecast weather conditions. A forecasting model using a recurrent neural network for prediction of hourly and daily solar radiation and wind speed was presented. The results of simulation indicated that recurrent neural network was ca[able of delivery acceptable future estimation to safely evaluate the available renewable energy.

Gallagher et al. (2018) [36] studied the properness of machine learning for optimization of uncertainty in the energy savings measurement and verification. In this paper, the new use of machine learning algorithms for energy savings M&V in industrial buildings was studied. The applied machine learning techniques were consist of k-nearest neighbors, support vector machines, artificial neural networks, decision trees and bi-variable and multi-variable ordinary least squares regression. The models prediction performances were validated to optimize model parameters. Results demonstrated that models based on ML algorithms were more precise than the conventional methods. Results of CV (RMSE) have been presented in Figure 17.

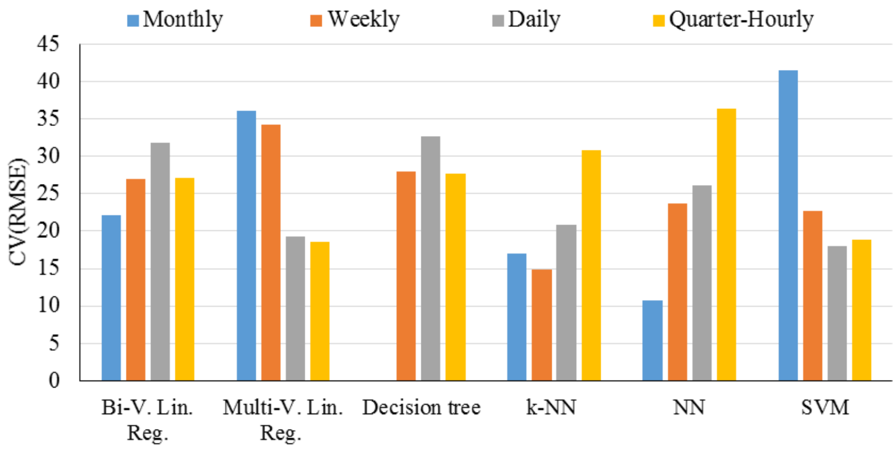


Figure 17. RMSE values for study by Gallagher et al. (2018) [36]

4.2. Multi Layered Perceptron (MLP)

MLP is an advanced version of ANN for engineering applications and energy systems which is considered as a feed forward neural network and uses supervised and back-propagation learning method for the training purposes [37-39]. This is a simple and popular method for modeling and prediction of a process and in more cases it is considered as the control model. Table 7 demonstrates some important papers in this field.

Table 7. Important paper about MLP method utilization for solar energy

Year	Reference	Journal	Application
2015	Ahmad et al [40]	Solar Energy	A day ahead prediction of hourly global solar irradiation
2017	Chahkoutahi et al [41]	Energy	Electricity load forecasting
2017	Kazem et al [42]	Energy Conversion and Management	Prediction of solar system power output
2017	Loutfi et al *[43]*	International Journal of Renewable Energy Research	Hourly global solar radiation prediction
2017	Shimray et al [44]	Computational Intelligence and Neuroscience	Ranking of different potential power plant projects

Ahmed et al. (2015) [40] performed a study for forecasting hourly solar irradiation for New Zealand. In this paper, the potential to provide a 24 hours ahead of hourly global solar irradiation forecast, utilizing several methods, especially incorporating autoregressive recurrent neural networks. Hourly time series were used for training and testing of the forecasting methods. MLP, NARX, ARMA and Persistence methods were compared using RMSE. Figure 18 presents the related results. Based on results, NARX method with a lowest value of RMSE presented a precision about 49%, 22% and 52% higher than that for MLP, ARMA and Persistence methods, respectively.

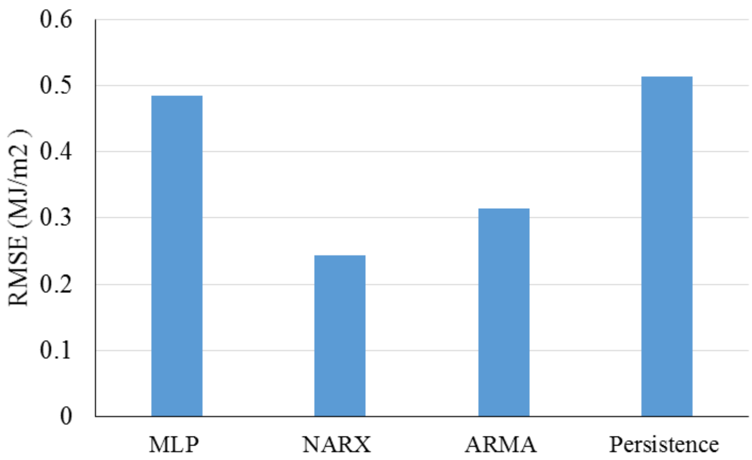


Figure 18. RMSE values for study by Ahmed et al. (2015) [40]

Chahkoutahi and Khashei (2017) [41] introduced a seasonal optimal hybrid model to forecast electricity load. In this study, a direct optimum parallel hybrid model as presented using multi-layer perceptron neural network, Seasonal Autoregressive Integrated Moving Average and Adaptive Network based Fuzzy Inference System to forecast electricity load. The main reason for using this model was to utilize these models advantages for modeling complex systems. The validation of the presented model implies that it was more accurate than its components. Figure 19 presents the results of the proposed DOPH method against SARIMA, MLP, ANFIS, DE-based and GA-based models. The output of each method were compared with target values using RMSE. Based on results, the proposed method could improve the prediction capability by 51.4, 33.18, 31.10, 16.44, and 12.8 %, compared with SARIMA, MLP, ANFIS, DE-based and GA-based models, respectively in test stage.

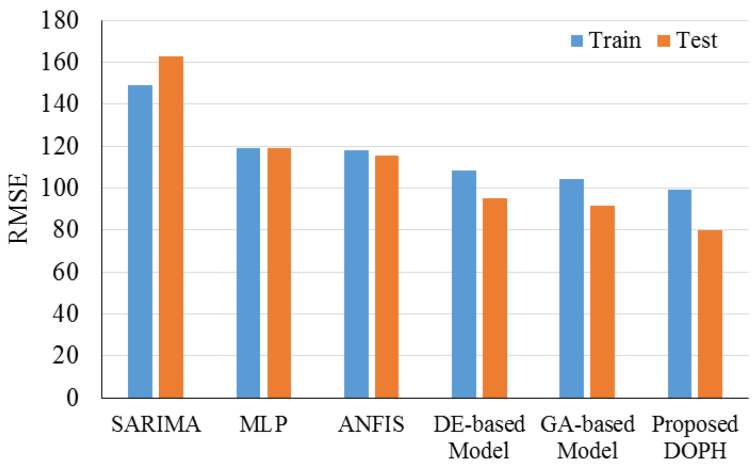


Figure 19. RMSE values for study by Chahkoutahi and Khashei (2017) [41]

Kazem and Yousif (2013) [42] designed and installed a photovoltaic system for electricity production. The output of system was measured for one year. The photovoltaic system output was simulated and predicted by self-organizing feature maps, feed-forward networks, support vector machines and multi-layer perceptron. Ambient temperature and solar radiation data were these model's inputs and the PV array current and current were the outputs. Outputs of each model were compared with the target values using RMSE factor. Results have been presented in Figure 20. Based on results, the SOFM generates the lowest RMSE value compared to the MLP model, GFF model and SVM model. Therefore the SOFM model is suitable for this purpose.

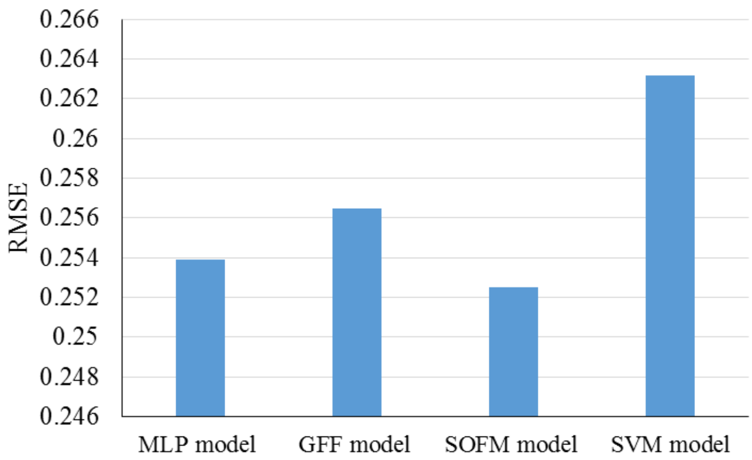


Figure 20. RMSE values for study by Kazem and Yousif (2013) [42]

Loutfi et al. (2017) [43] presented an analysis for design of solar energy systems. In this study, a comparison between multilayer perceptron and neural autoregressive with exogenous inputs were presented. The proposed model has good capability to produce hourly solar radiation forecast for cheaper data such as relative humidity and temperature. The results of the best model have been presents in Table 8 for the developed model. The study proposes the NARX method in challenging with MLP method. As is clear from Table 8, the proposed method has the best prediction capability refereeing to nRMSE and correlation coefficient values.

Table 8. Results of evaluations of models by Loutfi et al. (2017) [43]

	The best structure	r	nRMSE
MLP	5-30-1	0.938	23.31
NARX	1 5-10-1	0.974	15.1

Shimray et al. (2017) [44] performed a study for installation of hydropower plant sites ranking using Multi-layer Perceptron Neural Network. In this paper, a model for decision makers was developed to rank potential power plant sites based on water quality, air quality, energy delivery cost, natural hazard, ecological impact, and project duration. The case for this paper was ranking of several potential plant sites in India.

4.3. ELM and further advanced ANNs

In order to find advanced version of ANNs, here the keywords of search are: extreme learning machine, Feed-forward neural networks, Back-propagation neural networks, functional neural network, Feed forward, back propagation". The ELM has a high speed of learning and proper ability of generalization. Table 9 demonstrates some important papers in this field.

Table 9. Important paper about ELM method utilization for solar energy

Year	Reference	Journal	Application
2017	Arat, H., Arslan, O. [45]	Applied Thermal Engineering	Optimization of district heating system aided with geothermal heat pump
2015	Bagnasco, A., Fresi, F., Saviozzi, M., Silvestro, F., Vinci, A. [46]	Energy and Buildings	Electrical consumption forecasting model of a building
2018	Li, Q., Wu, Z., Xia, X. [47]	Applied Energy	Forecasting of PV power generation

2016	Premalatha, N., Valan Arasu, A. [48]	Journal of Applied Research and Technology	Monthly average global radiation prediction
2014	Yaïci, W., Entchev, E. [49]	Applied Thermal Engineering	Performance prediction of a solar thermal energy system

Arat and Arslan (2017) [45] presented optimum design for geothermal heat pump for district heating system. Therefore, three different back propagation learning algorithm were used. These algorithms were Pola-Ribiere Conjugate Gradient, Levenberg-Marquardt, and Scaled Conjugate Gradient. The presented ANN model was composed of two stages. Second stage of ANN structure was composed of three levels of ANN models in this proposed ANN model. The results of this paper showed that the values obtained from ANN were very close to the analytical data. Figure 21 demonstrates the correlation coefficient values and Table 10 presents the RMSE values for each parameters separately.

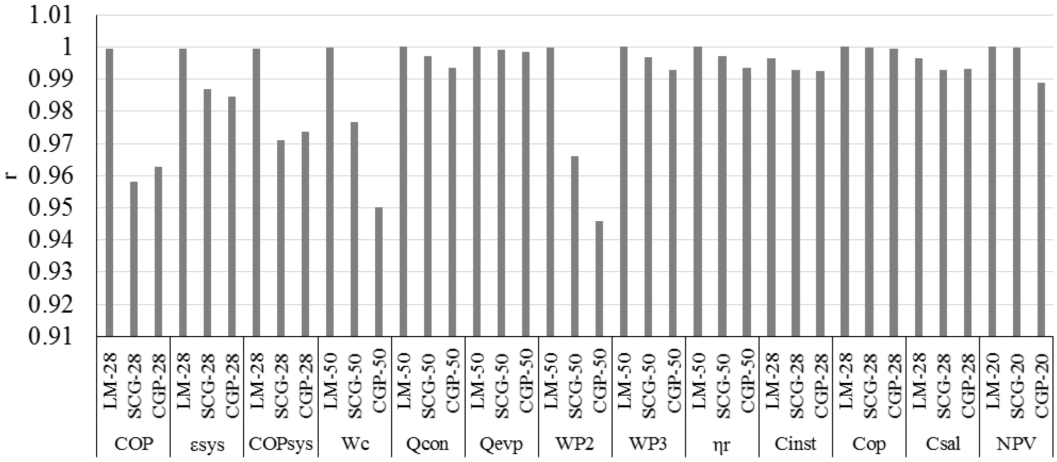


Figure 21. Correlation coefficient values for study by Arat and Arslan (2017) [45]

Table 10. RMSE values for the study by Arat and Arslan (2017) [45]

parameter	model	RMSE	parameter	model	RMSE	parameter	model	RMSE
	LM-28	0.07506		LM-28	229835		LM-50	58.3957
COP	SCG-28	0.79114	Cinst	SCG-28	335283	WP2	SCG-50	606.962
	CGP-28	0.77328		CGP-28	345108.6		CGP-50	862.943
	LM-28	0.00335		LM-28	32357.74		LM-50	1.14269
εsys	SCG-28	0.01616	Cop	SCG-28	183385.5	WP3	SCG-50	13.3365
	CGP-28	0.01963		CGP-28	384134.8		CGP-50	22.8781
	LM-50	98.07454		LM-20	45456.24		LM-50	25.2462
Wc	SCG-50	1044.513	NPV	SCG-20	3104498	ηr	SCG-50	294.616
	CGP-50	1939.327		CGP-20	20565006		CGP-50	498.103
	LM-50	87.0961		LM-28	0.03824		LM-50	2.208349
Qcon	SCG-50	1027.196	COPsys	SCG-28	0.31434	Qevp	SCG-50	465.1691
	CGP-50	1754.37		CGP-28	0.29927		CGP-50	575.9355

Bagnasco et al. (2015) presented a study for power consumption forecasting (load forecasting model) in hospitals. The presented artificial neural network utilizing a back propagation training algorithm can take loads, time of the day, data concerning the type of day (e.g. weekday/holiday) and weather data. The proposed forecast algorithm can be easily integrated into the Building

Management Systems real time monitoring system. Case A includes no weather data and Case B includes day-ahead temperature data. RMSE values have been presented in Figure 22.

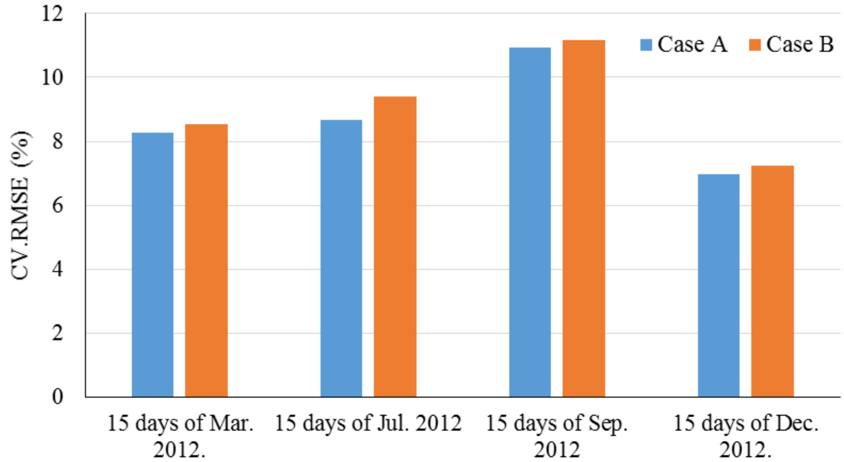


Figure 22. RMSE values for study by Bagnasco et al. (2015) [46]

Li et al. (2018) [47] presented multi clustered echo state network model to directly forecast PV electricty generation. Measured and estimated PV electricity generation data charactrictic such as stationarity (or non-stationarity), seasonality and complexity analysis were invetigated through data mining approaches. The simulation results showed that the presented multi clustered echo state network model can accurately forecast photovoltaic power output one-hour ahead. One-day forecast has 91–98% correlation coefficient for cloudy days and 99% for sunny days. Figure 23 presents the correlation coefficient values for the study based on day and method.

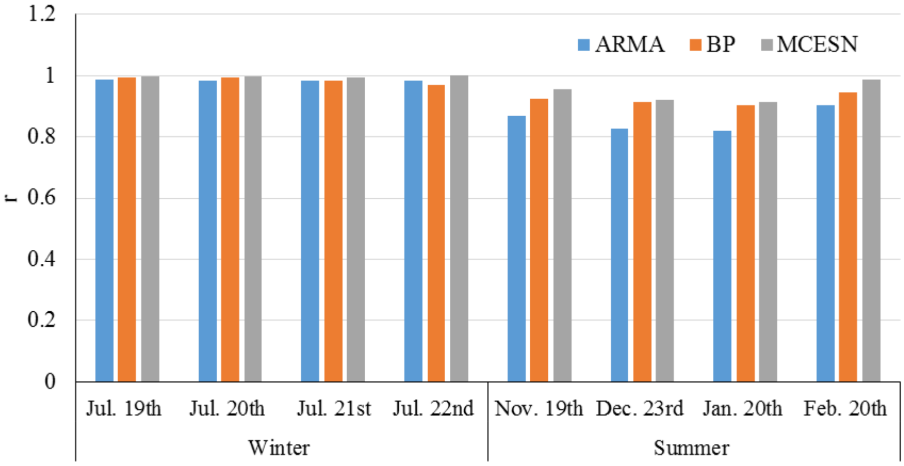


Figure 23. Correlation coefficient values for study by Li et al. (2018) [47]

Premalatha and Valan Arasu (2016) [48] utilized ANN models to predict global solar radiation. The main goal of this study was to develop and ANN model for accurate prediction of solar radiation. Two different ANN models based on 4 algorithms were considered in this paper. Last 10 years meteorological data was collected from 5 different sites in India to train the models. The criteria for determining best ANN algorithm were minimum mean absolute error, root mean square error and maximum linear correlation coefficient by 3.028, 3.646 and 0.927, respectively.

Yaïci and Entchev (2014) [49] utilized artificial neural networks to predict performance of a solar thermal energy system. This system was used for space heating and domestic hot water. Two different variants of back-propagation learning algorithm (scaled conjugate gradient algorithms and the Levenberg-Marguardt). The presented model was applied for predicting several performance parameters of the system such as temperature stratification of the preheat tank, the derived solar fractions, the solar collectors heat input to the heat exchanger and auxiliary propane-fired tank heat input. This methodology can be used for condition monitoring and fault detection solar thermal energy system.

4.4. Support Vector Machines

Support Vector Machines (SVMs) are machine learning algorithms built on statistical learning theory for structural risk minimization. For pattern recognition, classification and analysis of regression SVMs outperforms other methodologies. Significant range of SVM applications in the field of load forecasting is due to its ability is generalization. Also, Local minima leads to no problem in SVM. Table 11 presents some important papers in this field.

Table 11. Important paper about SVM method utilization for solar energy

Year	Authors	Journal	Application
2015	Arabloo et al [50]	Fuel	Estimation of optimum oxygen-steam ratios
2013	Arikan et al [51]	International Review of Electrical Engineering	Classification of power quality disturbances
2017	Ma et al [52]	IEEE Transactions on Circuits and Systems I: Regular Papers	Estimation of irradiance levels from photovoltaic electrical characteristics
2016	Özdemir et al [53]	Neural Network World	Harmonic estimation of power quality in electrical energy systems
2016	Pinto et al [54]	Neuro-computing	An electricity market price prediction in a fast execution time

Arabloo et al. (2015) [50] introduced a novel methodology for optimization of oxygen-steam ration in gasification process of coal. A methodology utilizing support vector machine algorithm was presented for estimation of proper steam-oxygen ratio to balance heat requirement and released heat in coal gasification process. The comparison of experimental data and predicted values showed the precision of the predictive model that can be used for industrial implications in coal gasification process.

Arikan and Özdemir (2013) [51] performed a study to classify of power quality disturbances utilizing support vector machines. In this paper, five kinds of power quality disturbances and pure sine was utilizing support vector machines that were based on wavelet. The proposed method performance was validated utilizing synthetic data derived from mathematical model and real time. Support vector machines, artificial neural network and same future vector and data Bayes classifier were compared. It was observed that support vector machines gives the best result both for synthetic data and real time.

Ma et al. (2017) [52] developed a soft sensor (a field-support vector regression) to upgrade the estimation accuracy of solar irradiance levels from photovoltaic electrical parameters. The soft sensor collected its input data into several groups based on ambient temperature. The introduced soft sensor can be implanted in a photovoltaic module, a current sensor or a thermometer. It was validated by experimental prototype and simulations utilizing measured outdoor conditions. Figure 24 presents the RMSE values for the study.

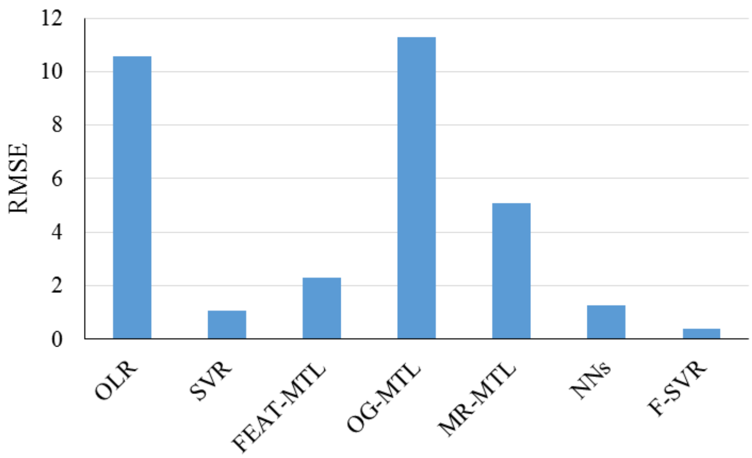


Figure 24. RMSE values for study by Ma et al. (2018) [52]

Özdemir et al. (2016) [53] used Support Vector Machine for harmonic distortion estimation. The power distribution network was studies and predicted results were compared with quantified real data. The presented approach was compared with Artificial Neural Network and Linear regression methods. The predicted results validation demonstrated that Support Vector Machine is robust for total harmonic distortion in the power network.

Pinto et al. (2016) [54] developed a multi agent system for modeling competitive electricity markets. This study proposed applying support vector machines to lay out decision support for electricity market players. The presented model was coupled with Adaptive Learning Strategic Bidding System to be used as decision support system. This methodology was validated and then compared with Artificial Neural Network. The results were encouraging: a robust price forecast for electricity market in a fast execution time.

4.5. Wavelet neural networks

Wavelet neural networks (WNN) benefits both theory of wavelets and neural networks and combines them. This method contains a FFNN with one hidden layer. One of the missions of WNNs is to estimate the function of a process or a trend or a computing. A WNN is able to train the structure of a function using a series of data, and to generate or compute an expected output value for a given input value [55]. WNN has several advantages over other neural networks. WNN needs smaller training amount than MLP method and it has a fast convergence. Table 12 presents some important papers in this field.

Table 12. Important paper about WNN method utilization for solar energy

Year	Authors	Journal	Application
2016	Doucoure et al [56]	Renewable Energy	Prediction of time series for renewable energy sources
2018	Gu et al [57]	Energy	Heat load perdition in district heating systems
2018	He et al [58]	Applied Energy	Wind speed forecasting (reduction of the influence of noise in the raw data series)
2018	Qin et al [59]	Algorithms	Simultaneous optimization of fuel economy and battery state of charge
2017	Sarshar et al [60]	Energy	Uncertainty reduction in wind power prediction

Doucoure et al. (2016) [56] developed a prediction methodology for renewable energy sources to promote use of renewable energy isolated and grid-connected power systems. The presented method was based on artificial neural networks and Wavelet decomposition. The predictability of every component of the input data utilizing the Hurst coefficient was analyzed in this study. Utilizing the predictability of the information, some components with low predictability potential was eliminated to reduce the algorithm computational complexity. Figure 25 presents the RMSE values for the study in three terms, with all data components, without random data and persistence data related to the proposed method.

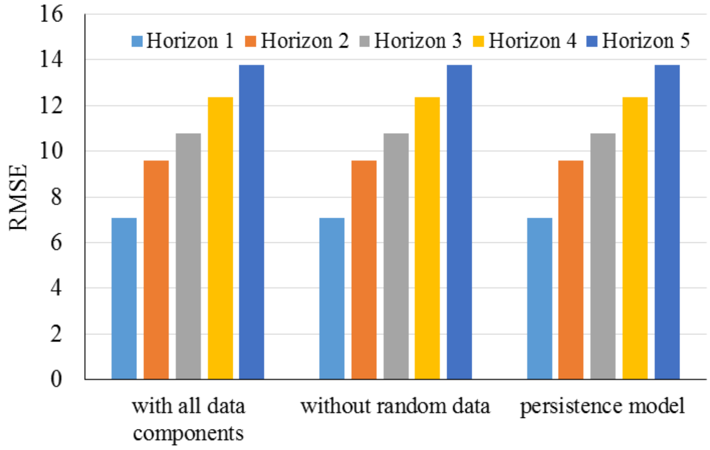
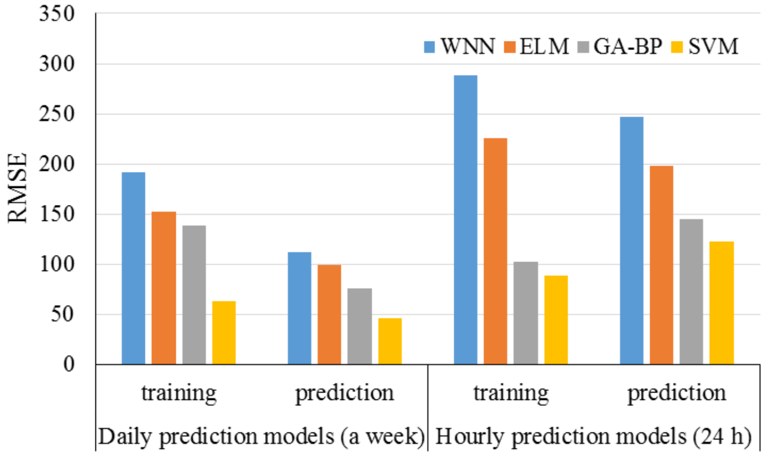
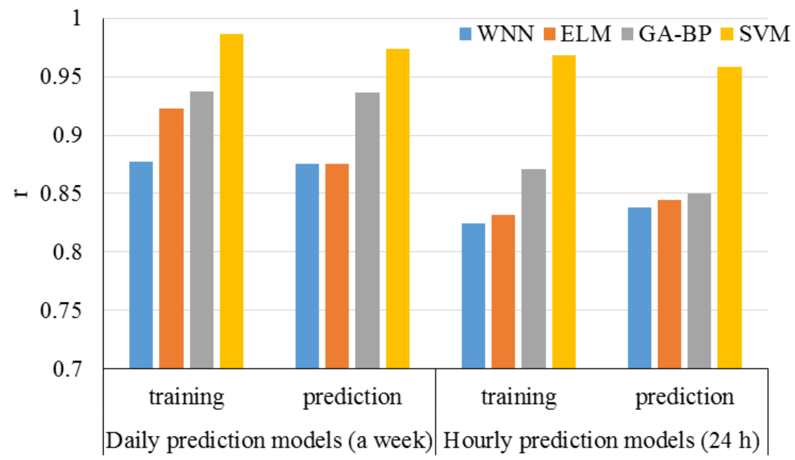


Figure 25. RMSE values for study by Doucoure et al. (2016) [56]

Gu et al. (2018) [57] studied heat load prediction utilizing different prediction models such as extreme learning machine, wavelet neural network, support vector machine, back propagation neural network optimized using a genetic algorithm and wavelet neural network. Historical loads and indoor temperature were assumed to be influential. The support vector machine demonstrated smaller errors comparing to the three other neural network algorithms. Figure 26 presents values of RMSE and correlation coefficient for the study.



(a)



(b)

Figure 26. (a) RMSE (a) and (b) r values for study by Gu et al. (2018) [57]

He et al (2018) [58] proposed a hybrid forecasting model which was composed of three modules: data clustering, data preprocessing and forecasting modules. The decomposing technique was used to decrease the noise influence within the raw data series to achieve a more stable sequence to extract traits from the original data. A similar fluctuation pattern was selected for training database in the forecasting module to improve the forecasting accuracy. The experimental data demonstrate that the presented model outperforms other discussed forecasting models in the paper. Figure 27 presents the RMSE values in cases of non-season and season datasets.

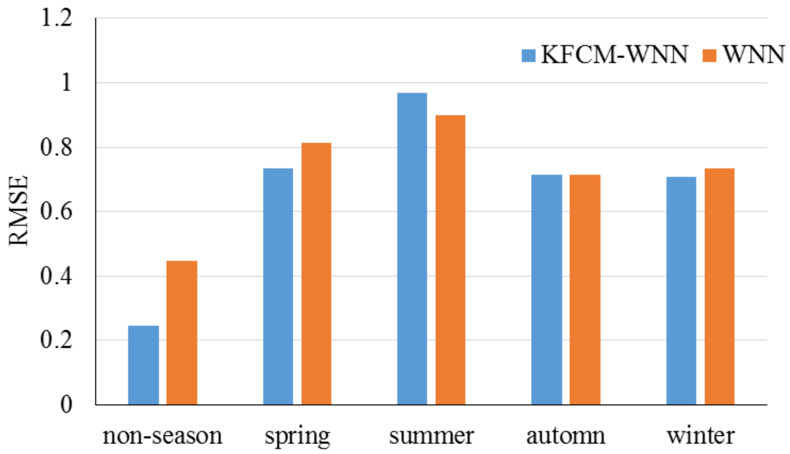


Figure 27. RMSE values for study by He et al. (2018) [58]

Qin et al. (2018) [59] introduced an online energy management control for applying for hybrid electric vehicles which was based on neuro dynamic programming (NDP) to optimize battery state of charge and fuel economy at the same time. In the proposed NDP method, the action network was a conventional wavelet neural network and the critic network was a multi-resolution wavelet neural network. The action network was constructed on the Morlet function and critic network was stem from the Meyer wavelet function. Based on results, the NDP EMS have a high capability same as the NDP in online applications. Based on comparisons, the RBFNN-based NDP EMS supports the efficiency of the CWNN and MRWNN.

Sarshar et al (2017) [60] presented an adaptive probabilistic concept of confidence interval for addressing randomness of wind speed. To increase forecasting accuracy, wavelet decomposition was utilized for time series of wind power and the results were used in artificial neural network. Then predicted wind power dependable levels adaptive probabilistic concept of confidence interval were calculated. An energy storage system were used to decrease the impact of forecasting errors on the micro-grid and to increase planning flexibility. Finally, the presented algorithm was validate with a typical micro-grid case study. The results evaluation demonstrated that the presented adaptive probabilistic concept of confidence interval worked well and the results indicated the superiority of WNN to ANN.

4.6. Adaptive neuro-fuzzy inference system (ANFIS)

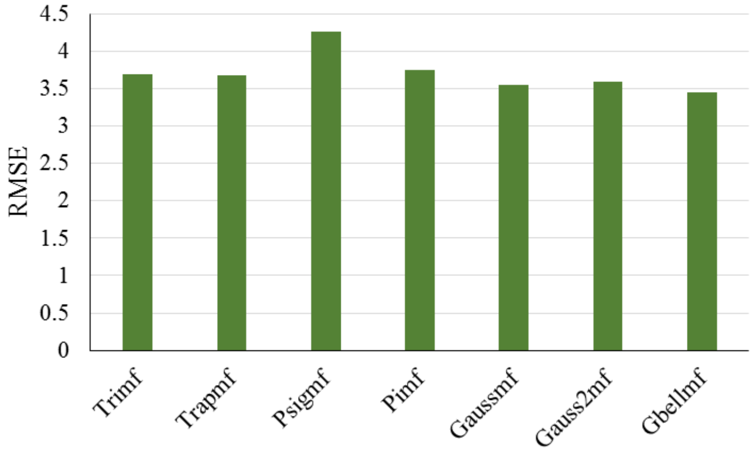
ANFIS is a modeling method which employs artificial neural network based on Takagi–Sugeno fuzzy inference system. This technique benefits both fuzzy logic and neural network capabilities, due to the integration of neural networks and fuzzy logic principles. ANFIS is a method with five main layers. In fact this method is considered as a hybrid method [11]. Table 13 presents some important papers in this field.

Table 13. Important paper about ANFIS method utilization for solar energy

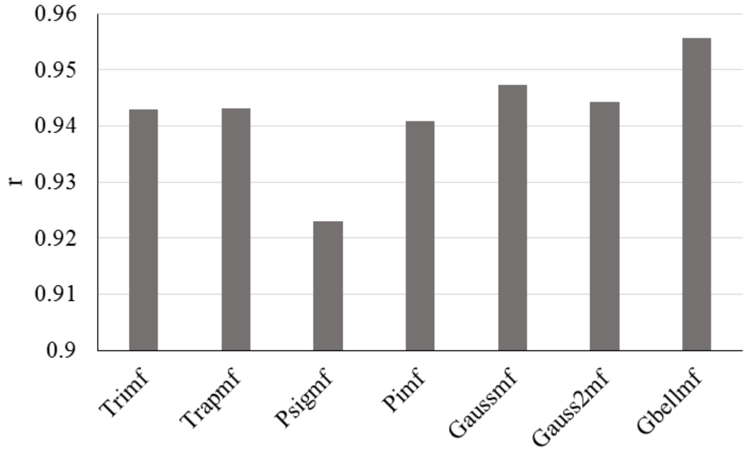
Year	Reference	Journal	Application
2018	Abdulwahid et al [61]	Sustainability (Switzerland)	A protection device for reverse power protection system
2017	Bassam et al [62]	Sustainability (Switzerland)	Module temperature estimation of PV systems
2018	Kampouropoulos et al [63]	IEEE Transactions on Smart Grid	Prediction of the power demand of a plant and optimization of energy flow
2016	Mohammadi et al [64]	Renewable and Sustainable Energy Reviews	Identification of the most relevant parameters for forecasting of daily global solar radiation
2016	Sajjadi et al [65]	Journal of the Taiwan Institute of Chemical Engineers	Transesterification yield estimation and prediction of biodiesel synthesis

Abdulwahid and Wang (2018) [61] introduced a novel protection method for preventing reverse power flow developed on neuro-fuzzy networks for utilization in smart grid. This study, presented an upgraded protection device using a newly developed intelligent decision support system (IDSS). The presented IDSS was a decision system support system which coupled the robust specification for fuzzy inference systems and neural networks. The proposed methodology can monitor extreme environmental condition.

Bassam et al. (2017) [62] developed an adaptive neuro fuzzy inference to estimate the temperature of photovoltaic systems. Experimental measurements for the learning process comprised of six environmental variables namely wind velocity, temperature, wind direction, irradiance, atmospheric pressure and relative humidity and PV power output as an operational variable, which were used for training parameters. The model was validated with experimental data from a photovoltaic system with a high value for fitness correlation parameter. The results of the model demonstrate that the presented methodology was reliable tool for modules temperature estimation using environmental variables. Figure 28 presents the RMSE (a) and correlation coefficient (b) values for the study. This comparison is in line with the choosing the best type of membership function for ANFIS. As is clear from Figure 28, Gbell membership function with a low RMSE and a high correlation coefficient value have the highest accuracy compared with that or the other types.



(a)



(b)

Figure 28. (a) RMSE and (b) correlation coefficient values for study by Bassam et al. (2017) [62]

Kampouropoulos et al (2018) [63] introduced a novel approach for multi-carrier energy systems energy optimization. In this study, an adaptive neuro-fuzzy inference system was applied to forecast the power demand of a factory and a genetic algorithm was used to its energy flow. The optimization algorithm objective was to fulfill power demand of the factory to reduce optimization criteria. The proposed method was validated in the car manufacturing plant in Spain (SEAT).

Mohammadi et al. (2016) [64] presented a method to identify the most important parameters for forecasting global solar radiation utilizing an ANFIS selection procedure. In this study, a methodology based on ANFIS was applied to identify the most related parameters for daily prediction of global solar radiation. Three different cities were considered as case studies. Nine parameters of extraterrestrial radiation, sea level pressure, relative humidity, water vapor pressure, minimum, average and maximum air temperatures, maximum possible sunshine duration and sunshine duration were considered for selection in ANFIS process. The results indicated that an optimal sets of inputs were different for different case studies. This study, demonstrated the significance of selection of input parameters for predicting daily global solar radiation. Figure 29 indicates the value of RMSE in terms of two and three inputs. Based on results, three inputs provide better prediction performance compared with that for the two inputs.

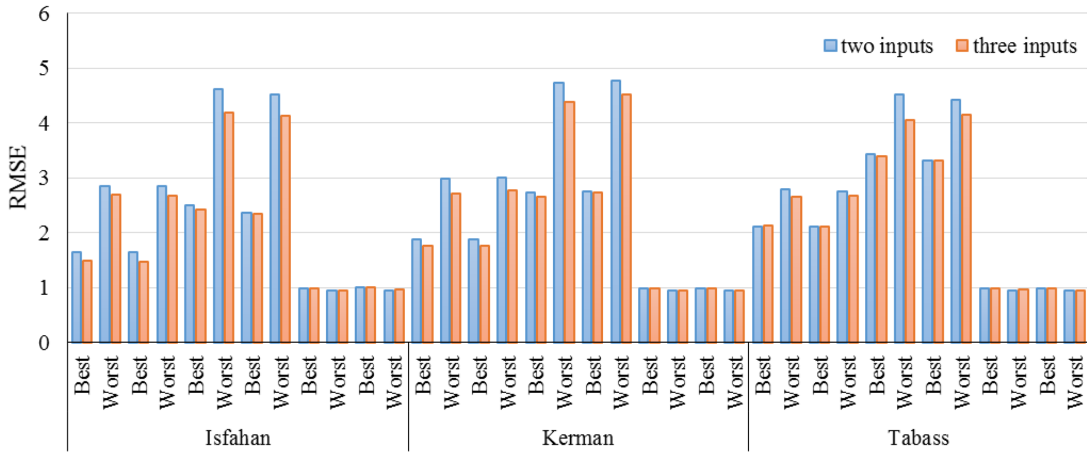


Figure 29. RMSE values for study by Mohammadi et al. (2016) [64]

Sajjadi et al. (2016) [65] performed sensitivity analysis for using catalyzed-transesterification as renewable energy production system by an adaptive neuro-fuzzy inference system (ANFIS) based methodology. Influential parameters on transesterification yield should be analyzed and predicted. ANFIS was applied in this paper to select the most important parameters based on operational variables. Experiment results were used to extract training data for adaptive neuro-fuzzy inference system network. The robustness of the presented method was verified by simulation results.

4.7. Decision trees

Decision tree method is used to approximate discrete-valued target functions that the learned function is illustrated by a decision tree. These methods are among the most powerful inductive inference algorithms and are successfully used for many different energy systems. Table 14 presents some important papers in this field.

Table 14. Important paper about Decision trees method utilization for solar energy

Year	Authors	Journal	Application
2018	Aguado et al [66]	IEEE Transactions on Smart Grid	Railway electric energy systems optimal operation
2016	Costa et al [67]	Electric Power Systems Research	Security dispatch method for coupled natural gas and electric power networks
2017	Kamali et al [68]	Applied Energy	Prediction of the risk of a blackout in electric energy systems
2016	Moutis et al [69]	Applied Energy	energy storage planning and energy controlling
2016	Ottesen [70]	Energy	Total cost minimization in energy systems for the prosumers' buildings

Aguado et al. (2018) [66] introduced a methodology for railway electric energy systems optimal operation considering PV panels and wind turbines as renewable energy sources, hybrid electric energy storage systems and regenerative braking capabilities. The uncertainties related to renewable energies were considered through a scenario tree methodology. All the complements were coupled into multi period optimal power flow problem. Results were reported for different cases for different operation modes.

Costa et al. (2016) [67] presented a security dispatch method based on decision trees which can be applied to coupled natural gas and electric power networks against contingencies that may cause interruptions. Preventive measures to the optimal gas production and electric energy generation were performed based on boundaries of controllable variables and security regions determined by decision trees. The decision tree's rules that give details of the security regions were tractable constraints and was included in the optimization procedures of gas production and power generation rescheduling.

Kamali and Amraee (2017) [68] presented a novel two-stage method to predict the risk about blackout in electric power network. Firstly, electric islands boundaries were determined utilizing a mixed integer nonlinear programming method which optimized the cost of load curtailment and power generation re-dispatch. Secondly, a data-mining method was completed to forecast the risk of an electric island separation from the rest of the network. Several scenarios such as island and non-island situations were analyzed and then used by the decision tree classification method to forecast the uncertainty about a possible blackout.

Moutis et al. (2016) [69] presented a novel tool for utilizing decision trees for planning storage systems in micro grids and to control energy resources to balance energy for a planned community micro grids. The presented methodology was validated by sensitivity analysis for several case studies. A test implementation was introduced for utilization of distributed controller hardware to run the algorithm of energy balancing in real-time.

Ottesen et al. (2016) [70] used decision tree for energy balancing and planning for planned community micro grids. The goal of this study was to minimize total cost by trading in an electricity market and considering grid tariffs costs, imbalance penalization and fuels use. The flexibility properties of the energy systems in the buildings of prosumers was modeled bidding rules and handling the interrelations between hours were considered. Uncertain parameters information structure were captured through scenario trees. Therefore, a two stage stochastic mixed integer linear program was applied for bidding decision and scheduling.

4.8. Deep learning

Deep learning tries to model hierarchical characterization behind data predicts patterns through stacking multi-layer information processing modules. Increasing computing power and increasing data size resulted in popularity of deep learning. Table 15 presents some important papers in this field.

Table 15. Important paper about deep learning method utilization for solar energy

Year	Authors	Journal	Application
2018	Chemali et al [71]	Journal of Power Sources	Battery State-of-charge estimation
2017	Coelho et al [72]	Applied Energy	Household electricity demand forecasting
2017	Kim et al [73]	Computational Intelligence and Neuroscience	Estimation of the power consumption of individual appliances in the distribution system
2016	Mocanu et al [74]	Sustainable Energy, Grids and Networks	Prediction of building energy consumption
2017	Wang et al [75]	Energy Conversion and Management	PV power forecasting

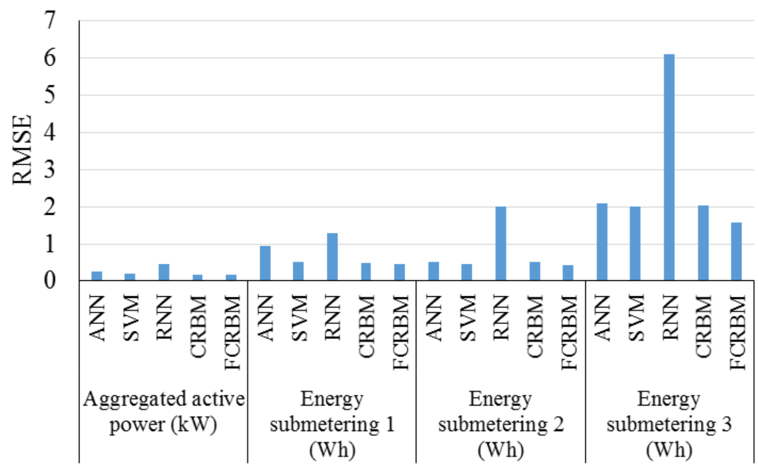
Chemali et al. (2018) [71] introduced a machine learning methodology for state of charge (SOC) estimation in Li-ion batteries utilizing deep neural networks. In this study, a new approach utilizing

Deep Neural Networks was presented for estimating battery SOC. Training data was generated in the laboratory through applying drive cycle loads for different ambient temperatures to a Li-ion battery. As a results, battery can be exposed to variable dynamics. The ability of Deep Neural Networks for encoding the dependencies in real time into the network weights was demonstrated.

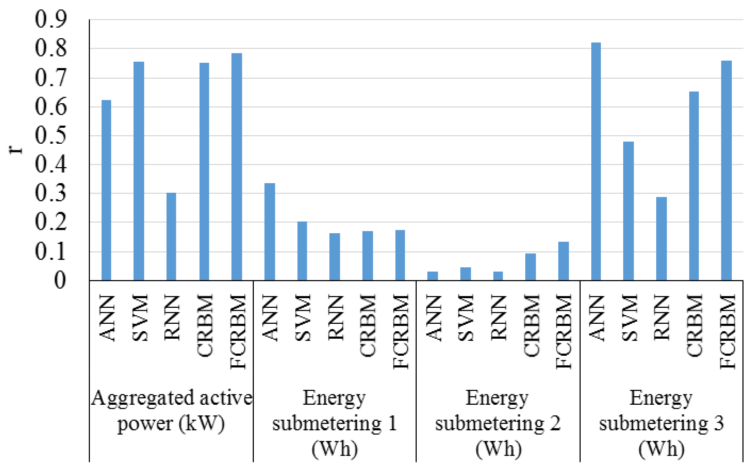
Coelho et al. (2017) [72] presented deep learning model for Graphics Processing Unit for time series forecasting. A new parallel methodology for time series learning was designed. The presented methodology was applied in a hybrid metaheuristic model for mini/micro grid forecasting problem (he household electricity demand). Calculated results demonstrated that the presented Graphics Processing Unit learning methodology was a robust deep learning tool to be used into smart sensors.

Kim et al. (2017) [73] presented a nonintrusive load monitoring method based on advanced deep learning. In this study, an energy disaggregation utilizing advanced deep learning and Long Short-Term Memory Recurrent Neural Network model was proposed. Then, a new signature to upgrade the proposed model classification performance in multistate appliance case. It was demonstrated that the combination between novel signature and advanced deep learning can be a robust solution for improving load identification performance.

Mocanu et al. (2016) [74] introduced two novel models, namely Factored Conditional Restricted Boltzmann Machine and Conditional Restricted Boltzmann Machine for energy consumption time series prediction. The models were evaluated by four years of one minute resolution electric consumption data gathered from a residential building. The results demonstrated that Factored Conditional Restricted Boltzmann Machine outperformed ANN, SVM, RNN and CRBM. In this study predictions were performed in various scenarios. RMSE and correlation coefficient were employed to compare the results in choose the best model. Figure 30 presents the RMSE (a) and correlation coefficient (b) values in case of prediction for a year with weekly resolution.



(a)



(b)

Figure 30. (a) RMSE and (b) correlation coefficient values for study by Mocanu et al. (2016) [74]

Wang et al. (2017) [75] introduced a new method for photovoltaic electricity forecasting utilizing wavelet transform and deep convolutional neural network. Deep convolutional neural network was used to extract invariant structures and the nonlinear features exhibited in each frequency. Numerical results demonstrated that the introduced methods can improve accuracy of forecasting for various seasons and different prediction horizons. Figure 31 presents the average RMSE values in two scenarios, 45 and 75 minutes-ahead PV power forecasting.

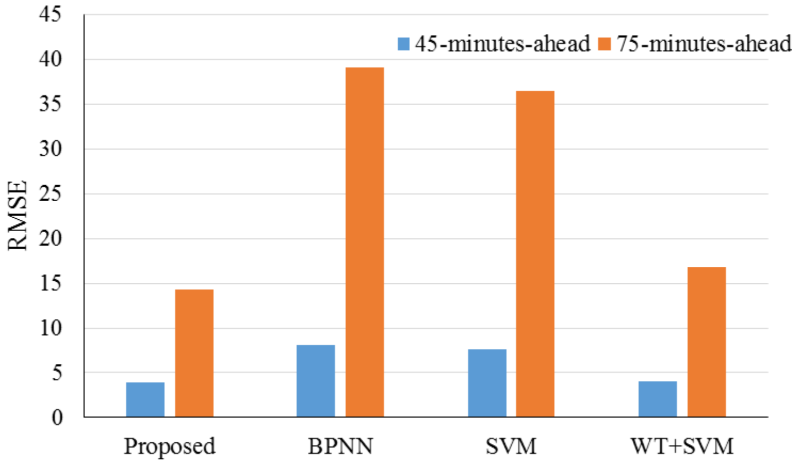


Figure 31. RMSE values for study by Wang et al. (2017) [75]

4.9. Ensemble methods

Ensemble methods employ multiple learning algorithms in machine learning and statistics, in order to reach the best modeling performance compared any other single learning algorithms. In statistical mechanics ensemble method contains only a concrete finite set of alternative models but actually allows for a flexible architecture to exist among alternative models [76]. Table 16 presents some important papers in this field.

Table 16. Important paper about Ensemble methods utilization for solar energy

Year	Authors	Journal	Application
2015	Burger and Moura [77]	Energy and Buildings	forecasting of building electricity demand
2017	Changfeng et al	International Journal of Control and Automation	Non-linear fault features extraction
2018	Fu, G [78]	Energy	Cooling load forecasting in buildings
2015	Gjoreski et al [79]	Applied Soft Computing Journal	Human energy expenditure estimation
2016	Hasan and Twala [80]	International Journal of Innovative Computing, Information and Control	Prediction of the underground water dam level

Burger and Moura (2015) [77] worked on generalization of electricity demand forecasting by formulating an ensemble learning method to perform model validation. By learning from data streams of electricity demand, this method needed little information about energy end use, which made it desirable for real utilizations.

Changfeng et al. (2017) used ensemble empirical mode decomposition (EEMD) and multiclass relevance vector machine for diagnosis of faults of self-validating air data sensing system. The EEMD working principle was highlighted for distinct faults features extraction. The multiclass relevance vector machine was utilized for the faults diagnosis in self-validating air data sensing system. In accordance with failure mode analysis and prototype design of the self-validating air data sensing system, an experimental system was designed to verify the execution of the presented methodology.

Fu (2018) [78] presented an ensemble approach for forecasting of cooling load of air-conditioning system. The presented approach was used for deterministic forecasting of cooling load with high precision. In this approach deep belief network, empirical mode decomposition and ensemble technique were utilized. The data series of the original cooling load was decomposed into several components. Ensemble method was used to mitigate the influence of uncertainties such as data noise and model uncertainty, on forecasting precision. Figure 32 presents the RMSE values of the study for each seasons by the employed models.

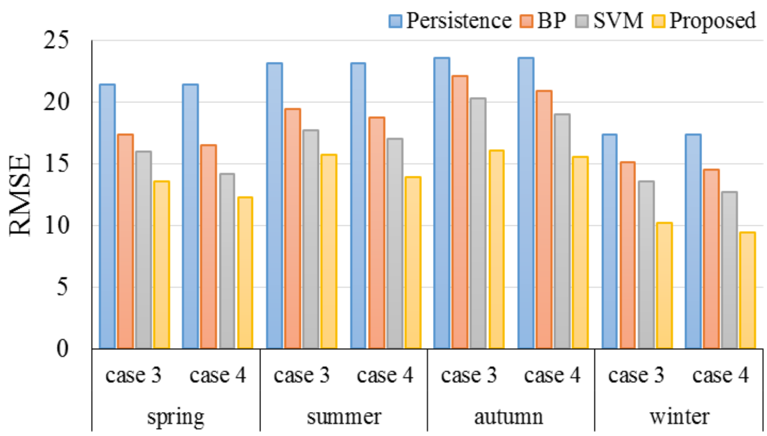


Figure 32. RMSE values for study by Fu (2018) [78]

Gjoreski et al. (2015) [79] utilized ensemble method for estimation of human energy expenditure. In this paper, a multiple contest ensemble method was presented to extract multiple features from the sensor data. Every feature was utilized as context for building multiple regression models and applying other features as training data. The models related to the feature values in the evaluated sample were assembled regression models ensemble to estimate energy expenditure of the user. Figure 33 presents the RMSE values of the study for each activity by the employed models.

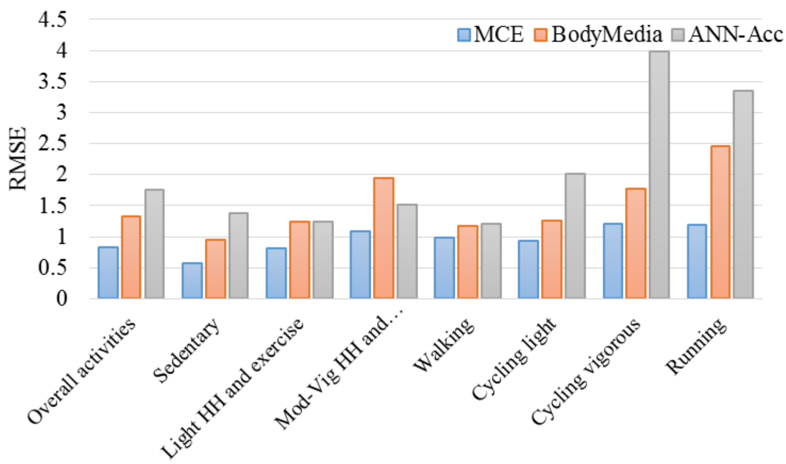


Figure 33. RMSE values for study by Gjoreski et al. (2015) [79]

Hasan and Twala (2016) [80] presented an ensemble technique to monitor and predict the underground water dam level. Six different classifiers methods were applied for this goal. The paper introduced a new method to select the most appropriate classifiers to construct the most accurate ensemble. This methodology was based on determination of mutual information amount between pairs of classifiers and was utilized to find optimum number of the classifiers to build the most precise ensemble.

4.10. Hybrid

Hybrid methods benefits two or more modeling techniques in order to improve the prediction capabilities. In these models, usually, one part is for prediction or acts as estimator and the other part acts as optimizer. These models mainly be employed when there is a need for an accurate estimation. ANFIS is one of the common hybrid methods [39, 81]. Table 17 presents some important papers in this field.

Table 17. Important paper about Hybrid methods utilization for solar energy

Year	Reference	Journal	Application
2018	Deng et al [82]	Journal of Renewable and Sustainable Energy	Short-term load forecasting in micro grids
2016	Dou et al [83]	Electric Power Components and Systems	prediction of renewable energy loads in micro grids
2016	Peng et al [84]	Energies	Electric load forecasting
2016	Qu et al [85]	Advances in Meteorology	Reliable wind speed prediction
2017	Yang and Lian [86]	Applied Energy	Electricity price prediction
2019	Dehghani et al [87]	Energies	Hydropower generation forecasting
2017	Mosavi et al [88]	Intelligent systems	General energy sectors

Deng et al. (2018) [82] presented and a hybrid short term load predicting model which was optimized by Switching Delayed Particle Swarm Optimization. In this study, this method was proposed based on Switching Delayed Particle Swarm Optimization, Extreme Learning Machine with different Kernels and Empirical Mode Decomposition. At first stage, the load database history was decomposed into independent Intrinsic Mode Functions and the Intrinsic Mode Function sample entropy values were computed. The Intrinsic Mode Function were categorized into three groups. Then the Extreme Learning Machine with was applied to predict the three groups. Lastly, the prediction results were gathered to achieve the final prediction result. The experimental results showed that the presented perdition model was quit robust. Figure 34 presents the RMSE values of the study for each load by the employed models.

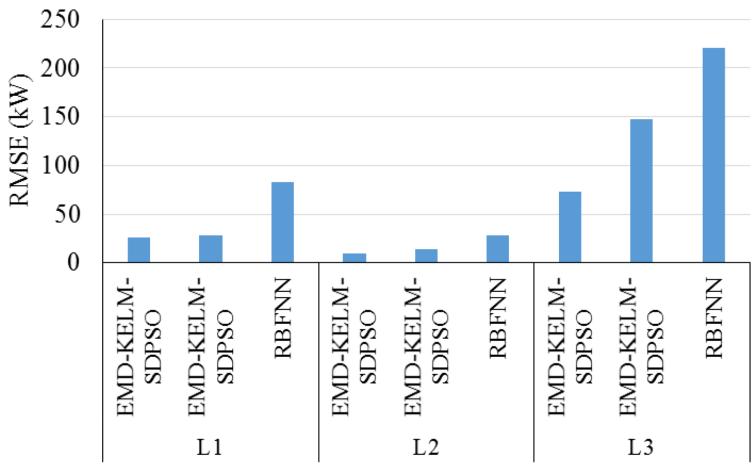


Figure 34. RMSE values for study by Deng et al. (2018) [82]

Dou et al. (2016) [83] presented energy management strategies for micro grid by utilizing renewable energy source and load prediction. An energy management system based on a two level multi agent was built. Then, in the upper level EMA, strategies of the energy management was constructed by using a PSO method based on renewable energy sources and loads probabilistic forecasting. Ensemble empirical mode decomposition coupled with sparse Bayesian learning was used for forecasting of the lower level renewable energy source and load agents. The validity of proposed method was examined by simulation results.

Peng et al. (2016) [84] introduced a method to hybridize differential empirical mode decomposition and quantum particle swarm optimization algorithm with support vector regression in electric load forecasting. The differential empirical mode decomposition method was applied for decomposing the electric load to several parts related to high frequencies and an approximate part related to low frequencies. The quantum particle swarm optimization algorithm was utilized for optimizing the parameters of support vector regression. The validation of the method demonstrated that it can provide forecasting with good precision and interpretability.

Qu et al. (2016) [85] introduced a hybrid model for wind speed forecasting based on Fruit Fly Optimization Algorithm and Ensemble Empirical Mode Decomposition. The original data of wind speed was divided into a set of signal components using ensemble empirical mode decomposition. Then, fruit fly optimization algorithm was used to optimize parameters of prediction artificial intelligence models. The final prediction values were acquired by reconstructing the refined series. The empirical results demonstrate that the presented hybrid model was better that some of the existing forecasting models. Figure 35 presents the RMSE values of the study by the employed models.

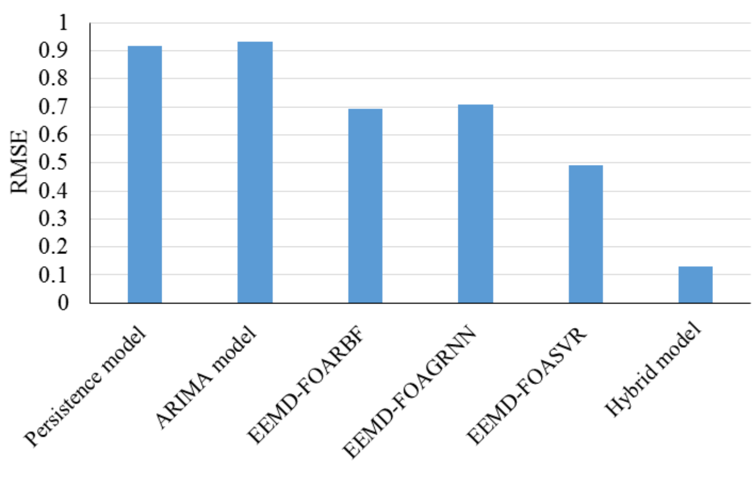


Figure 35. RMSE values for study by Qu et al. (2016) [85]

Yang et al. (2017) [86] presented a hybrid model for electricity price forecasting utilizing ARMA, wavelet transform, kernel-based extreme learning machine (KELM) methods. Self-adaptive particle swarm optimization (SAPSO) was applied for searching the optimal kernel parameters. After test of the wavelet decomposition components, the ARMA model was used to predict stationary series. SAPSO-KELM model. The proposed method performance is validated utilizing electricity price data from several cities. The real data demonstrated that the presented method was more accurate than individual methods. Figure 36 presents the RMSE values of the study for each season by the employed models.

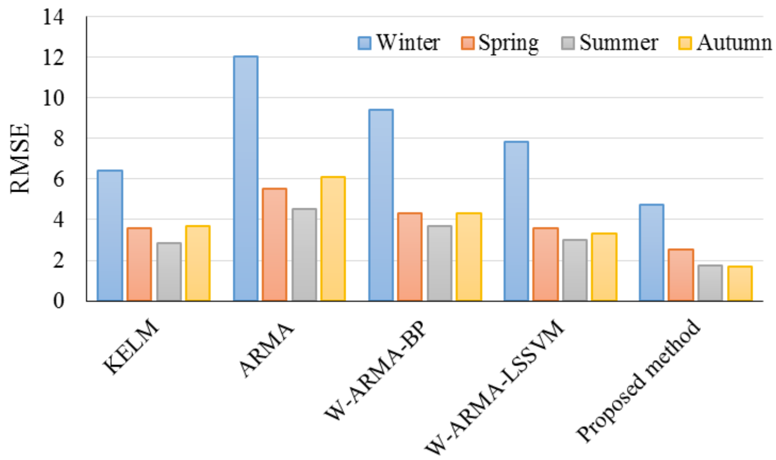


Figure 36. RMSE values for study by Yang et al. (2017) [86]

5. Discussions and conclusions

The smart grid is on its way. Many opportunities and challenges lie ahead. In future energy generation systems, we will have an increased flow of information. Demand forecasting for price-considering customers and forecasting of changing power generation will shape future energy systems. This survey has been entangled with this matter by presenting the state-of-the-art machine learning methods applied in energy systems along with a comprehensive taxonomy for them. The presented machine learning methods will be used for automated decision makings. By using machine learning methods, creative ways can found to re-schedule the power demand, helping smart grid to be balanced. In other words, by enhancement of energy demand and wind and solar energies predictability, energy storage, peak load management, dynamic energy pricing can be improved.

The renewable energy sources utilization growing is huge. The rapid pace of technological advances makes it economically acceptable to extract energy from wind, sun and other renewable energy resources. The main aspect of all renewable energy resources is their dependence on environment and huge barriers for controlling and planning in advance. For instance, in electricity grid, it is necessary to forecast future amount of power and future amount of power demand and specially unpredictability and fluctuations in wind and solar energies and energy demand has negative impact on the grid and its users. Therefore, it is very important to study different machine learning methods to solve these problems.

Through the literature review in the background and review sections of this chapter, it is demonstrated that machine learning robustness for analyzing, modeling, forecasting and optimization of energy systems. In the reviewed literature in this work, one or more methods are introduced and their validity and accuracy are assessed by related experimental data. This survey also contains pros and cons for each of the presented methods to, evaluate their accuracy regarding to the error rate.

There have been significant advances in the utilization of the algorithms which are the foundation of machine learning.

Based on what is obtained from the results, all studies are in the direction of moving towards a precise method to replace previous models. In this regard, they have been somewhat successful. What comes out of the results is that the ML methods have a high precision compared with that for the other methods. It can be argued that the hybrid methods in this field are slightly more precise than individual methods. But in general, what affects the accuracy of modeling tools, is the nature of the dataset. However, efforts to find an accurate and effective method are ongoing which the ML methods are pre-emptive, progressive and upgradeable models.

The hybrid methods followed by ML methods have the highest degree of accuracy than other methods. This discrepancy continues to increase as data become larger

This makes possible further working and viewpoints from which we can conclude that hybrid methods are the best choice to be applied in this field and indicates a clear way to move toward making hybrid ML methods.

In future, prediction projects ML and DL techniques worth to be further investigated. To develop an improved way of any methodology in line with the purpose of this study, it is planned to accomplish a clear systematic mapping for having a comprehensive classification including their potential of relationships, and presenting a clear way to aid in the future choice of any ML techniques.

در منابع زیر همه اسامی نویسندگان نیاورده شده است.

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