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# A review on renewable energy and electricity requirement forecasting models for smart grid and buildings

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ABSTRACT

The benefits of renewable energy are that it is sustainable and is low in environmental pollution. Growing load requirement, global warming, and energy crisis need energy-intensive management to give sincere attempts to promote high accuracy energy monitoring techniques in order to enhance energy system efficiency and performance. The energy consumption data of domestic, commercial and industrial are becoming accessible to estimate the notable share of various sectors in the energy market. Energy forecasting algorithms play a vital role in energy sector development and policy formulation. Energy prediction and power supply management are the key roots of energy planning. A large number of prediction models have been used in the recent past. The selection of a prediction model usually based on available data, the objectives of the model network mechanism and energy planning operation. In this review, we conduct a critical and systematic review of renewable energy and electricity prediction models applied as an energy planning tool. The forecasting intervals is divided into three sections including: i) short-term; ii) medium-term; iii) and long-term. Three renewable energy resources, i.e. wind, solar, and geothermal energy, and electricity load demand requirement are considered for review forecasting analysis. Three major states-of-art forecasting classifications: i) machine learning algorithms; ii) ensemble-based approaches; iii) and artificial neural networks are analyzed. These approaches are investigated for prediction applicability; accuracy for spatial and temporal forecasting; and relevance to policy and planning objectives. The machine learning models can handle large amount of data with accurate forecasting analysis. Applying ensemble techniques enables us to obtain higher forecasting accuracy by combining different models. Artificial neural networks if used in the right way can contribute a robust choice, given that it is capible to extract and model unseen relationships and features. Furthermore, unlike these conventional techniques, artificial neural networks do not force any limitation on residual and input distributions. Findings from this review would help professionals and researchers in obtaining recognition of the prediction approaches and allow them to choose the relevant methods to satisfy their desired tasks and forecasting requirements.

## 1. Introduction

One of the major issues for the world energy sector in the near future is to be secured with operation safety by the increasing integration of renewable energy (RE) resources (Benali, Notton, Fouilloy, Voyant, & Dizene, 2019;Renné, Zelenka, Wilcox, Perez, & Moore, 2006). The electricity generation market by RE systems, including wind and solar energy is hugely significant for future. The growth rate of the global business of wind energy, and photovoltaic farms are continuously expanding with 51 GW h of wind turbines networks (European Comission. (EurObserv'ER) (2016a)), 100 GWhof PV farms (EurObserv'ER, 2012) and 100 Megawatt of concentrated solar power (Sangster, 2014) incorporated in 2017. Therefore, the cumulative energy capacity of the Global and the Europe markets reached up to 405 GW and 106.6 GW for Photovoltaic (PV) respectively (EurObserv'ER, 2013), 539.3 GW and 169.0 GW for wind power farms (European Comission. (EurObserv'ER) (2016b)) and 4845 Megawatt and 2314 Megawatt for concentrated solar power (Sangster, 2014) in 2017. From 2017, total 353.5 TW h of wind energy and 113.9 TW h of PV were generated in Europe. The continuous usage of fossil resources, environmental and energy issues frequently are displaying more serious concerns for the globe. It's essential to get an appropriate solution to determine the ecological problems of electricity and attain sustainable growth. Consequently, RE has obtained much consideration in the entire globe and been immediately expanded in the recent era (Sun, Wang, Zhang, & Zheng, 2018).

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**Nomenclature**

| | |
|---|---|
| AdaBoost | Adaptive boosting |
| AI | Artificial intelligence |
| ANNs | Artificial neural networks |
| ARIMA | Autoregressive integrated moving average |
| AIMA | Autoregressive integrated moving average |
| BP | Backpropagation |
| BN | Bayesian network |
| R | Coefficient of correlation |
| CV | Coefficient of variation |
| CDT | Compact decision tree |
| CEM | Competitive ensemble model |
| DT | Decision tree |
| DE | Differential evolution |
| EGS | Enhanced geothermal system |
| EL | Ensemble learning |
| GW | Gigawatt |
| GHI | Global horizontal irradiation |
| HVAC | Heating, Ventilation and Air Conditioning System |
| ISO | Independent system operators |
| kWh | kilowatt-hour |
| LRM | Linear regression model |
| ML | Machine learning |
| MAE | Mean absolute error |
| MAPE | Mean absolute percentage error |
| PV | Photovoltaics |
| RFM | Random forest models |
| RE | Renewable energy |
| RMSE | Root mean square error |
| SVM | Support vector machines |
| TWh | Terawatt Hour |
| ELMs | The electrical load management system |

Among different RE sources, like solar, geothermal and tidal energy, the use of wind energy is definitely neat and clean, indispensable and inexpensive (Mohandes & Rehman, 2014; Wang, Song, Liu, & Hou, 2016; Wang, Zhang, Wang, Han, & Kong, 2014). Though, the wind power usage still faces many hurdles – it is an unstable provision of energy to the electricity networks and it is spatial and temporal variable presented in these references (Gnana Sheela & Deepa, 2013; Georgilakis, 2008; Söer et al., 2007; Smith, Milligan, DeMeo, & Parsons, 2007). The essential challenges for future world energy supply and demand will be the high RE integration resources into the future power demand-supply networks (Voyant et al., 2017).

Power utilities should guarantee an accurate balance between the consumption and energy generation to ensure the realibility of the electricity transmission and distribution networks. Because of the particular challenge, the utilities usually have some complexities to keep this stability with controllable energy generation and conventional system, particularly in the isolated or small power grid (as located in different areas of the island). The energy system reliability and security should become reliant on the capability of the operation to support unexpected and expected dispersion (in consumption & generation) and distortion between sustaining continuity and service quality of assistance to the consumers. Furthermore, the power producers must maintain the system management with different temporal horizons (see Fig. 1) (Voyant et al., 2017). Load planning for electrical networks should include network capacity, yearly planning, optimization generation and construction of networks and system reliability.

Renewable power prediction is applied to forecast the available generation capacity of renewable resources in the near future (Voyant, Soubdhan, Lauret, David, & Muselli, 2015). Many approaches have been used by researchers across the world such as time series models, which have frequently been employed (Bulut & Büyükalaca, 2007;Wang, Hu, Srinivasan, & Wang, 2018). The renewable power prediction can be classified into two classes: indirect forecast classifications and direct prediction approaches (Marčiukaitis et al., 2017). Energy demand forecasting is also fundamentally vital for either in defying the abnormal energy consumption trends or source-conserving intention. Indeed, it's a non-trivial business because energy usage is associated with various complicated factors, including the historical values of past load consumption, holidays, calendar dates, and domestic energy consumption practices (Lei, Tang, Li, & Ye, 2019).

The solar energy can be predicted in the short-term, medium-term and long-term by latest technologies like satellite imaging networks and ground-based atmosphere imaging that represents a collective potential drawbacks associated with cloud dissipation and formation. The wind energy prediction is identified as an essential tool to give system engineers with significant estimates of accessible wind energy data in future time duration. These kinds of assessments are frequently used in energy scheduling and resource balancing (Foley, Leahy, Marvuglia, & McKeogh, 2012; Lara-Fanego, Ruiz-Arias, Pozo-Vázquez, Santos-Alamillos, & Tovar-Pescador, 2012; Jung & Broadwater, 2014; Qian, Pei, Zareipour, & Chen, 2019). Electricity demand prediction has been doing an essential part in the energy industry for over a century (Singh et al., 2011). The traditional means of energy prediction is deterministic load demand forecasting, which has been extensively used in the power plants control and electrical power market with the interconnected networks (Mohandes, 2002; Sun, Wang et al., 2018).

The efficiency, stability and performance of the prediction approaches are the primary concentration of this review. This review also intends to give a summary of the present techniques for prediction of energy requirement consumption of buildings, utilities, private and government sector and so on. The domestic, commercial and industrial building owners will get help from this review to choose suitable models to perform different kinds of tasks to fulfil their required needs. The classifications investigated in this review include the ML models, ensemble-based approaches and Artificial neural networks (ANNs) methods. An effort has been initiated to precisely show the most essential technical and scientific aspects and percent accuracy of forecasting results of many published papers, and readers can understand the prediction concept in a productive way. Further it can assist like a valuable design for the future study in RE energy system, operation, planning, and energy management.

This review is conducted on published researches for the knowledge of determining the prediction models in future sustainable electricity demand and renewable energy management with effective manner. The primary analysis is carried out to find a summary of the issues associated with predictions classifications in energy resources planning and management.

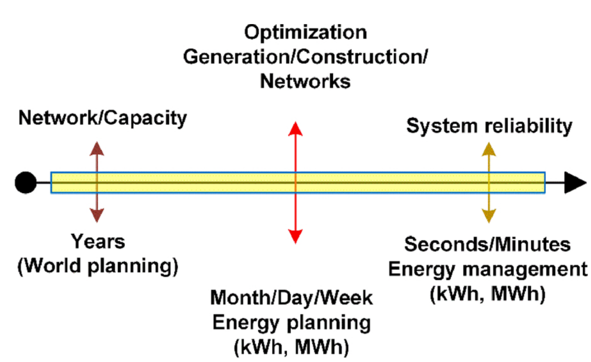


**Fig. 1.** Forecasting scale for load planning in an electrical network.

**Table 1**
Objective of this study.

| Models | Forecasting duration | Energy sources | Aim and objective | Geographical |
|---|---|---|---|---|
| Machine learning models<br>Ensemble-based approaches<br>Artificial neural networks | Short-term, medium-term, and long-term | Solar radiation prediction<br>Wind energy forecasting<br>Geothermal energy forecasting<br>Electricity load forecasting<br>Electricity price forecasting | Energy planning and management, Accuracy and speed, model selection, forecasting models' compatriots | City<br>Province<br>Country<br>Multiple locations<br>Region |

The main classified problems were: supply model/energy demand/or prediction; energy management and planning approaches; time series forecasting analysis; emission mitigation techniques; renewable energy importance and prediction; the role of RE in the future perceptive; world total energy supply/demand and their future challenges; and prediction. These issues were applied to distinguish important key headings of this review, shown in Table 1.

### 1.1. Importance of renewable energy and electricity requirement forecasting

Various stakeholders in the energy industry apply solar predictions. Power companies are utilizing solar forecasts to procure operating reserves, schedule production and assure that there is enough versatility to handle differences between the input and output. Market shareholders practice predictions to control their energy production portfolios. Fig. 2 explains the techniques of the algorithm based on temporal and spatial resolution (Diagne, David, Lauret, Boland, & Schmutz, 2013). Precise wind energy prediction is essential in decreasing the length or occurrence of curtailments (that shows the effective cost of energy savings), increased operator safety measures, and minimizing the human effects of serving climate on wind operations.

Geothermal energy is a kind of energy stored and generated from in the earth. It's more competing in different lands that have a small number of hydrocarbon sources. The purpose of geothermal energy is a possible alternative resource of power that will grow more prominent as a result to avoid the more focuses on fossil power generation sources. The new expectation of world use of geothermal energy within the decade end is that the yearly installation capacity will cause the present around 12.6 GW to approximately 21.5 GW, with less progress in 2016–2017 (Lund, Bertani, & Boyd, 2015) presenting the alternative to higher annual improvements from 2018 to 2020, according to a survey conducted in April by Ruggero Bertani such as shown in Fig. 3[1] . In Asia Pacific, it shows a large share in geothermal generation capacity with about 1.81 GW, which is higher than those of North America, Latin America, Africa and Europe. The installed generation capacity of the Unites State of America is three times higher than Mexico and two times higher than Philippines.

Electricity requirement (or electricity load) prediciton is vitally essential for the utility industries in the deregulated economics. There are a series of applications including electricity production and purchasing, contract evaluation, load switching, and power infrastructure extension. An expanding series of numerical approaches have been proposed for energy prediciton. In this review, we examine several methods of RE and electricity prediciton. A comprehensive literature review reveals that includes the substantial studies by experts have been published on short-term energy prediciton for various load situations. Fig. 4 shows the applications and kinds of electricity requirement prediciton intervals for short, medium and long-term perceptive for efficient and reliable energy, control, planning, and management systems (Raza & Khosravi, 2015). Main objectives of power companies for load forecasting include optimal reserve capacity, accuracy and reliability, unit commitment corporate planning and optimal reserve capacity handling.

Fig. 5(a & b) shows the energy source and consumption structures in the whole world and Unites States (US), respectively, based on the data collected from December 18$^{th}$, 2018 (Lawrence Livermore National Laboratory, 2017; World Energy Flow, 2017). Firstly, the energy sources majorly include Wind, Nuclear, Hydro, Solar, Geothermal, Natural Gas, Coal, Biomass and Petroleum. The energy consumption sectors are divived into residential, commercial, industrial, nano-energy and transportation. Different coloured pipelines show the total net requirement of energy of the different consumption sectors.

These plots could be very helpful for making energy policies to tackle environmental change. It can be observed that conventional energy sources still construct the major part of the global energy consumption. In contrast, the shared of RE resources is quite small. From 2011, the Global used 534,000 petajoules of energy, and it shows that most (60 %) of the energy sources came from oil, unsurprisingly. The average American resident utilized about 39 billion Joules (BJ) of energy in 2013. The world's largest energy-consuming area is the industrial sector, with transport close behind it. What's especially striking is that transportation of the energy sector — that's the trains, planes as well as automobiles — is the largest consumers of the petroleum, which is shocking and terrible for the climate change.

### 1.2. Paper organisation

Section 2 gives a detailed analysis of short-term solar, wind, electricity and geothermal energy demand forecasting. Further, it is classified into four basic parts including: i) solar radiation forecasting models; ii) wind energy forecasting models; iii) electricity demand forecasting models; and iv) geothermal energy forecasting models. Each section is further classified into three basic parts including machine learning models, ensemble models and artificial neural networks. Section 2 also includes the medium and long-term wind, solar and electricity demand forecasting with different state-of-the-art models. Section 3 gives a summary of the reviewed models and Section 4 concludes this review.

## 2. Renewable energy and electricity requirement forecasting models

Renewable and electricity requirement prediction models to the real time applications render and overlook state-of-the-art electricity and renewable energy technology. Energy prediction is an essential and integral part in virtually and for the domestic, commercial and industrial sectors. Power companies control the power grid, recognized as the several complicated human-made systems on the globe, to produce power to more than 7.53-billion peoples throughout the world. Energy prediction, mainly pointing out to prediction electricity requirement is being utilized throughout the whole sections of the utility industry, including transmission, generation, distribution as well as the retails. Energy forecasting applications spread distribution and transmission

[1] http://geothermalresourcescouncil.blogspot.com/2016/01/global-outlook-for-geothermal-industry.html

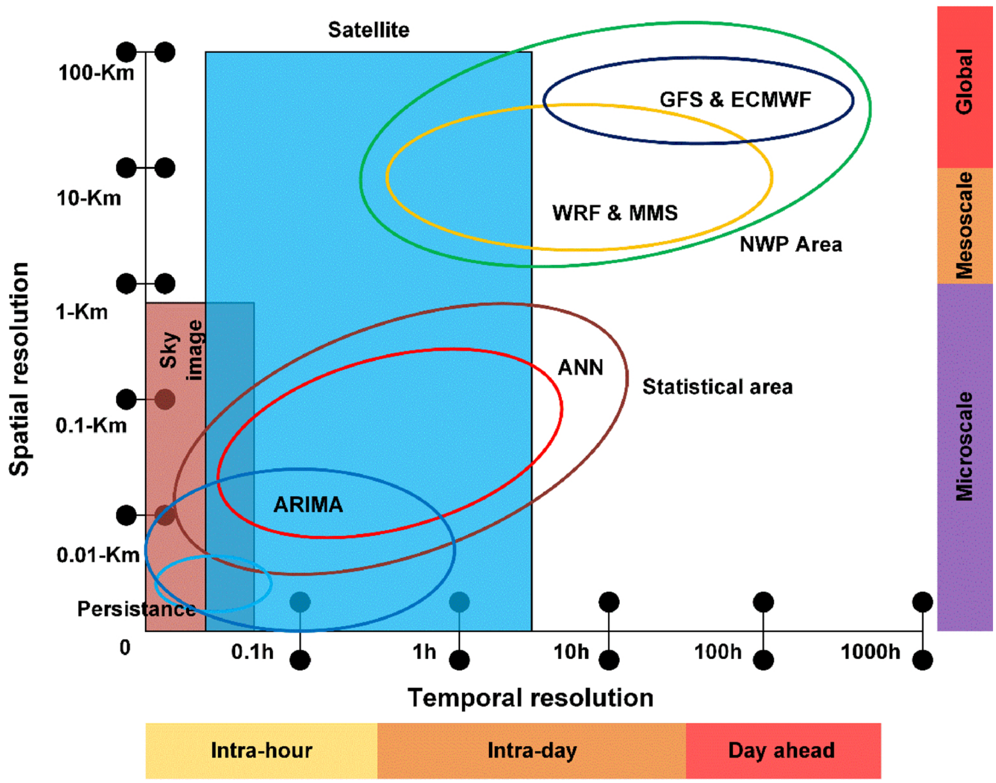


**Fig. 2.** Forecasting classifications which are based on the input data of temporal and spatial resolution (Diagne et al., 2013).

planning, power supply planning, power system maintenance and operations, demand-side management, rate design, financial planning and so onward. Because of the primary role of energy prediction in the utility's business services, incorrect energy prediction may result in an economic loss or even failure of the power companies. Though energy prediction gives a significant input to control the systems planning and operations, imprecise energy prediction can start to equipment malfunctions or even operations-wide blackout.

The issue of sustainable energy is typically unique to every energy planner based on their conditions, which involve the sector coverage, geographical location, and available sources. The World Energy Council (WEC) invented an expression power trilemma to represent some essential difficulties in the sustainable advancement in the energy sector, an on-going discussion concentrates throughout the agenda of the United Nation's initiated seventeen sustainable development goals, which displace the previous millennium development agenda and satisfy the wide-area by sustainable development growth problems. Mainly, the object #7 "Assure feasibility to reliable, affordable and smart power usage to each and everyone". This problem affects the globe as a world-unit; however, it leads to determine the legislative discussion of power supply in particular continents or countries. With the increasing attention of weather transition, energy demand and supply has shifted a frequently significant problem. Because of the rising world energy requirement, strict emissions targets, players within the power planning and management must obtain difficult decisions comprised of risk-based estimations concerning the future. Considering the particular goals, there is a requirement for assistance mechanisms which aid the decision-making rule throughout power networks.

Under the pressure of environmental protection and economic development, the transforming and cleaning of energy construction

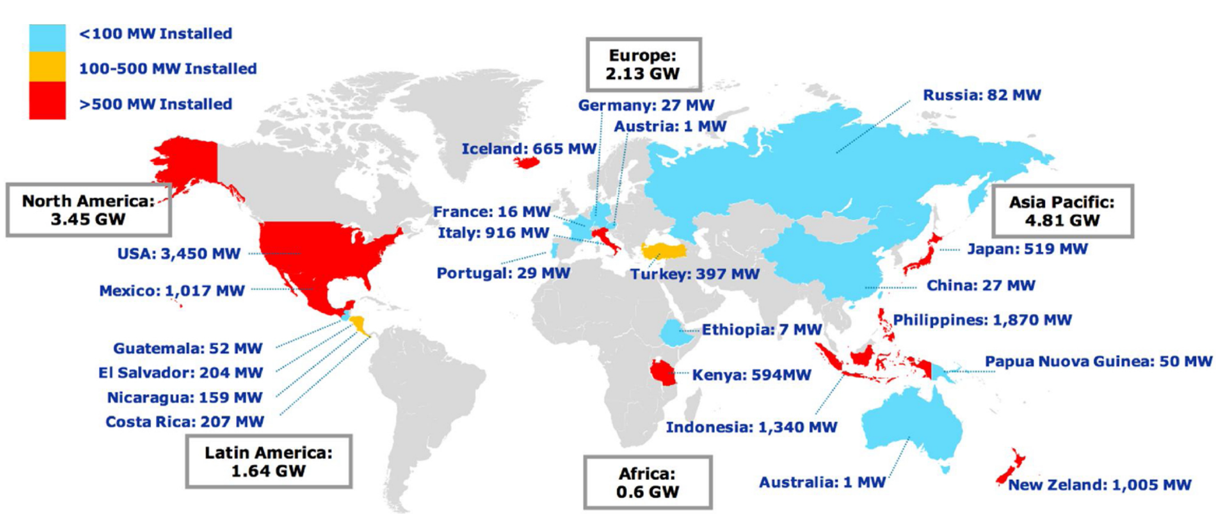


**Fig. 3.** Installed geothermal generation capacity in 2015 of the global market (Lund et al., 2015).

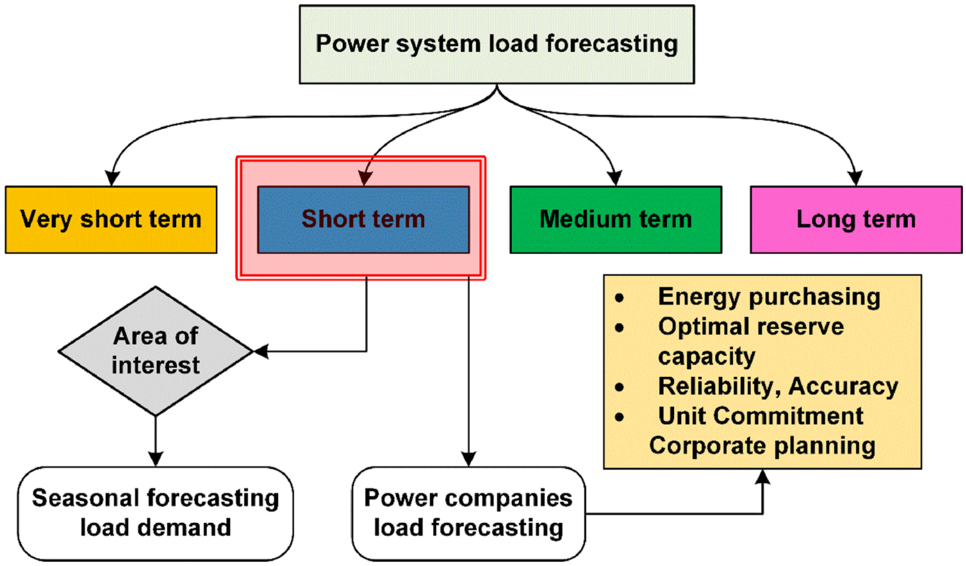


**Fig. 4.** Types of load forecasting and applications (Raza & Khosravi, 2015).

initiated the distributed power operation to display some unique features. There are some new system side theories, like Pan Energy Net (PEN), Energy Internet (EI), micro-grid and active distribution systems have been broadly affected under the knowledge of the development of world energy internet. While, by the renewable energy introduction, the distributed power networks would suffer difficulties in different perspectives of the design phase, operation, and application.

The structure of information operation and application is developed fundamentally from 3 technical areas: model predictive control (MPC) in control area, the knowledge of data-mining, and the optimization operation area of ML section in the building operations, like air conditioning and refrigeration. The field where these 3 areas cross or overlap improves fast advancement of the energy prediction approach in the optimization and operation of the distribution. The data mining (DM) approach which renders helpful information could be obtained by a huge number of samples data points, the information gathered by DM should be unknown. The method of DM is complicated which needs iterative adjustment, human-computer interaction and increasing realization to create a high degree of information. The ML is the essence of artificial intelligence (AI), which points to the ample use in the area of AI because it creates the network intelligently. The ML such as support vector machine and ANNsartificial neural networks are often applied for energy prediction, which can considerably increase the forecast efficiency and accuracy. Ensemble learning is ML paradigm where different algorithms are trained to solve complicated issues of the model's network and combined to acquire better results.

### *2.1. Short-term renewable energy and electricity requirement forecasting*

Very short-term prediction comprises up to nine hours applies in transmission lines planning and load management, intraday market, and ancillary duty management. Short-term forecasts explain up to seventy-two hours and use to day-ahead demand, reserve scheduling, maintenance schedule management, and planning of energy networks or wind plants as well as the unit commitment. Usually, prediction ranges between 24 − 72 hours show the time-step as hourly (Kim & Hur, 2018). In this section the detailed analysis has been conducted for solar, wind, electricity and geothermal energy forecasting through ML, ensemble and ANNs based forecasting models.

#### *2.1.1. Solar radiation forecasting*

Because its intermittency, the integration of large-scale solar energy into power grids is a problem and further particularly in an isolated context. Therefore, The solar energy prediction output is an essential characteristic to maintain the demand and supply balance efficiently (Boland, David, & Lauret, 2016). It can be considered two essential perspectives to solar energy prediction, which of the required level of power as well as putting the sensible forecasting error bounds of that prediction. This review will focus on the past, and in specific, that horizontal global solar irradiation prediciton.

*2.1.1.1. Machine learning models*. The RE integration into a power system increases the grid station continuity and complexity of the consumption/generation balance due to their unpredictable and intermittent nature (Lara-Fanego et al., 2012; Pelland, Remund, Kleissl, Oozeki, & Brabandere, 2013). The non-controllable features and intermittency of the solar energy generation bring a large number of other issues like local power quality, voltage fluctuations, and power network stability problems (Moreno-Muñoz, De La Rosa, Posadillo, & Pallarés, 2008; Anderson & Leach, 2004). Therefore, predicting the output of solar energy is needed for efficient control of the power station as well as optimal control, planning, and load fluxes occurred toward the solar farms (Paulescu, Paulescu, Gravila, & Badescu, 2013).

The ML is a significant area in computer science; further, it's listed as artificial intelligence (AI) models. It applies in different areas, and the benefit of these approaches is that resolve the issues which are complicated to be described by explicit models. In this study (Inman, Pedro, & Coimbra, 2013), the researcher can observe a complete analysis of some deterministic and ML approaches for solar energy prediciton. The ML approaches perceive relationships between outputs and inputs even though if the description is confusing; this feature allows the application of ML approaches in several states, for instance in classification problems, pattern recognition, spam filtering, prediciton issues, and data mining. The demand for reliable solar predictions describes the current surge in many types of research on this subject (Inman et al., 2013; Yang, Kleissl, Gueymard, Pedro, & Coimbra, 2018). The prediciton of solar radiation methods may be divided concerning the forecasting horizon, different kinds of input data into four main classifications, as defined in recent studies (Yang et al., 2018):

- Artificial Intelligence and statistical techniques: generally used for prediction ranges ranging from 5 min up to 6 h (Benmouiza & Cheknane, 2013; Lauret, Voyant, Soubdhan, David, & Poggi, 2015);
- Classification of remote-sensing models: used for prediction boundaries from minutes to hours (Marquez & Coimbra, 2013);
- Numerical climate forecasting approaches: for prediction

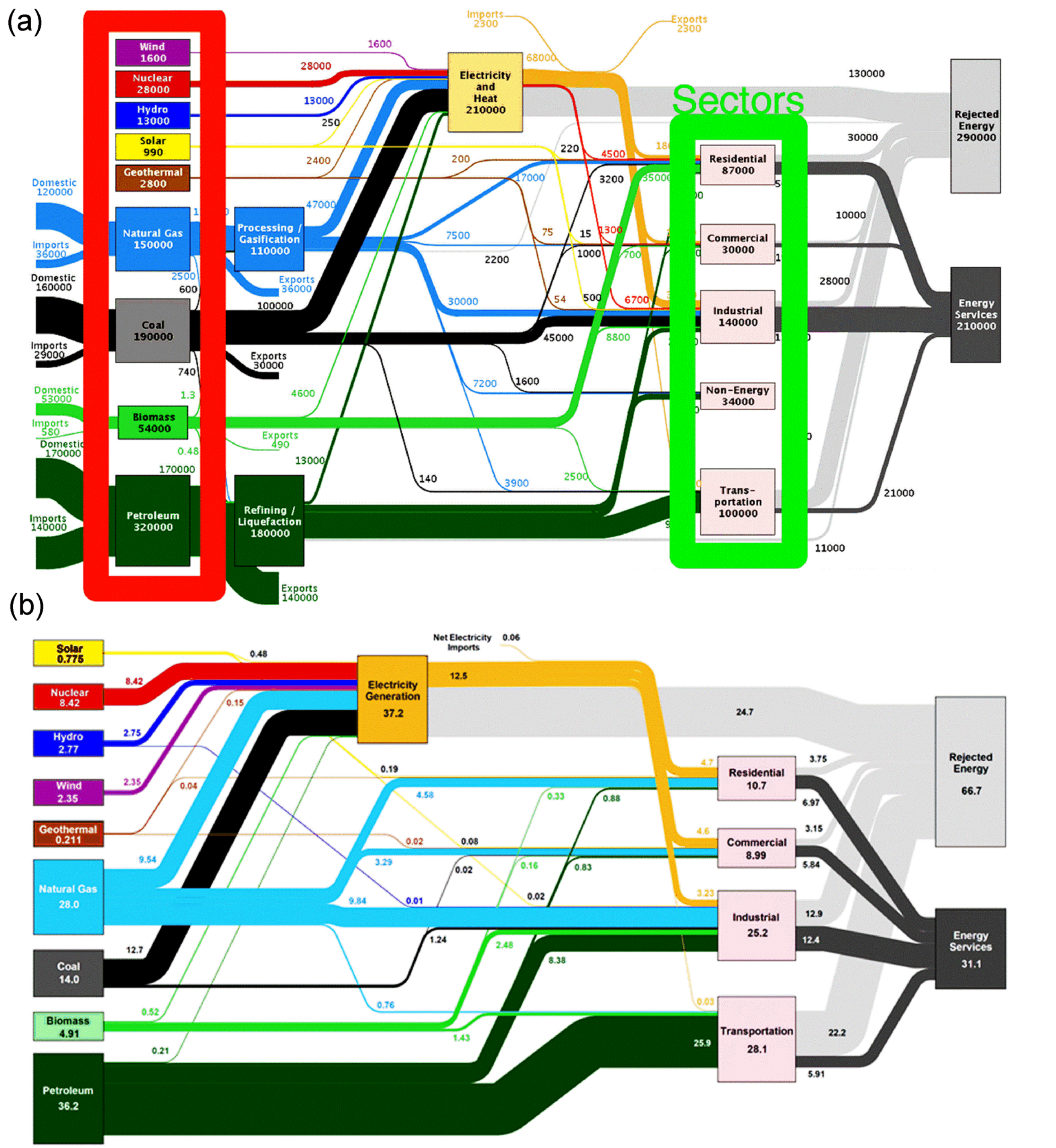

**Fig. 5. (a).** This plot illustrates where whole the world's energy demand goes and comes from (World Energy Flow, 2017). **(b).** The plot demonstrates where total US energy goes and comes from in 2017 (Lawrence Livermore National Laboratory, 2017).

boundaries exceeding six hours (Lorenz, Heinemann, & Kurz, 2012);

- The hybrid forecasting approaches: for conceivably more reliable predictions based on the past prediciton levels (Mellit, Benghanem, Arab, & Guessoum, 2005).

The current reviews present the new ML classification to estimate the global horizontal irradiation (GHI) for a short-term duration (suitable to sub-hourly, hourly duration) from a present and past time-series. These models rely on a mutual information measure to choose a set of optimal organized of the most important numbers (probably recent) in time-series intervals (henceforth, input parameters), and the ANNs of extreme learning class (ELM) class to determine the day ahead patterns of GHI which are comprised of a recently proposed technique (Peng, Long, & Ding, 2005). Table 2 shows the short-term solar radiation forecasting with ML models. It shows the name of forecasting engine, real time advantages, region and performance evaluation indexes with best accuracy.

*2.1.1.2. Ensemble-based approaches*. Ensemble prediction models are meteorology classical for risk quantification (Thorey, Mallet, Chaussin, Descamps, & Blanc, 2015). Meteorological predictions can be unique deterministic predictions or and ensemble-based predictions,

**Table 2**
Short-term solar radiation forecasting with machine learning models.

| Sr. No. | Models | Advantages | Year | Region (Dataset) | Ref. | Accuracy | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | Fourier series plus linear ARMA models | No obligation to construct complicated models like ANNs | 2016 | One coastal and one inland a | (Boland et al., 2016) | – | – | – | 13.59 % | – |
| 2 | Regression tree, Random forest, Gradient boosting | The model can determine issues which are complicated to be described by explicit models | 2017 | Multiple locations | (Voyant et al., 2017) | 3.73-9.45 | – | 6 % | 5 % | 0.72 |
| 3 | Extreme learning machine, Wrapper mutual information methodology | Maximizing the common information measure concerning the target to be the prediction | 2019 | Madina and Tamanrasset | (Bouzgou & Gueymard, 2019) | – | – | 8.4–11.55 % | – | 0.87 and 0.91 |
| 4 | Auto-regressive moving average, Multi-layer perceptron | Best and highly accurate forecasting algorithm for the energy sector | 2018 | Ajaccio, Tilos and Odeillo | (Fouilloy et al., 2018) | 98.48 | – | – | 46.56 % | – |
| 5 | FoBa, leapForward, spikeslab, Cubist and bagEarthGCV | Measures a particular kind of data with higher accuracy & performance | 2018 | National renewable energy laboratory | (Sharma & Kakkar, 2018) | – | – | – | 23.73 % | 0.9 |
| 6 | Extreme learning machines models, Satellite solar model | Many sites with different features are applied in the model training | 2019 | Australia | (Deo, Şahin, Adamowski, & Mi, 2019) | 1.140 | – | – | 0.049 % | 0.91 |
| 7 | Extreme learning machine (ELM) algorithm | Address complicated and ill-defined prediction issues | 2017 | Toowoomba, Australia | (Deo, Downs, Parisi, Adamowski, & Quilty, 2017) | – | – | – | 0.629 % | 0.90 |
| 8 | Random forest regression, Support vector regression, Gradient boosted regression | Comfortable to replicate that in the situation with physical methods | 2016 | Spain | (Gala, Fernández, Díaz, & Dorronsoro, 2016) | 14.84 | – | – | – | – |
| 9 | Weighted Gaussian process regression | Mainly to it is simple training and implementation at different sites | 2018 | Algeria | (Guermoui, Melgani, & Danilo, 2018) | – | – | – | 3.18 % | 0.85 |
| 10 | Gaussian processes and support vector machines | Improvement resembles to be more noticeable in case of unpredictable sky circumstances | 2015 | French islands: Corsica, Reunion | (Lauret et al., 2015) | – | – | – | 15.15 % | – |
| 11 | Self-organizing map | By recognizing anomalies and different trends and neglecting outliers | 2015 | Different locations | (Ghayekhloo, Ghofrani, Menhaj, & Azimi, 2015) | – | – | – | 0.39 % | – |
| 12 | Boosted regression trees, Least absolute shrinkage and selection operator | Its insensitive to outliers, flexible to show characteristics of solar data, strong to fit complicated nonlinear relationship | | Different locations | (Huang, Wang, & Lai, 2018) | – | – | – | 18.36 % | – |
| 13 | K-nearest-neighbors, Gradient boosting | A broad area of solar variability micro-climate | 2018 | Folsom, CA | (Pedro, Coimbra, David, & Lauret, 2018) | – | – | – | 8 % | – |
| 14 | Convolutional neural networks | Variability can be perfectly characterized including comparatively easy equations | 2017 | Stanford's Yang & Yamazaki Energy and Environment | (Sun, Szucs, & Brandt, 2018) | – | – | – | 26.0%–30.2% | – |
| 15 | Support vector machines, K-nearest neighbors | K-nearest neighbors can achieve higher performance and accuracy | 2018 | Inner Mongolia | (Wang, Zhen et al., 2017) | – | – | – | – | 0.007 |
| 16 | Multi-task learning for time series | Increasing the imputation of past PV data is extremely helpful for time-series modeling | 2018 | Multiple locations | (Shireen et al., 2018) | 0.31 | – | 40.475 | 0.385 | – |
| 17 | Machine learning approach | Ability to render excellent and bias-calibrated predictions, and it is the computationally scalable algorithm | 2017 | Italy | (Cervone, Clemente-Harding, Alessandrini, & Delle Monache, 2017) | – | – | – | – | – |

**Table 3**
Short-term solar radiation forecasting with ensemble-based classifications.

| Sr. No. | Models | Advantages | Year | Region | Ref. | Accuracy | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | Analog ensemble | Needs a single design prediction and denied to the multiple algorithms runs | 2015 | Southern Italy | (Alessandrini, Delle Monache, Sperati, & Cervone, 2015) | 6–7 | – | – | | – |
| 2 | Least square support vector regression, Ensemble empirical mode decomposition | The basic function is obtained immediately of the real signal instead a priori-fixed basis network function | 2018 | Beijing, China | (Sun, Wang et al., 2018) | – | – | 3.09 % | 3.27 % | – |
| 3 | Random forest regression, Gradient boosted regression, Extreme gradient boosting | Comparative processing uniformity allows them to get the advantage of parallelization methods | 2019 | China and India | (Torres-Barrán, Alonso, & Dorronsoro, 2017) | 2190.9 | – | – | – | – |
| 4 | Grand global ensemble | Better prediction for the daily spatial patterns and load trends | 2015 | European centre | (Thorey et al., 2015) | 20.0 | – | – | 8.3 % | – |
| 5 | Analog ensemble | Knowledge to give excellent and bias-calibrated estimates, and it is a computationally scalable model | 2017 | Italy | (Cervone et al., 2017) | – | – | – | – | – |
| 6 | Probabilistic forecasting model | These various kinds of predictions to get the support of their diversity | 2018 | Météo France | (Thorey, Chaussin, & Mallet, 2018) | 0.081 | – | – | 0.101 % | – |
| 7 | Ensemble forecast framework | Capacity to manage nonlinear, dynamic and abrupt meteorological changes | 2018 | Queensland | (Raza, Mithulananthan, & Summerfield, 2018) | 4.17 % | – | – | – | 0.87 |
| 8 | Climate research and prediction algorithm | Benefits to develop a large number of ensemble divisions of the network, higher accuracy | 2016 | Japan | (Liu et al., 2016) | – | – | – | 59.6 % | – |
| 9 | Ensemble methods | It uses terrain and other geographic variations into account and decreases the error of the forecast | 2015 | Multiple locations | (Ren et al., 2015) | 17.07 % | – | 15.67 % | 3.02 % | – |
| 10 | Glowworm swarm optimization | Gave excellent accuracy | 2017 | India | (Jiang, Dong, & Xiao, 2017) | – | – | 13.24 % | 28.05 % | – |
| 11 | Extremely randomised trees, Random forest, Decision trees | The trained algorithm can express logical perceptive, that are simple to grasp from a non-expert | 2018 | Cardiff, Wales, UK | (Ahmad, Mourshed, & Rezgui, 2018) | 1.58 | – | – | 2.30 % | 0.921 |
| 12 | Ensemble forecast | The mixed prediciton will be unbiased | 2018 | Multiple locations | (D. Yang & Dong, 2018) | – | – | – | 15.40 % | – |
| 13 | Gradient boost, Bagging, Random forest, the Ensemble method | The best order of prediciton and stability accuracy | 2017 | Egypt, Jordan, Tunisia, Algeria, Morocco | (Hassan, Khalil, Kaseb, & Kassem, 2017) | – | – | – | – | 0.97 |
| 14 | Multi-centre grand ensemble | Significant predictor for the discovery of prediction busts in the geographical estimate | 2018 | Japan | (Uno, Ohtake, Matsueda, & Yamada, 2018) | – | – | – | 41.0 % | – |
| 15 | Extreme learning machines | Rapid training speed, give the least training errors | 2017 | China | (Ni, Zhuang, Sheng, Kang, & Xiao, 2017) | – | – | – | – | – |

usually at a coarser resolution. In Ref. (Inman et al., 2013), give a survey of photovoltaic (PV) prediciton approaches with deterministic forecasts. Ensemble models or probabilistic prediciton has been extensively described in the meteorological society (Gneiting & Katzfuss, 2014). In the recent past, ensemble-based prediciton approaches examined for PV (Zamo, Mestre, Arbogast, & Pannekoucke, 2014); however, these methods are more famous for wind power and wind speed prediction (Ren, Suganthan, & Srikanth, 2015). In climatology, an ensemble approaches (Roulin, 2007; Wei, Toth, Wobus, & Zhu, 2008) applied to estimate the security/reliability of the climate predictions for different kinds of studies and further used for commercial load forecasting methods.

An ensemble approach is general in ML and statistics. It practices multiple forecasters to get an aggregated determination which is useful as compared any of the base forecasts (Opitz & Maclin, 1999). According to Opitz & Maclin (1999), the ensemble models can be divided into two classes: cooperative and competitive for ensemble analysis. Competitive prediciton is used to train various features separately with multiple kinds of datasets or with the similar datasets though with numerous variables and then the forecasting is taken by equating the determinations of total individual forecasters (base prediciton). The cooperative ensemble prediction is to distribute the forecast assignment into many selecting suitable predictors and sub-tasks for specific sub-tasks comprised on the properties of sub-tasks; furthermore, the last choice is the total number of aggregate outputs of the previous base forecasts (Ren et al., 2015). Table 3 shows a comprehensive review with accuracy indexes for short-term solar radiation forecasting with ensemble-based classifications.

In Ref. (Ren et al., 2015), ensemble models for wind and solar prediction are used into two classes, each comprising further two sub-classes, as given in Fig. 6. The competitive ensemble model (CEM) utilizes various variables and models to start predictions. The last projections are estimated from the weighted averaging by different predictions of the network. The CEM distributes the prediciton task into multiple steps, where many classifications which applied in various stages to achieve the final accurate and reliable predictions.

*2.1.1.3. Artificial neural networks*. The ANNs is a part of AI which operates as an excellent modeling tool for investigation such as its competitors to determine the non-linear network function evaluation, pattern detection, sorting of data, simulation, clustering and optimization. Such kind of setup called 'black-box' optimization methods to take out the non-linear trends. It is designed primarily includes a hidden layer, input layer, biases and weights, output layer, summation node, and the activation function. It is stepping into two steps: generalization (recalling) and learning (training). In the network training, biases and weights are applied to produce the output target by decreasing the error of the network function. The systems improved through ML, and the network trained from repetitions that are the remaining cycle of each dataset for training purpose to exist in the model networks. The modeling learning methods classified into reinforcement supervised learning, evolutionary and unsupervised approaches. For specific use of these, the supervised models are consisting of adding of deviation among the preferred output and actual network output results. The network biases, as well as weights, are adjusted by making training trend set as well as resultant forecasting errors among the subsequent network output and a preferred output network.

Though, supervised approaches continue as a closed-loop network feedback mode where the forecasting variation considered as the model feedback sign — the degree error identified by mean square error (MSE). The MSE defined a particular variation of the network, but the network training and learning rule ended when the MSE is decreased (Yadav & Chandel, 2014). Many researchers have proposed empirical classifications for the forecasting of solar radiation (Batlles, Rubio, Tovar, Olmo, & Alados-Arboledas, 2000; Karakoti, Pande, & Pandey, 2011; Khatib, Mohamed, & Sopian, 2012; Jebaraj & Iniyan, 2006; Khorasanizadeh & Mohammadi, 2013; Sonmete, Ertekin, Menges, Haciseferoğullari, & Evrendilek, 2011). The forecasting observed to be precise with the quality estimated datasets (Coskun, Oktay, & Dincer, 2011; Myers, 2005).

Wange et al. developed a feature's extraction methodology for solar irradiance and the support vector machine (SVM) based climate trend identification method for short-term Photovoltaic power forecasting (Wang, Zhen et al., 2015). Moreover, they estimated the accuracy of k-nearest neighbors and SVM methods, and then examined the sample-scale influences, amount of different classes as well as the distribution of data in various divisions on the everyday climate modeling results (Wang, Zhen, Wang, & Mi, 2017). Though, the fundamental disadvantage of these before-mentioned conventional classification approaches is their simple network learning with higher network dispersion. These models are inefficient to obtain ideal distribution efficiency due to deficient in achieving the deep nonlinear characteristics of the network data used for input, mainly when supplying vast numbers of complicated sets (different input feature variables) of data. One useful approach to mark the slight algorithm problem is the performance of the ANNs because it is the knowledge to determine the internal general characteristics variables and high-level hidden invariant constructions of the network in data (He, Zhang, Ren, & Sun, 2015). It's observed through previous studies that the ANNs based distribution algorithms start developing as the large scale accuracy in different applications, exceeding classical statistics techniques such as the SVM (Sezer & Ozbayoglu, 2018). Fig. 7 gives the various kind of solar systems based applications using ANNs (Qazi et al., 2015). Table 4 shows a comprehensive review with accuracy indexes for the short-term solar radiation forecasting with ANNs classifications.

*2.1.2. Wind energy forecasting*

With the increasing growth of wind energy demand into the electricity grid station, reliable, accurate, and precise wind energy prediction is a necessary portion of the management and operation of electrical systems networks (Qian et al., 2019). The total global installed capacity of wind energy production predicted to lead 817 GW until 2021 (GWEC, 2017). Several approaches have been reported and applied in the different research to present wind energy speed predictions for the next few hours to the next couple of days (Foley et al., 2012). Existing classifications can be usually divided into three sections, e.g., data-driven models, physical numerical climate forecasting approaches, data-driven approaches with historical and the numerical weather prediction data (Chen, Qian, Nabney, & Meng, 2014; El Moursi, Al Hinai, Ssekulima, & Anwar, 2016; Lei, Shiyan, Chuanwen, Hongling, & Yan, 2009). In this section, the detailed analysis conducted on ML, ensemble and ANNs for wind energy forecasting.

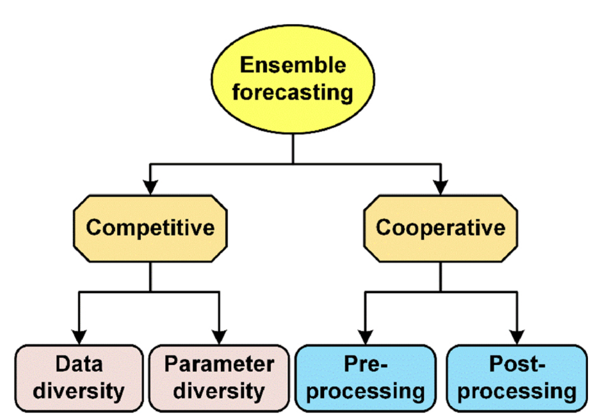


**Fig. 6.** Division of ensemble models for solar and wind energy prediciton (Ren et al., 2015).

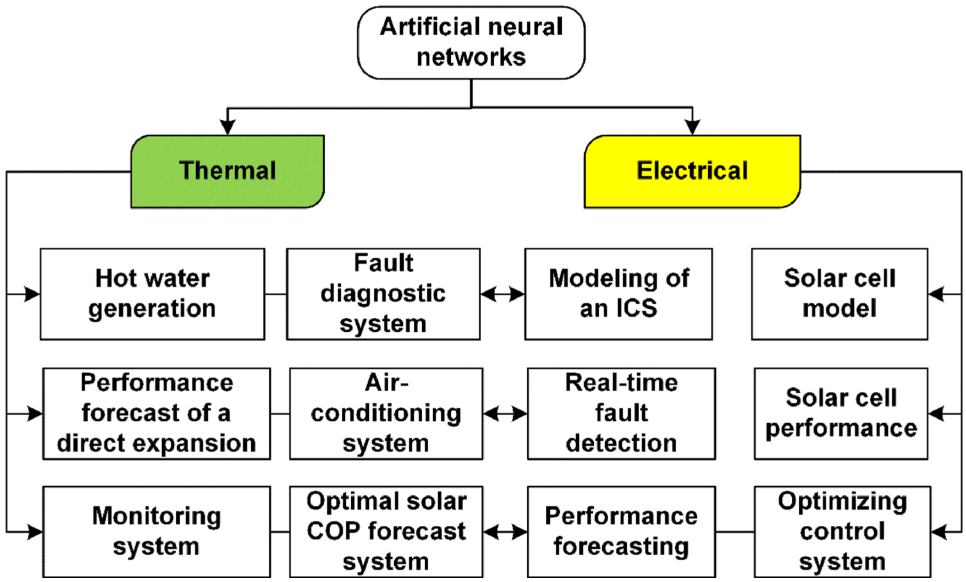


**Fig. 7.** The ANNs based network for solar systems (Qazi et al., 2015).

*2.1.2.1. Machine learning models.* Empirical and conventional approaches have been utilized conventionally to predict the solar energy and wind energy resources, although they have determined insufficient precision and other significant deficiencies (Lawan, Abidin, Masri, Chai, & Baharun, 2017; Qazi et al., 2015). Wind power prediciton error was compared and examined in (Hodge & Milligan, 2011) and (Bludszuweit, Domínguez-Navarro, & Llombart, 2008). Though, the before-mentioned study didn't investigate the forecastability and the prediction errors in combination with the prediciton manner. Several kinds of research tried to increase the predictability by improving forecasting techniques (i.e., ANNs (Wang, Luo, Grunder, & Lin, 2017), random forests based approaches (Min & Mitsuhashi, 2012), and fuzzy methods (Damousis, Alexiadis, Theocharis, & Dokopoulos, 2004) including higher learning ability, that can be studied in these review articles (Costa et al., 2008; Foley et al., 2012; Lei et al., 2009). These prediciton models classified based on various standards (i.e., look ahead duration (Okumus & Dinler, 2016), input data and model principles (Foley et al., 2012)). Including the rapid development of ML and big data analytics, wind prediction (notably, the short-term wind prediciton) has been substantially increased. Among several statistical approaches for short-term wind prediciton, deep learning and ensemble techniques have been obtained to operate better than ML-based single-algorithm methods (Feng, Cui, Hodge, & Zhang, 2017; Wang, Wang, Li, Peng, & Liu, 2016). However, these powerful ML approaches are essential for wind prediciton; the predictably is considerably influenced by other circumstances, like wind farm characteristics and local environmental conditions. Table 5 explains the short-term wind energy forecasting with machine learning models.

*2.1.2.2. Ensemble-based approaches.* Nonlinear ensemble forecasting classifications pointed out to be a higher efficient tool for getting higher forecast accuracy than the linear ensemble methods (Tian & Hao, 2018). In Ref. (Qiu, Ren, Suganthan, & Amaratunga, 2017) developed an ensemble-deep learning approach for energy demand prediction. Moreover, ensemble learning (EL) has been recognized extensively that the network inner layer learning accuracy could be improved by combining and using with paralleling learning approaches effectively (Ren, Zhang, & Suganthan, 2016). However, the present combined approaches for wind energy and speed prediction can be considered as one kind of ensemble forecast; most of their prediction accuracy of network results of individual predictors is a linear combination. The general ensemble learning (EL) perceptive, ensemble forecasting comprised of non-linear learning could be more researched and investigated. Different ensemble models used for wind energy forecasting with higher accuracy and performance (Jiang & Huang, 2017; Liu, Tian, Liang, & Li, 2015; Wang, Li, & Bai, 2018; Wang, Zhang, Wu, & Wang, 2016; Wu & Huang, 2009). The forecasting accuracy of the hybrid algorithms is not that useful due to the variables like ensemble number and amplitude of noise are not accurately determined for decomposition. In the applicability of these methods to power and wind speed prediction, the central objective was a quantification of uncertainty for such kind of projections. The ensemble techniques developed for electricity and wind energy forecasting (Mein et al. (Men, Yee, Lien, Ji, & Liu, 2014; Men, Yee, Lien, Yang, & Liu, 2014; Wang, Wang, & Wang, 2013), and other different areas. The significant benefits of the ensemble models are the network confidence duration to the predicted electricity and wind energy can be taken efficiently, and later it can be applied as standards for the prediction estimation. Alternatively, Bremen (Bremnes, 2004) applied the quantile regression local for probabilistic prediction. Genting et al. (Gneiting, Larson, Westrick, Genton, & Aldrich, 2006) applied the Gaussian truncated forecast approach for the probabilistic predictions of one hour-averaged wind energy at the specific location. Furthermore, the ensemble-based learning models have been confirmed as an efficient method to dispose of the idea drift issues. Table 6 shows the short-term wind forecasting with ensemble-based classifications.

*2.1.2.3. Artificial neural networks.* From the recent past, many experts have given themselves to study on techniques to increase the prediction performance of wind energy and have explained a selection procedure of prediction approaches to accomplish this objective (Du, Wang, Guo, & Yang, 2017; Heng, Wang, Zhao, & Xiao, 2016; Jiang, Liu, & Song, 2017). An upgraded autoregressive integrated moving average (ARIMA) approach in the mathematical application was used by in Ref. (Hodge et al., 2011) to forecast the wind energy and they got satisfactory forecast accuracy and proposed network structure shows higher forecasting performance. Though, a single mathematical algorithm sometimes fails to obtain accurate information about wind speed prediction efficiently. The AI like ANNs (Li & Shi, 2010; Liu, Tian, Pan, & Li, 2013; Liu, Wang, & Wang, 2015) and SVM (Ramesh Babu & Jagan Mohan, 2017) also commonly used for wind energy prediction. Though, the limitation of such methods while training duration of the algorithm is quite expensive. This type includes fuzzy systems (Liao &

**Table 4**
Short-term solar radiation forecasting using ANNs.

| Sr. No. | Models | Advantages | Year | Region | Ref. | Accuracy | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | The multivariate neural network, Feedforward neural network, Elman backpropagation network | Strength to handle nonlinear, dynamic and abrupt meteorological differences | 2018 | Queensland | (Raza et al., 2018) | 4.17 % | – | – | – | 0.87 |
| 2 | Artificial neural networks | Reducing the mutual information measure concerning the validation to be predicted | 2019 | Madina and Tamanrasset | (Bouzgou & Gueymard, 2019) | – | – | 8.4–11.55 % | – | 0.87 and 0.91 |
| 3 | Artificial neural networks | Models obtain notable prediction improvements | 2019 | Pyrenees Orientales, France | (Benali et al., 2019) | – | – | – | 34.11 % | – |
| 4 | BP neural network | Efficiently applied for short-term solar irradiance prediciton | 2011 | United States | (Wang, Wang, & Su, 2011) | – | – | – | 0.03 % | 0.99 |
| 5 | Convolutional neural networks, Generative adversarial networks | Decreased the number of variables to be measured because of the weight sharing method | 2019 | Multiple locations | (Wang, Zhang, Liu et al., 2019) | – | – | – | – | – |
| 6 | Artificial neural network | The most efficient algorithm as compared to independent approaches | 2018 | India | (Mittal, Bora, Saxena, & Gaur, 2018) | – | – | – | – | −0.04 |
| 7 | Artificial neural network | Higher accuracy, higher speed | 2014 | Multiple locations | (Yadav & Chandel, 2014) | – | – | 2.99 % | 1 % | 0.99 |
| 8 | Relief algorithm, Random-frog model, and Laplacian score algorithm Monte Carlo uninformative variable elimination model | Reliable forecasting of solar radiation correlated with utilizing all the available features | 2018 | Saudi Arabia | (Almaraashi, 2018) | 304.75 | – | – | 14.34 % | – |
| 9 | Artificial neural network | The main advantage of ANNs is it is highly non-linear modeling | 2017 | Kuwait | (Bou-Rabee, Sulaiman, Saleh, & Marafi, 2017) | – | – | 86.3 % | – | – |
| 10 | Artificial neural network | Predicting solar irradiance with various time structures and in multiple parts | 2016 | Spain | (Gutierrez-Corea, Manso-Callejo, Moreno-Regidor, & Manrique-Sancho, 2016) | 35.55 | – | – | 12.88 % | – |
| 11 | Artificial neural network | It can be used in real time solar engineering applications at different levels | 2012 | Turkey | (Izgi, Öztopal, Yerli, Kaymak, & Şahin, 2012) | – | – | – | 33–55 % | – |
| 12 | European Centre for Medium-Range Weather Forecasts -Based solar prediction model | An efficient alternative to determine SE and help with energy modeling for SR-rich places | 2019 | Southeast Queensland | (Ghimire, Deo, Downs, & Raj, 2019) | 7.97-11.74 | – | – | 9.07 % | – |
| 13 | Artificial Neural Networks | Multiple designs in a comprehensive set of anthropic projects and operative areas | 2016 | Italian peninsula | (Alsina, Bortolini, Gamberi, & Regattieri, 2016) | – | – | 1.67 % | – | – |
| 14 | Multi-objective particle swarm optimization | A single run can take forecast intervals for any target coverage probability | 2017 | State of Oklahoma | (Galván, Valls, Cervantes, & Aler, 2017) | – | – | – | – | 0.99 |
| 15 | Autoregressive moving average | Updates the operation and planning of photovoltaic systems and yields numerous economic benefits for electric companies | 2017 | Canada | (Alzahrani, Shamsi, Dagli, & Ferdowsi, 2017) | – | – | – | 0.16 % | – |
| 16 | Data processing and neural networks, Multi-parameter-based ANN | The flexibility of the model is higher, better speed and convergence | | Multiple climates China, UK, India | (Kashyap, Bansal, & Sao, 2015) | – | – | – | 25–35 % | – |
| 17 | MLP artificial neural network | Higher credibility and accuracy compared to the algorithms that have been developed in previous studies | 2017 | Tehran, Iran | (Vakili, Sabbagh-Yazdi, Khosrojerdi, & Kalhor, 2017) | – | – | 1.50 % | – | – |
| 18 | Artificial neural network | Applied to calculate the PV energy output with a satisfactory degree of accuracy | 2014 | Southern Spain | (Almonacid, Pérez-Higueras, Fernández, & Hontoria, 2014) | – | – | – | – | – |

**Table 5**
Short-term wind energy forecasting with machine learning models.

| Sr. No. | Models | Advantages | Year | Region | Ref. | Performance evaluation statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | The hybrid mode decomposition method | Ability to further improves the forecasting accuracy | 2019 | Denver West Pkwy, Gold | (Zhang, Peng, Pan, & Liu, 2019) | 0.01 | – | 0.12 % | 0.015 % | – |
| 2 | Time series models | Increasing the accuracy of power forecasting and wind speed | 2019 | United States | (Feng et al., 2018) | – | – | – | – | 0.62 |
| 3 | Backtracking search optimization model, Regularized extreme ML | Enhance prediction stability and accuracy | 2018 | Sotavento | (Sun, Zhou et al., 2018) | 24.99 | – | 18.15 % | 11.86 % | – |
| 4 | Sparse Bayesian-based robust functional regression model | More precise predictions than the contrasted models | 2019 | Dongshan, China | (Wang, Wang, Srinivasan, & Hu, 2019) | 0.33 | – | 8.66 % | 0.46 % | 0.74 |
| 5 | Multi-task learning, Deep neural networks | Models can determine two outputs with less than 5 % error | 2019 | Multiple locations | (Qin et al., 2019) | – | – | 0.78 % | – | – |
| 6 | Empirical mode decomposition, Autoregressive moving average approach, Wavelet packet decomposition, Extreme ML | The models have the higher forecasting performance, accuracy and stability | 2017 | China | (Mi, Liu, & Li, 2017) | 0.99 | – | 4.42 % | 1.23 % | – |
| 7 | Multimodel machine learning-based ensemble deterministic forecasting framework | Developed two-step probabilistic prediciton methodology has increased the loss of pinball metric score about 35 % contrasted to a baseline quantile regression approach | 2019 | Multiple locations USA | (Sun, Feng, Chartan, Hodge, & Zhang, 2019) | 4.92 | – | 3–5 % | – | 0.99 |
| 8 | Gradient boosted machines | Algorithms are efficient of being used to any such wind prediction task with least modeling exercise | 2016 | Multiple locations | (Landry, Erlinger, Patschke, & Varrichio, 2016) | – | – | – | – | – |
| 9 | Fuzzy set theory, Multi-objective slap swarm model | Very satisfying results in both objects among least width and high coverage | 2019 | Shandong Province, China | (Jiang, Li, & Li, 2019) | – | – | – | – | – |
| 10 | Empirical mode decomposition, Secondary hybrid decomposition, Wavelet packet decomposition | The great benefit over different past hybrid algorithms with respect to load demand forecasting accuracy | 2017 | Spain | (Yin et al., 2017) | 0.10 | – | – | 0.13 % | – |
| 11 | Deep belief network | The locality-sensitive hashing search model is used to cluster the nearest training data samples to increase forecasting efficiency | 2019 | Jiangsu Province of China | (Zhang, Le, Liao, Zheng, & Li, 2018) | 1.79 | – | – | 2.76 % | – |
| 12 | Quantile based regression outlier-robust extreme ML | Efficient to increase the calculation and forecast ability | 2017 | National Renewable Energy Laboratory data | (Zheng, Peng et al., 2017) | 0.009 | – | 0.42 % | 0.01 % | – |
| 13 | Decomposition-based models | It has the benefit of treatment non-linearity | 2019 | | (Qian et al., 2019) | – | – | – | 2 % – 80 % | – |
| 14 | Regularized extreme ML, Empirical wavelet transform | The used hybrid algorithm has a higher multiple-step forecasting accuracy | 2018 | China | (Liu, Wu, & Li, 2018) | −0.71 | – | 1.46 % | 9.12 % | – |
| 15 | Autoregressive integrated moving average | Concise training time and its suitability for short-term predictions | 2018 | China | (Wang, Li et al., 2018) | 0.14 | – | 7.63 % | 0.21 % | – |
| 16 | Sequence transfer correction algorithm | Strong generalization capability to various correction algorithms | 2019 | China | (Wang, Han, Liu, Yan, & Li, 2019) | – | – | – | 9.8 % | – |
| 17 | Multi-objective optimization, Least squares support vector machines | The basic benefits of this approach are that it's easy and simple to implement | 2018 | Penglai, China | (Li & Jin, 2018) | – | – | – | – | – |
| 18 | Deep learning | More accurate and robust in extracting the trend knowledge | 2018 | China | (Liu, Mi, & Li, 2018) | −5.88 | – | 36.12 % | 1.35 % | – |
| 19 | Gaussian process, Uncertainty propagation | Gives an innovative systematic structure for iterative multi-step interval predictions | 2018 | Ireland | (Yan et al., 2018) | 0.02 | | | 0.03 % | |

**Table 6**
Short-term wind forecasting with ensemble-based classifications.

| Sr. No. | Models | Advantages | Year | Region | Ref. | Performance evaluation statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | Analogue ensemble method | Only needs a single predicting algorithm, as opposed to the different algorithm runs | 2015 | Sicily, Italy | (Alessandrini, Delle Monache, Sperati, & Nissen, 2015) | – | – | – | – | 0.95 |
| 2 | Multi-objective optimization algorithm, Extreme learning machine | The developed model is better performance to all the different considered algorithms with respect to both stability and accuracy | 2019 | Canada and Spain | (Hao & Tian, 2019) | 8.15 | – | 3.64 % | 8.45 % | – |
| 3 | Ensemble learning, Extremal optimization | Can obtain a better prediction performance | 2018 | Inner Mongolia, China | (Chen, Zeng, Zhou, Du, & Lu, 2018) | 1.14 | – | 17.10 % | 1.53 % | 0.93 |
| 4 | Convolutional neural network | Increased the accuracy and help to reduce the probabilistic uncertainties | 2017 | China | (Wang, Li et al., 2017) | – | – | – | – | – |
| 5 | Multi-Objective Grey Wolf Optimizer, Wavelet packet decomposition | Ensemble algorithm outperforms other benchmark methods significantly | 2018 | Xinjiang Province, China | (Liu, Duan, Li, & Lu, 2018) | 0.76 | – | 0.79 % | 1.43 % | – |
| 6 | Hybrid evolutionary approach | High stability and precision of wind-speed prediction | 2017 | China | (Qu et al., 2017) | 0.77 | – | 1.025 | – | – |
| 7 | Ensemble empirical mode decomposition, Hybrid model | Actual and forecasted values are more than smaller variations | 2018 | Xinjiang region of China | (Santhosh, Venkaiah, & Vinod Kumar, 2018) | 27.06 | – | 15.70 % | 31.78 % | – |
| 8 | Ensemble forecasting, Gaussian mixture | Confidence duration for the predicted load and wind speeds can be achieved rigorously and then applied as criteria for the prediction estimation | 2016 | Taiwan | (Men, Yee, Lien, Wen, & Chen, 2016) | 146.50 | – | – | 170.10 % | – |
| 9 | On-line sequential Outlier Robust Extreme ML, Time-varying mixture copula function | Solution convergence and accuracy speed addressing complicated optimization issues | 2017 | Texas, USA | (Peng et al., 2017) | 0.01 | – | 0.62 % | 0.02 % | – |
| 10 | Empirical mode decomposition | Good multi-resolution and broad applicability | 2016 | Mongolia in China | (Wang, Zhang et al., 2016) | – | – | 8.08 % | 0.71 % | – |
| 11 | Fast ensemble empirical mode decomposition | The benefits of mutual knowledge in estimating the nonlinearity | 2018 | China | (Sun & Wang, 2018) | 0.68 | – | 14.41 % | 1.14 % | – |
| 12 | Ensemble methods | Higher speed and accuracy | 2016 | Multiple locations | (Nagy, Barta, Kazi, Borbély, & Simon, 2016) | – | – | – | – | – |
| 13 | The generalized autoregressive conditional heteroskedasticity models | Higher forecasting results for point forecasting and wind power density forecast | 2009 | United Kingdom | (Taylor, McSharry, & Buizza, 2009) | – | – | – | 51 % | – |
| 14 | Deep learning | Increases the function of activation to optimize the convergence speed | 2019 | Multiple locations | (Yu et al., 2019) | – | – | – | 5.61 % | – |

**Table 7**
Short-term wind energy prediction using the ANNs.

| Sr. No. | Models | Advantages | Year | Region | Ref. | Performance evaluation statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | Adaptive wavelet neural network | Actual and forecasted variation is smaller and higher accuracy | 2018 | Xinjiang region of China | (Santhosh et al., 2018) | 27.06 | – | 15.70 % | 31.78 % | – |
| 2 | Genetic algorithm backpropagation neural network | Good multi-resolution networks and wide applicability in different fields | 2016 | Mongolia in China | (Wang, Zhang et al., 2016) | – | – | 8.08 % | 0.71 % | – |
| 3 | Improved BP neural network | The benefit of mutual learning in estimating the nonlinearity | 2018 | China | (Sun & Wang, 2018) | 0.64 | – | 11.77 % | 0.88 % | – |
| 4 | Wavelet-based neural network | With decreased complexity, the algorithm needs less historical data as contrasted to that in available kinds of literature | 2017 | India | (Abhinav, Pindoriya, Wu, & Long, 2017) | 51.47 | – | – | 32.83 % | – |
| 5 | Multi-task learning, Deep neural networks | Useful in prediction oncoming atmosphere circumstances | 2019 | Different location | (Qin et al., 2019) | – | – | 1.10 % | – | – |
| 6 | Artificial neural networks | There is no cost or time benefit contrasted to other combination algorithms | 2019 | China | (Wang, Zhang, & Lu, 2019) | 21.61 | – | 21.69 % | 21.56 % | – |
| 7 | Echo state approach, Nonlinear echo state approach, Adaptive neuro-fuzzy inference approach | The scheme is simple with higher learning ability and forecast efficiency | 2019 | Nevada | (Chitsazan, Sami Fadali, & Trzynadlowski, 2019) | 0.3 | – | – | 0.74 % | – |
| 8 | Hybrid decomposition technique | Highly fit for non-stationary multi-step wind energy prediction | 2019 | Shandong, China | (Qu, Mao, Zhang, Zhang, & Li, 2019) | 0.06 | – | 2.23 % | 0.08 % | – |
| 9 | Type-2 fuzzy ANNs, Particle swarm optimization model | Precise wind energy prediction in an energy system control centre | 2018 | Island, Canada | (Sharifian, Ghadi, Ghavidel, Li, & Zhang, 2018) | – | – | 0.88 % | 3.38 % | – |
| 10 | Empirical wavelet transforms, Deep learning | High-precision wind speed forecast | 2018 | China | (Liu, Mi, & Li, 2018) | 0.58 | – | 4.43 % | 0.57 % | – |
| 11 | Covariance matrix adaptation evolutionary approach | Render precise forecasts when forecasting multiple time-steps energy in the future perceptive | 2018 | Ireland | (Mason, Duggan, & Howley, 2018) | – | – | 5.02 % | 41.04 % | – |
| 12 | Functional network | Cost-efficient for energy planning and dispatch plans by precisely forecasting | 2018 | Dodge City, KS | (Ahmed & Khalid, 2018) | 24.79 | – | 17.38 % | 27.31 % | – |
| 13 | Fast ensemble empirical mode, Wavelet packet decomposition | Adequate performance in the multi-step wind energy forecasts | 2015 | Algeria | (Liu, Tian, Liang, & Li, 2015) | 0.05 | – | 0.28 % | 0.06 % | – |
| 14 | Elman neural network, Gradient boosted regression trees | Wind prediction by gathering characteristic data into different parts | 2018 | Sichuan Province, China | (C. Yu, Li, Xiang, & Zhang, 2018) | 0.08 | – | 3.0 % | 0.11 % | – |
| 15 | Local linear fuzzy neural network | The performance of the forecast increased contrasted with conventional predicting algorithms | 2017 | China | (Dong, Sun, & Li, 2017) | – | – | – | 0.028 % | – |
| 16 | Artificial neural networks | Higher speed and accuracy | 2018 | Multiple locations | (Camelo et al., 2018) | 0.44 | – | 8.70 % | 0.56 % | – |
| 17 | Support vector machines, Artificial neural networks | ANNs prediction accuracy improves significantly with increasing the ensemble size | 2015 | San Francisco | (Tagliaferri, Viola, & Flay, 2015) | 0.81 to 0.78 | – | – | – | – |
| 18 | Generalized dynamic fuzzy neural network | A simple and effective tool for the energy management and planning of smart grids | 2017 | China | (Ma, Jin, & Dong, 2017) | 0.83 | – | 1.07 % | 19.71 % | – |

Tsao, 2006; Park, Kim, Hwang, & Kim, 1995) expert systems (Park et al., 1995), ANNs (Yun et al., 2008), type-2-fuzzy ANNs (Wan, Xu, Pinson, Dong, & Wong, 2014) and the Kernel-density estimator (Tascikaraoglu, Sanandaji, Poolla, & Varaiya, 2016). Moreover, applying the extreme ML (Fang & Chiang, 2017; Kavousi-Fard, Khosravi, & Nahavandi, 2016), the Gaussian process regression (Ren, Suganthan, & Srikanth, 2016) and SVR (Xydas et al., 2017; Rodan & Tiňo, 2011) are becoming famous for wind energy and wind speed prediciton. These methods are more suitable and practical for real-time online applications. The most practical and popular AI methods are the Type-2-fuzzy ANNs that connects the linguistic feature interception of Type-2-fuzzy sets as well as the network learning function of the ANN (Lou & Dong, 2015; Mohammadzadeh & Ghaemi, 2015; Sharifian & Sharifian, 2015). Furthermore, this system can manage the associated uncertainty with input variables. Table 7 shows the short-term wind energy prediction using the ANNs.

### 2.1.3. Geothermal energy forecasting

In the past few decades, a large number of challenges concerning global economic instability, the boost in climate and the competitiveness change (Dodoo, Gustavsson, & Sathre, 2010). Under these conditions, the increasing cost of raw materials as well as the leading dependency on the fossil fuels as a result environment disaster headed to explore a new way in the usage area of alternative energy sources (Pouliezos, 2012). The renewable energy supply is unlimited, and it is the advantage is a comparatively clean environment. For these purposes, from the last decades, several governments have supported strategies that support the benefit of these types of clean energy use like geothermal energy (Jacobsson & Lauber, 2006). The world's fundamental energy usage requirement, a very least portion provided by the source of geothermal energy, e.g., lower than 1 % of the total world energy demand. It was observed in 2015, that the world geothermal energy capacity increased to 13.20 GW because of a substantial addition of 315.0 Megawatt of installed ratio in 2018. The geographic positions of geothermal energy farms, that provide about 72.01 % of entire world geothermal energy potential are adjacent Rim-Pacific hotspot characteristics. An unstable rate of total geothermal energy installation capacity about 43.01 % which positioned on island nations or regions, and is fit for uses like heating, energy generation, and the heat storage in ambient conditions (IRENA, 1980; Tareen et al., 2018). A significant hurdle in proposing the different geothermal areas is the higher up-front price of resource characterization and exploration (European Comission. (EurObserv'ER) (2016a)). Recognizing the productive potential of such kinds of geothermal sources needs the expedient models and inexpensive development for evaluating and identifying the unmeasured reservoirs of geothermal energy. The enhanced geothermal system (EGS) approach has evolved from the last forty years in different areas: hence, the primary attempt from the United States of America (USA) in it is Hill Fenton design by 1973 (Duchane & Brown, 2002; Lei, Zhang et al., 2019), a list of enhanced geothermal system study designs 85 new systems throughout the globe, like Rosemanowes in the United Kingdom (1977–1991) (Deep geothermal UK-United downs project, 2011), Hijiori project in Japan (1981–1986) (Kuriyagawa & Tenma, 1999), and Basel project in Switzerland (2005–2006) (Wyss & Rybach, 2010), in which Germany's Landau energy station was second commercial-level EGS and France's Soultz-sous Forêts station plants. The first GES plant was the Soultz EGS operating commercial energy plant in the globe. The Soultz EGS station has given a generation capacity of about 25 kg/s and recently renders consistent hydrothermal energy production (Lu, 2018). Furthermore, the EGS Pohang station in the Republic of South Korea, the noel EGS Insheeim station located in Germany, additionally the EGS Desert-Peak station located in the USA possess expedite the speed of new studies and analysis on geothermal energy (Benato & Taron, 2014; Goldstein et al., 2009). A particular plant called 'Forge programme' completed from the USA energy department supposed to obtain technological enhancement

**Table 8**
Geothermal energy forecasting.

| Sr. No. | Models | Advantages | Year | Region | Ref. | Performance evaluation statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | Time series modeling, TDNN, ARIMA, Ridge regression, Decision trees | Enable the networks to get various instants in time, higher forecasting accuracy and fast speed | 2019 | Spain | (Baruque, Porras, Jove, & Calvo-Rolle, 2019) | 1.72 | – | – | | 0.55 |
| 2 | Monte Carlo simulations | Estimate the uncertainty in reservoir variables, Higher efficiency and better forecastability | 2018 | Horn River, Clarke Lake, Prophet River and Jedney | (Palmer-Wilson, Banks, Walsh, & Robertson, 2018) | – | – | – | – | – |
| 3 | Numerical modeling | Estimates the optimized requirements for keeping the concentration | 2019 | Japan | (Yanaze, Yoo, Marumo, & Ueda, 2019) | – | – | – | – | 0.89 |
| 4 | Geothermal-solar power plant | The hybrid plant may considerably help from the increase of a thermal energy storage in different units | 2018 | Fallon, NV | (Ciani Bassetti, Consoli, Manente, & Lazzaretto, 2018) | – | – | – | – | – |
| 5 | Geothermal power plants, Geothermal exergy | Most fit zones for energy plants installations | 2015 | Ischia volcanic island | (Paoletti et al., 2015) | – | – | – | – | – |

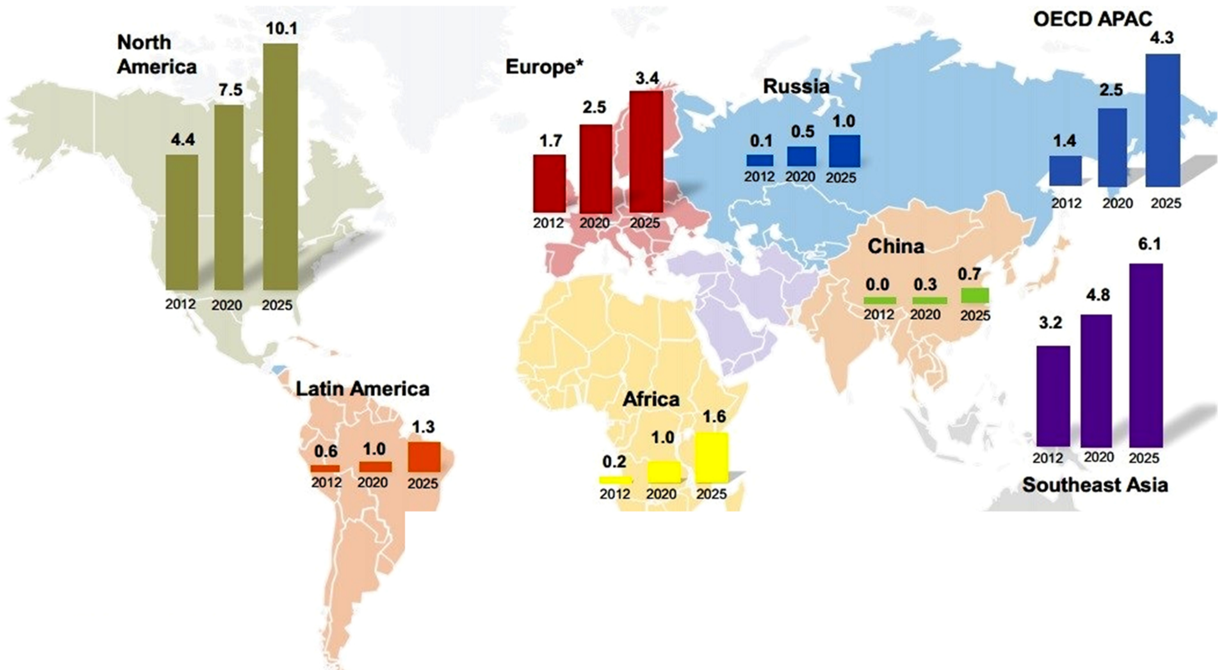


**Fig. 8.** Annual geothermal energy outlook: The total geothermal global forecast installed capacity, 2012, 2020, and 2025.

in geothermal system breakthroughs like: creation of reservoir, exploration, maintenance of repository, and different methods that will hopeful to facilitate the EGS installation potential in the USA and to give 100 GWe estimated potential by 2050 (Workshop, Geothermal, & Development, 2013). There are different models presented in Table 8 and it shows that the monte Carlo simulations estimates the uncertainty in different kinds of reservoir parameters and give higher efficiency and forecastability.

Table 8 shows the detailed analysis of geothermal energy demand forecasting.

Furthermore, the Sullivan & Frost published a new report which predicts the world total installed capacity of EGS to more than double by 2025 - rising from 1566 GW in 2012 to 3203 GW in 2025 which has been presented in Fig.8[2] .

### 2.1.4. Electricity requirement forecasting models

Future electricity requirement prediction, also identified as energy electricity requirement prediction or load prediction, is not a novel theory. The primary study on electricity requirement prediciton can back to history in 1965 (Heinemann, Plant, & Nordman, 1966). Reliable electricity requirement prediction is essential such as critical economic importance (Bunn, 2000). In Ref. (Hobbs, 1999), with 1 % decrease in the prediciton for mean absolute percentalge error (MAPE), 10,000 MW h energy can be conserved, it explains that a precise energy method may conserve up to 1.6 $ million in a specific fiscal year. Electricity requirement prediction is doing a significant part in system operations, energy production, transmission, and storage, while accurate prediciton is shifting considerable attention of energy planning and management (Khuntia, Rueda, & van der Meijden, 2016). However, more studies also concentrated on how to increase the accuracy and robustness of energy demand prediction.

*2.1.4.1. Machine learning models*. Electricity requirement prediction technologies based on ML models are extensively applied in the area of applied energy, like wind energy and wind speed prediction (Meng, Ge, Yin, & Chen, 2016), load demand and peak demand prediciton (Hernandez et al., 2014), building load requirement forecasting (Ahmad, Chen, & Shair, 2018), cooling load prediction (Ahmad & Chen, 2018b) and so on. The heating, ventilation and air conditioning (HVAC) system in the commercial sector accounts for about 40 % of real-time energy expenditure, specifically for subtropical regions, therefore the fundamental tools to increase the building energy performance, reliability and accuracy (Fan, Xiao, & Wang, 2014). The rapid advancement in the ML approach do this an efficient system of univariate time-series prediction, and the basic challenge extends in the choice and selection of prediction techniques (Bontempi, Ben Taieb, & Le Borgne, 2013).

Current studies of load prediction give an overview of the present recent forecasting classifications and their further distribution in different sectors. Studies (Deb, Zhang, Yang, Lee, & Shah, 2017) has analyzed and compared the forecasting accuracy results of prior researches like (Deb et al., 2017; Zhao & Magoulès, 2012). They investigated the nine general prediction approaches which comprised of the ML platform. Magoules and Zhao (2012) reviewed the proposed classifications for forecasting energy load demand, including complicated and complex statistical techniques, AI approaches and engineering-based techniques (Zhao & Magoulès, 2012). Though, from these studies, analyzed that the past studies are based on forecasting analysis results but including the different kinds of database. The accuracy of these models is further presented in Table 9.

*2.1.4.2. Ensemble-based approaches*. Ensemble-based approaches consist of a different number of ensemble methods (ELMs) used for model training. It is observed that the ensemble approaches possess the strengths in term of unique methods for increased robustness and accuracy. Many ensemble techniques have been proposed for short-term energy prediction (Abdel-Aal, 2005; Brown, Wyatt, & Tino, 2005; Taylor & Buizza, 2002). For instance, in Ref. (De Felice & Yao, 2011), the negative regularized correlation learning approach was applied to improve the forecastability of the ensemble network.

Ensemble learning techniques, which achieve higher prediction accuracy and efficiency by strategically connecting recurring learning models, has been extensively used in different research areas including

[2] https://cleantechnica.com/2015/01/29/frost-sullivan-predict-renewables-double-2025/

**Table 9**
Short-term electricity forecasting with machine learning models.

| Sr. No. | Models | Advantages | Year | Region | Ref. | Performance evaluation statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | Grey wolf optimization, Least-squares SVM | A practical technique that can increase the prediciton performance remarkably | 2019 | Australia | (Yang, Li, & Yang, 2019) | 32.20 | – | 0.555 | – | 0.99 |
| 2 | Autoregressive integrated moving average | The model can gain the various characteristics connected with power load | 2018 | Australia | (Zhang, Wei, Li, Tan, & Zhou, 2018) | 113.6 | – | – | 1.42 % | – |
| 3 | CDT, FitcKnn, LRM, and Stepwise-LRM | Facilities for investment management by power companies, commercial and industrial consumers | 2018 | Beijing, China | (Ahmad & Chen, 2018c) | 1.67 | – | 0.03 % | 15.10 % | – |
| 4 | Machine learning models | Support consumer in energy planning and management | 2018 | New Taipei City, Taiwan | (Chou & Tran, 2018) | 0.02 | – | 15.65 % | 0.09 % | 0.79 |
| 5 | An artificial neural network with nonlinear autoregressive exogenous multivariable Inputs, Multiple linear regression model, AdaBoost | Appearances or accuracy are shown to be promising | 2018 | ISO New England | (Ahmad & Chen, 2018a) | – | 4.99 % | 0.01 % | – | – |
| 6 | Chaos–support vector regression | The developed algorithm could also be applied in different forecasting areas | 2019 | – | (Xuan et al., 2019) | – | 2.44 % | 3.89 % | – | 0.74 |
| 7 | Extreme learning machine model | Useful mapping capability and can adequately handle with a considerable variety of designing and mapping difficulties | 2018 | – | (Chen, Kloft, Yang, Li, & Li, 2018) | 71.00 | – | 0.92 % | 83.93 % | – |
| 8 | Machine learning, Support vector regression, Regression trees | Capability to find world energy minima rather than local minima in the forecasting solution space, higher speed and accuracy | 2017 | University of New South Wales | (Yildiz, Bilbao, & Sproul, 2017) | – | – | 1.04 % | – | 0.99 |
| 9 | Recurrent extreme learning machine | Higher potential to be used in modeling dynamic systems efficiently | 2016 | Portugal | (Ertugrul, 2016) | – | – | – | 0.02 % | – |
| 10 | Machine Learning algorithms | Better and higher performance | 2018 | Canada | (Saloux & Candanedo, 2018) | – | – | – | 2.9 % – 3.9 % | – |
| 11 | Nadaraya–Watson Kernel density estimator approach | Captures one of the higher reliability indicator numbers | 2018 | Spain and Portugal | (Monteiro, Ramirez-Rosado, Fernandez-Jimenez, & Ribeiro, 2018) | 5.55 | – | – | – | – |
| 12 | Machine learning model | Big-data can be consolidated in the forecasting approach to increase the performance and interpret complicated data analytic issues | 2016 | United States | (Naimur Rahman, Esmailpour, & Zhao, 2016) | – | – | 4.13 % | – | – |
| 13 | Supervised based machine learning models | Higher speed, higher accuracy, the stability of the network | 2018 | ISO New England | (Ahmad, Chen Huang et al., 2018) | – | 1.60 % | 0.98 % | – | – |
| 14 | Stepwise regression, nonlinear autoregressive model | Algorithms are guaranteed the precise design and network operation of the different distributed energy system operations | 2019 | ISO New England | (T. Ahmad & Chen, 2019) | – | 4.53 % | 3.19 % | 402 % | – |
| 15 | Deep learning, Multi-modal | Calculate the energy tendency more perfectly with lower errors | 2018 | New York City | (Tong et al., 2018) | – | – | 1.72 % | – | – |
| 16 | Multiple linear regression | Precise cooling prediction in the building sector | 2018 | Beijing, China | (Ahmad, Chen Shair, 2018) | 0.73 | – | 1.70 % | 0.78 % | – |
| 17 | Multivariate adaptive regression spline | Helpful scientific tools for the different investigation of real-time power requirement data prediciton | 2018 | Queensland, Australia | (Al-Musaylh, Deo, Adamowski, & Li, 2018) | 0.76 | – | – | 0.995 | – |
| 18 | Chaos-SVR, WD-SVR, SVR and BP | Several features which are suitable for various kinds of cooling load in time series | 2017 | | (Xuan, Zhubing, Liequan, Junwei, & Dongmei, 2017) | – | – | – | – | 0.85 |
| 19 | Artificial fish swarm and gene expression programming | The benefits in mean time-consumption, the mean number of convergences, higher predicted efficiency and most top parallel performance in scale-up and speedup | 2018 | Multiple locations | (Deng, Yuan, Yang, & Zhang, 2018) | – | – | 3.69 % | – | – |
| 20 | Gaussian process regression | Models are useful in forecasting the abnormal behavior in the datasets as well as cooling energy requirement prediciton | 2019 | Beijing, China | (Ahmad, Chen, Shair, & Xu, 2019) | 0.19 | 2.05 % | 2.59 % | – | 0.99 |

time-series forecasting, regression and pattern classification. Dietterich has presumed three primary causes for the success and achievement rate of ensemble techniques: representational, computational and statistical characteristics (Dietterich, 2007). Furthermore, the decomposition of bias-variance (Geman, Bienenstock, & Doursat, 1992) and strong relationship also demonstrate why ensemble models have higher accuracy and efficiency than their non-ensemble classifications. Between the many ensemble techniques (EMD based AdaBoost-BPNN method for wind speed forecasting, 2014; Hu, Bao, & Xiong, 2014; Qiu, Zhang, Ren, Suganthan, & Amaratunga, 2014; Ren, Suganthan et al., 2016; Wei, 2016), conquer and divide (Radhakrishnan, Kolippakkam, & Mathura, 2007) is a theory which holds models which frequently used in the time series prediction. The wavelet transform approach is generally applied in time-series decomposition model. It disintegrates the primary time series into several orthonormal subseries from seeing at a different domain of frequency-time in the network (Benaouda, Murtagh, Starck, & Renaud, 2006) use multistate decomposition wavelet-based nonlinear approach for energy demand prediction. Adaptive wavelet ANNs applied for short-term prediciton with the feed-forward network and different hidden layers with neurons. Table 10 shows the short-term electricity forecasting with ensemble-based approaches. It can be observed that the ensemble-based empirical model decomposition and deep learning-based ensemble models widely used in different kinds of research including classification and time series analysis.

*2.1.4.3. Artificial neural networks*. A considerable number of researches have been carried on load demand forecasting, and various methods, like autoregressive integrated moving average (AIMA), SVM, and ANNs have been introduced to solve such kinds of complex problems. For places where no accurate technique has been recognized, the combination of energy prediction has been one of the most effective, essential and successful study aspects used since it is the introduction part by Granger and Bates (Bates & Granger, 1969) in earlier 1960s. However, defining these determinants is a vital and challenging issue for the ANNs applications. Therefore, the systematic approach prevails unavailable; various heuristic methods have been developed in different literature such as presented in (Aladag, 2011; Aladag, Egrioglu, Gunay, & Basaran, 2010; Anders & Korn, 1999; Aras & Kocakoç, 2016; Egrioglu, Yolcu, Aladag, & Bas, 2015; Heravi, Osborn, & Birchenhall, 2004; Lachtermacher & Fuller, 1995).

A substantial number of researches have studied the building energy forecast applying various computational intelligence techniques. In the field of building load, the ANNs recognized as the common favourite option for forecasting load demand in the buildings sector (Ahmad, Mourshed, & Rezgui, 2017). The ANNs was applied to estimate the load demand for the passive solar house in reference (Kalogirou & Bojic, 2000). A single backpropagation ANN for building short-term energy prediction was applied by Gonzales et al. (González & Zamarreño, 2005). A customary regression-based ANNs was applied to predict the cooling energy demand which associated with energy usage for three main buildings (Ben-Nakhi & Mahmoud, 2004). Four forecasting models consist of the conventional back-propagation ANNs, general regression ANNs, the radial function and SVM were applied to forecast the one-hour cooling energy demand of a building located in China (Li, Meng, Cai, Yoshino, & Mochida, 2009). Several other studies have concentrated on ANNs for short-term energy prediciton (Hippert, Pedreira, & Souza, 2001; Rodrigues, Cardeira, & Calado, 2017). The forecasting results from these studies explain that the ANNs approaches a comparatively efficient method to predict the short-term energy demand for commercial buildings and homes. Table 11 explicates the advantages of ANNs. It also presents the that the ANNs improves the stability and accuracy of forecasts with simplicity and higer perfroamnce.

### 2.2. Medium-term renewable energy and electricity forecasting

Three major types including short, medium and long-term used in energy operations control and scheduling, planning and management and transmission/production extension planning(Arora & Taylor, 2018; González-Romera, Jaramillo-Morán, & Carmona-Fernández, 2006). For this purpose, retailers, and large customers require an accurate probabilistic price and energy forecasting in the medium-term (start from one-week, months to one year) to optimize their energy scheduling and operation to adjust accurately in the short-term market as well as profitable sign agreements. From the above discussion, several studies have been concentrated on short-term forecasting approaches, but the least number of researches has been conducted on dedium-term load demand forecasting as well as heating and cooling load. Maximum predicted approaches only analyzed the effects of environmental determinants/factors, whereas the thermal inertia and indoor temperature of the buildings sector were still neglected. Furthermore, the weather condition, particularly the outdoor dry bulb temperature is one of the key factors that change the cooling and heating load demand and it needs to analyzed well for actual HVAC load. Table 12 shows the dedium-term renewable energy forecasting models and explicates that the supervised give more accurate resutls. Support vector machine and ANNs give least forecasting errors. Stochastic progrmming can be used in rea time energy consumption data analysis at differt kinds of locations.

### 2.3. Long-term renewable energy and electricity forecasting

The long-term annual energy load prediciton represents a critical role in the country's energy mix development and planning. Reliable and accurate results can efficiently increase the efficiency of the load planning projects. Though, the long-term forecasting has been influencing by several factors such as: economic growth, policy adjustment, and technology advancement, that make long-term prediction as a complicated task (Xia, Wang, & McMenemy, 2010). From the recent past, several efforts at different levels for long-term energy planning have been established. Some models are econometrics, regression analysis, fuzzy logic, ANNs and grey algorithm (Bohi & Zimmerman, 2003; Suganthi & Samuel, 2012). Usually, these predictions approaches can be distributed into three classes: ANNs classifications, TS approaches and uncertainty classifications. The uncertainty and accuracy difference of the long-term energy requirement, fuzzy feed-forward neural network forecasting approaches and collaborative principal component analysis were reported in Ref. (Jia, Yokoyama, Zhou, & Gao, 2001). Therefore, some update model like the Bayesian network (BN) and Bayesian vector autoregression were developed to increase the probability density performance and methodology (Yao, Song, Zhang, & Cheng, 2000). Recently, in different studies, the top-down and bottom-up methods applied to calculate the long-term energy consumption requirement. The top-down approaches are the way to handles the network parameters at all, giving the effects directly for them; therefore, the bottom-up method divides such parameters into different network components, and model the output are then combined to produce the new feature variables. The energy effiriceny measures are very significant as they enable decreasing future load requirement and consequently used to increase the fertility of industrial methods (Farlat et al., 1997; Fleiter, Fehrenbach, Worrell, & Eichhammer, 2012; He et al., 2017; Worrell, Laitner, Ruth, & Finman, 2003). According to Zhang and Rajbhandari (Rajbhandari & Zhang, 2018; Silva, Souza, Cyrino Oliveira, Lourenco, & Calili, 2018; Silva et al., 2018), the load forecasting accuracy identified as a fundamental strategy option for weather change reduction as well as an industrial strategy to increase the economic growth. The Gaussian mixture based models show their higher generalization capability with supplementary testes on outliers toward kernel density estimation of the network such presented in Table 13

**Table 10**
Short-term electricity forecasting with ensemble-based approaches.

| Sr. No. | Models | Advantages | Year | Region | Ref. | Performance evaluation statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | Partial least squares regression approach, Extreme learning machine | The different numerical results determine that the developed approaches can substantially increase prediction accuracy | 2016 | ISO New England | (Li, Goel, & Wang, 2016) | – | – | 1.14 % | – | – |
| 2 | Ensemble method | Achieve better prediction results in contrast with different state-of-art standard approaches | 2016 | ISO New England | (Li, Wang, & Goel, 2016) | – | – | 0.91 % | – | – |
| 3 | Deep learning, Ensemble method | Fault reliability and prediction is higher in real time applications | 2014 | National Aeronautics and Space Administration | (Qiu et al., 2014) | – | 0.11 % | 27.33 % | 0.16 % | – |
| 4 | Empirical mode decomposition, Deep learning ensemble method | Widely used in different research areas including pattern classification, time-series, and regression prediciton | 2017 | Australia | (Qiu et al., 2017) | 266.58 | – | 3.00 % | – | – |
| 5 | Autoregressive integrated moving average | Benefits of some predictive algorithms to obtain reliable results | 2016 | Iran | (Barak & Sadegh, 2016) | 12.59 | – | – | 15.74 % | – |
| 6 | Random forests, Gradient boosting regression trees | Gradient boosting and random forests trees can be suitable for energy prediciton applications and yield actual results | 2015 | Burlington, Concord, Portland, Boston, Bridgeport | (Papadopoulos & Karakatsanis, 2015) | – | – | 1.97 % | 270.6 % | – |
| 7 | Generalizable approach | Ensemble approach is proficient of incorporating complicated forecasters | 2015 | California | (Burger & Moura, 2015) | – | – | 7.5 % | – | – |
| 8 | Ensemble empirical mode decomposition | Great generalization capability, Higher training accuracy and speed and a better balance of error | 2018 | Jiangsu, China | (Li, Tao, Ao, Yang, & Bai, 2018) | 26,765 | – | 5.31 % | 22,3.0 % | – |
| 9 | Ensemble learning | Ensemble learning approach an accurate and convenient method to forecast household energy usage requirement | 2018 | United States | (Chen, Jiang, Zheng, & Chen, 2018) | – | – | – | 1562 % | 0.16 |
| 10 | Ensemble Kalman filter | The efficiency of developed algorithms is substantially higher than the present state-of-art approaches | 2016 | Japan | (Takeda, Tamura, & Sato, 2016) | – | – | 1.86 % | – | – |
| 11 | Evolutionary algorithms, Multi-objective optimization | Results show reliability and higher accuracy of used models | 2018 | New Zealand | (Peimankar, Weddell, Jalal, & Lapthorn, 2018) | – | – | 0.02 % | 0.09 % | – |
| 12 | AdaBoost ensemble model | Don't require a pre-assumed form of the method; higher nonlinear mapping capability; can solve the complex nonlinear problems | 2018 | China | (Xiao, Li, Xie, Liu, & Huang, 2018) | – | – | 1.20 % | 0.46 % | – |
| 13 | Ensemble learning, Robust regression | Conceptual advantages of ensemble learning, relying on the need for diversity within different kinds of network datasets | 2018 | France | (Alobaidi, Chebana, & Meguid, 2018) | – | – | 11.39 % | 296.34 % | – |
| 14 | Ensemble forecasting, Echo state network | Boosting models more appropriate for unstable time-series prediction | | China | (Wang, Lv, & Zeng, 2018) | 4.18 | – | 4.69 % | 6.48 % | – |
| 15 | Ensemble approach | Can be used immediately to HVACs to tackle the time-lag issue | 2018 | Hong Kong | (Wang, Lee, & Yuen, 2018) | – | – | – | – | 0.86 |
| 16 | Ensemble learning, Bagging trees | Can be used for the real-time energy networks such as system fault detection and diagnosis | 2018 | Gainesville, Florida | (Wang, Wang, Srinivasan, 2018) | – | – | 3.68 % | 1.91 % | 0.89 |

**Table 11**
Short-term electricity forecasting with artificial neural networks.

| Sr. No. | Models | Advantages | Year | Region | Ref. | Performance evaluation statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | Least absolute shrinkage and selection operator, quantile regression Neural network, probability density forecasting | Can not only higher get the high-dimensional of the data in energy demand prediciton, but also give more accurate results | 2019 | Guangdong province, China | (Yaoyao He, Qin, Wang, Wang, & Wang, 2019) | – | – | – | 0.16 % | – |
| 2 | Probabilistic load forecasting, Neural networks | Very precise predictions among the top machine learning models | 2019 | ISO New England | (Dimoulkas, Mazidi, & Herre, 2018) | – | – | 2.54 % | 26.2 % | – |
| 3 | Artificial neural network | An effective method to calculate the short-term load for commercial and homes buildings | 2018 | Japan | (Yuan, Farnham, Azuma, & Emura, 2018) | – | – | – | – | 0.99 |
| 4 | Neural networks | Specify models parsimoniously at a lower computational cost | 2018 | Egypt | (Tealab, 2018) | – | – | – | | – |
| 5 | Neural networks-based linear ensemble framework | Attempting to determine the familiar overfitting issue of the networks | 2018 | Northern Canada | (Wang, Wang, Qu, & Liu, 2018) | −0.49 | – | – | – | – |
| 6 | Back-propagation (BP) neural network | Improves the stability and accuracy of forecasts, and it's appropriate for the short-term forecasting | 2018 | China | (Ye & Kim, 2018) | – | – | – | 659.4 % | – |
| 7 | Wavelet transform with best basis selection | It decreases the dimensionality of data without losing relevant information | 2016 | Australia & Spanish | (Rana & Koprinska, 2016) | 23.58 | – | 0.26 % | – | – |
| 8 | Deep neural network | Models are quite adjustable and can be used to other time-series forecast tasks | 2017 | China | (W. He, 2017) | 99.41 | – | 1.34 % | – | – |
| 9 | Deep belief networks, Restricted Boltzmann machines | Concentrate on the parameters that are very important for the network output and neglect the learning rate that has a small influence on the output | 2016 | Macedonia | (Dedinec, Filiposka, Dedinec, & Kocarev, 2016) | | | 8.6 % | | |
| 10 | Time series forecasting | Simplicity, higher accuracy | 2018 | University of Granada, Granada, Andalucía, Spain | (Ruiz, Rueda, Cuéllar, & Pegalajar, 2018) | – | – | – | – | – |
| 11 | Artificial Neural Network, Bayesian regularisation | Algorithm with adaptive training classifications is intelligent of predicting the power consumption | 2016 | International Business Machines Building | (Chae, Horesh, Hwang, & Lee, 2016) | – | 9.35 % | – | – | – |
| 12 | The artificial neural network, COCO framework | Give the advantage of shorter training time | 2018 | New Pool England | (Singh & Dwivedi, 2018) | | – | 3.28 % | – | – |
| 13 | Forecast neural network, CID-STNN forecasting model | The models have a substantial power to prepare unconstrained issue | 2018 | West Texas | (Cen & Wang, 2018) | 0.89 | – | 1.21 % | – | – |
| 14 | Artificial neural networks | Higher performance and forecasting accuracy | 2018 | Multiple locations | (Ahmad, Chen, Guo, & Wang, 2018) | 21.45 | – | – | – | – |
| 15 | Artificial intelligence approaches | Ability to generalization and construct-in cross-validation and low sensitivity to variable costs | 2017 | France | (Mordjaoui, Haddad, Medoued, & Laouafi, 2017) | | | 3.26 % | 2604.4 % | |
| 16 | Artificial neural networks | Calculate the maximum peak load and minimum off-peak order with greater efficiency | 2018 | Taiwan | (Hsu, Tung, Yeh, & Lu, 2018) | – | – | 1.90 % | – | – |
| 17 | Combined forecasting method, BP, ANFIS, diff-SARIMA | The methods are effective to decrease errors and increase the performance between the forecasted and real time load consumption effectively | 2016 | | (Yang, Chen, Wang, Li, & Li, 2016) | 139.65 | – | 1.59 % | – | – |
| 18 | Artificial neural networks, Ensemble neural networks | Higher prediction accuracy and performance as they can accurately algorithm the highly non-linear correlation | 2017 | New England | (Khwaja, Zhang, Anpalagan, & Venkatesh, 2017) | – | – | 1.99 % | – | – |
| 19 | Fruit fly optimization model, General regression ANNs | This kind of methods present the full play to the benefits from every single approach | 2019 | Langfang, China | (Liang, Niu, & Hong, 2019) | 7.35 | – | 0.80 % | 9.58 % | – |

**Table 12**
Medium-term renewable energy forecasting.

| Sr. No. | Models | Advantages | Year | Region | Ref. | Performance evaluation statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | Supervised ML models | Electricity prediciton accuracy is more accurate, precise | 2018 | New England | (Ahmad, Chen Huang et al., 2018) | – | 1.60 % | 0.98 % | | – |
| 2 | Monte Carlo simulation | Benefits of not relying on the availability of recent past knowledge to make forecasts | 2016 | Spanish | (Bello, Reneses, Muñoz, & Delgadillo, 2016) | 4.81 | – | – | – | – |
| 3 | Support vector machine, Neural network | Smaller relative errors in the algorithm forecasting | 2018 | Shijiazhuang, China | (Gu, Wang, Qi, Min, & Sundén, 2018) | – | – | 1.80 % | 45.96 % | 0.93 |
| 4 | Boeing Fuel Flow Method 2 | The forecasting performance and accuracy of the algorithms are based on the quarterly, monthly and traffic demand series is higher | 2016 | Hefei | (Chen, Hu, Han, Zhang, & Yin, 2016) | – | – | 0.64 % | – | – |
| 5 | Stochastic programming | The model can be used in real time energy consumption data at different kinds of locations with higher forecasting performance | 2017 | Portugal and Spain | (Marí, Nabona, & Pagès-Bernaus, 2017) | – | – | – | – | – |
| 6 | LEAP-Beijing model | Used to analyse the total number of GHG emissions | 2019 | China | (Zhang, Liu et al., 2019) | – | – | – | – | – |
| 7 | Vector autoregressive model | Higher speed, lower error | 2015 | China | (Li, Liang, & Wang, 2015) | – | – | 2 % | – | – |
| 8 | Nonlinear regression | Lower cost of water supply solution for the different country | 2017 | Australia | (Bertone, Halloran, Stewart, & de Oliveira, 2017) | – | – | – | – | – |
| 9 | Autoregressive approach, Moving-average approach, Time-series prediciton | Can be extensively applied for various sets of data training without deteriorating the predictor's accuracy | 2017 | United States | (Boroojeni et al., 2017) | 0.92 | – | 0.86 % | 1.24 % | – |
| 10 | Feedforward neural networks | An advantage of getting extensive use of the computation time expended | 2019 | Israeli | (Doveh, Feigin, Greig, & Hyams, 1999) | – | – | – | – | – |
| 11 | Probabilistic forecast | Potential benefits in applying seasonal forecasts | 2015 | European Centre | (Matteo De, Alessandri, & Catalano, 2015) | – | – | 1.6 % | – | – |
| 12 | SVM, Elman recurrent ANNs, Hybrid algorithm | Predict the periodic wind velocities including the higher precise degree of efficiency | 2015 | Xinjiang, China | (Wang, Qin, Zhou, & Jiang, 2015) | 0.90 | | 11.67 % | | |
| 13 | Polynomial regression | The developed models are generic, Can be used to the one hourly energy consumption of any energy system networks | 2011 | Amman, Jordan | (Abu-Shikhah & Elkarmi, 2011) | – | – | – | – | – |
| 14 | SVM, RBF-NN | Higher accuracy, higher speed | 2012 | Ontario | (Torbaghan, Motamedi, Zareipour, & Tuan, 2012) | – | – | 13.2 % | – | – |
| 15 | Mycielski algorithm | It is a pattern search model is simple to implement and is recognized for good results | 2015 | Fuhrländer | (Croonenbroeck & Ambach, 2015) | 70.25 | – | – | 99.46 % | – |

**Table 13**
Long-term renewable energy forecasting.

| Sr. No. | Models | Advantages | Year | Region | Ref. | Performance evaluation statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | MAE | CV | MAPE | RMSE | R |
| 1 | Gaussian Mixture Model | Higher generalization capability with supplementary tests on outlier samples toward Kernel density estimate | 2019 | China | (Zhong, Tan, & Lin, 2018) | – | – | – | | – |
| 2 | Fuzzy Bayes | The proposed methodology has higher adaptability and accuracy | 2019 | China | (Tang et al., 2019) | 54.78 | – | 1.61 % | 99.76 % | – |
| 3 | Electricity demand model | Set more accurate investments energy plans in the rural electrification | 2019 | India | (Riva, Gardumi, Tognollo, & Colombo, 2019) | – | – | – | – | – |
| 4 | Differential evolution (DE) algorithm | The DE-LSTM algorithm outperforms existing prediction algorithms in terms of prediction accuracy | 2018 | New South Wales, Germany/ Austria, and France | (Peng, Liu, Liu, & Wang, 2018) | 7.12 | – | 1.79 % | 1.53 % | – |
| 5 | Hierarchical linear model, Markov chain Monte Carlo methods | Suitable to get the trajectory of the real load consumption with higher accuracy, higher speed | 2019 | Brazil | (da Silva, Cyrino Oliveira, & Souza, 2019) | – | – | – | – | – |
| 6 | Energy demand models | Higher prediction performance | 2018 | Multiple locations | (Riva, Tognollo, Gardumi, & Colombo, 2018) | – | – | – | – | – |
| 7 | Strategic modeling | Its sensible to at limited implicitly consider more extensive linkages in these bounded algorithms | 2019 | UK | (Blainey & Preston, 2019) | – | – | – | – | – |
| 8 | Energy systems models | Calculate the differences in determinants like annual driving attitude and distances towards uncertainties of modern technology | 2018 | United States of America | (Ramea, Bunch, Yang, Yeh, & Ogden, 2018) | – | – | – | – | – |
| 9 | LSTM model, Deep learning | Gives a notable improvement in seizure forecasting performance correlated to both conventional ML techniques | 2018 | Ioannina, Greece | (Tsiouris et al., 2018) | – | – | – | – | – |
| 10 | Multiple models | Widespread geographic viability, large storage capacity, and lack of pollution, higher convergence speed | 2017 | Multiple locations | (Zheng, Wang, & Li, 2017) | – | – | – | – | – |

## 3. Discussion of forecasting models

The short-term energy prediction is an essential tool for all power utilities. A large number of operational arrangements consist of short-term energy prediction. The efficiency of these predictions heads to important energy savings in operational costs as well as to increase the system safety and reliability. The technical research is sufficient with approaches and techniques for increasing short-term energy prediction. A large number of techniques operate well with several energy networks or some particular geographical regions, while some of them are failed because of different nature of electrical consumption requirement: its highly nonlinear, complex, and reliant on seasonal, weather and social factors (Kyriakides & Polycarpou, 2006). The dedium-term energy prediction is an essential class of load prediciton that includes a time-span starts from one-week to one-year ahead duration. It accommodates the maintenance and outage planning and the energy switching operation of the power networks (Abu-Shikhah, Elkarmi, & Aloquili, 2011). Especially, the long-term energy prediction plays a significant part in energy management and system load planning. Classical methods for long-term system energy prediction are particularly in three classes: time series approaches (Carpinone, Langella, Testa, & Giorgio, 2010; Li, Han, & Yan, 2018), correlation classifications (Hyndman & Fan, 2010; Sanstad, McMenamin, Sukenik, Barbose, & Goldman, 2014) and AI algorithms (Ghelardoni, Ghio, & Anguita, 2013; Torrini, Souza, Cyrino Oliveira, & Moreira Pessanha, 2016; Yang, Lin, Zhu, Han, & Wang, 2015; Yang et al., 2015). Time series prediction models for future load estimation based on past energy and the climate data. Therefore, the prediciton error will substantially rise once the weather trend increases or decrease. The major issue of time series prediciton is that they do not accommodate adequately to a changing the climate. Meanwhile, due to the complex sets of determinants affecting the insufficient annual patterns of the data, energy demand, correlation algorithms and AI classifications sometimes doesn't operate well either.

The power systems and infrastructure are undergoing an imminent transition to describe the developed variability in the production and actual net energy demand, introduced by a series of power generators, specifically solar and wind. Several methods to decrease the adverse ramping impacts have been proposed, i.e., demand response, resources, and total energy prediciton and increased storage capacities, etc. The essence of complete solutions for combining the higher numbers of parameter solar and wind production is to develop the available flexibility options in the smart grid (Bird, Milligan, & Lew, 2013; Bott, 2014; Yang et al., 2015). However, in the recent past, the regulatory officials in various jurisdictions reconstructed the business environments to provide the resilient energy selling programs, planned to exploit temporal and spatial diversity in demand and generation adequately. This reorganization began in northern Europe by providing short-term, cross-border energy trading tariffs, motivated by the requirement to combine the developing portions of variable wind production. Through most comprehensive studies has been conducted on short-term energy, solar and wind speed forecasting. It's because of the lack of availability of real-time data, the accuracy of forecasting performance and variation of forecasting accuracy. The short-term prediction is more precise and accurate than the medium and long-term. Furthermore, three well know forecasting classifications including: i) ML-based approaches; ii) ensemble-based approaches; iii) and ANNs are prominently applied in many areas.

The ML is a data analysis approach that automates rational design building. It's a part of AI-based on the concept that schemes operations can discover from big data, recognize trends and build the decisions with least human interference. Due to the new computing technologies, ML in the present era is not the same as ML models used in the past. It was produced from theory and pattern recognition that ML networks can determine without doing processed to complete particular assignments; experts interested in AI needs to understand if systems of a specific program of the computer could determine from big data. The repetition features of ML are robust due to the methods are displayed to the new big data and they are also capable of independently readjust. They discover the network function from previous estimates to provide repeatable decisions, reliable and results. Many ML models have been examined for long-term planning tasks, further the capability to automatically use the complicated mathematical estimates to big data – faster and faster, over and over – is a new addition in it. Fourier series plus models render no obligation to construct complicated network layers with different input feature variables. Wrapper mutual information methodology maximizing the common information measure of training network. ML models are capable to handle different kinds of data from different sites with different input feature variables. Extreme learning defines the complicated and ill-defined prediction issues. Random forecast regression, support vector regression and gradient boosted regression models are comfortable to replicate that in the situation with physical methods. Weighted Gaussian regression models are mainly simple to train and ease to implement at different sites.

The ensemble-based forecasting models are also ML approaches that combine different base methods to give one optimal forecast model. The ensembles methods are consists of two kinds including random forest and bagging, or bootstrap approaches. Bagging takes it is the name due to its consolidates aggregation and bootstrapping to determine one ensemble algorithm. Presented the data samples, subsamples of multiple bootstrapped are extracted. A decision tree determined on each of the subsamples of bootstrapping. After all subsample of the decision tree has been further established, a model applied to combine over the decision tree to develop the multiple useful predictors. When selecting the tree where to divide and how to obtain decisions, bagged decision tree possess the complete order of network characteristics and features to determine from.

Consequently, the bootstrapped data points/samples may be somewhat inconsistent and because of the use of big data going to break-off at the related variables throughout the specific algorithm. On the other hand, the random forest models (RFM) determine where to divide comprised of a random collection of network features and hidden neurons. The RFM achieve a differentiation level because every network tree will diverge based on various parameters. This differentiation level gives a better ensemble model to sum over, ergo providing a higher reliable predictor. Analog ensemble approach is to give excellent and bias-calibrated estimates and it a computationally scalable model. Ensemble forecasting framework has the capacity to manage the nonlinear characteristics of the data and dynamic and abrupt meteorological changes as well. Its further benefits to developing large number divisions of the network with higher accuracy.

The ANN is a non-linear approach that is simple to apply constructs the statistical models. The ANN is a nonparametric approach though, a large number of statistical classifications are the parametric models which require a more extensive background of the statistics. The ANN with backpropagation model extensively applied in determining different classification and prediciton issues. Though the ANNs is blackbox classification, which cannot interpret the correlation between outputs and inputs and cannot deal with various kinds of contingencies. To overcome these issues, different approaches have been coupled/connected with the ANNs like network variable feature collection for training and so on.

Meanwhile, the Fuzzy logic is quite useful at handling variability and can interpret the correlation between output/input by constructing rules. Hence, to improve the capacity of ANN and Fuzzy, hybridization of fuzzy and ANN is customarily executed. Benefits of ANNs are: i) good storing knowledge on the whole network; ii) capacity to operate with inadequate information; ii) possessing fault threshold; iv) possessing a shared memory; v) gradual corruption; vi) ability to build ML model; vii) and capability of parallel processing, etc. The limitations of ANNs include: i) hardware dependence; ii) unexplained operation of the network; iii) problem in the determination of individual network construction' iv) challenge of exposing the issue to the system; v) the network duration is unknown. Multivariate neural networks and Elman backpropagation show their strength to handle nonlinear, dynamic and abrupt meteorological differences. It holds capacity reducing information measure concerning the validation point to be predicted. ANNs are very useful for short-term solar irradiance forecasting, and it gives higher network speed, accuracy and performance. The ANNs are highly non-linear with various time structures and multiple network layers. The ANNs are suitable with less or higher number of climate and energy consumption data for forecasting analysis. Hybrid decomposition models are highly fit for non-stationary multi-step wind energy prediction. Further, ANNs are cost-efficient for energy planning and dispatch plans.

## 4. Conclusion

Renewable energy leads to endless energy generated from the natural environment that doesn't leave a bad impact on the environment. In response to the exhaustion of oil supplies and demands, increasing renewable energy has become the prime attention of world's energy planning approaches, energy policy help stakeholders to measure the influence of future and current energy strategies. The current performance of energy planning models depends on using suitable prediction algorithms for supply and demand sector forecasts. This review primarily calculates the growth patterns in the RE usage and energy demand requirement. Three forecasting intervals short, medium and long-term are reviewed. It is observed that the most of the researches are conducted on short-term instead of medium and long-term. When the power sectors were organized, power companies' monopolies use short-term energy prediction to guarantee the supply and reliability; and use long-term load requirement predictions as the references for investing and planning in the current position. Large industrial customers or utility companies who are capable of calculating the unstable wholesale rates including a reasonable context of efficiency can modify its bidding policy, consumption or production schedule to decrease the uncertainty or increase the profits of companies in day-ahead speculation. Furthermore, the ML, ensemble-based approaches and artificial neural networks are reviewed for renewable energy and electricity demand forecasting. The ML classification helps better planning of energy consumption and generation. Several ML approaches are applied in various steps of a RE power grid integration, relying on the specifications and features of predicament. For an electric grid with RE sources rendering a substantial number of ratio of the power demand, it's important to predict short-term and long-term load requirement. This could expedite the problem formulation of highly-informed power planning and management, electricity policies, for instance, by assisting in defining essential features to the relative spinning reserve levels as well as storage demands. On the contrary, it's also important to determine the load output demand from RE power generation plants by their self, because the output load from certain power stations relies on several climate factors which cannot be regulated. The ensemble forecast spread shows how it is confident the predictor can be in use for different kinds of prediction. The spread shows the drastic change between actual and forecasted energy demand. When the ensemble spread is lower, and the prediction explications are compatible with various algorithm runs, predictors observe more reliance on the prediction in general. On the other hand, when the spread is high, this shows more change or variation in the forecast. The ANNs with their exceptional knowledge to determine the mean from complex data can be applied to obtain trends and identify patterns that are too complicated to be observed by both individuals and different computer classifications. The ANNs can be used to a growing amount of real-world issues of noteworthy complexity. They are further applied to determining problems which extremely complicated for traditional technologies or those kinds of intricacies that don't possess an algorithmic solution. The extended benefits of ANNs allows the modeling of physical appearances in complicated systems without needing specific mathematical descriptions or without expecting exhaustive measures. The ANNs can forecast the system desired output when adequate experimental datasets are given. In the present era, only a few researches which have been examined on geothermal energy prediction. It is observed through various types of approaches such as data-mining, ML, grey-box models and so on. The accuracy of state-of-the-art models measured/reviewed through well-known performance evaluation indicators mean absolute error (MAE), MAPE, RMSE, CV and R indicators. It's observed that the forecast accuracy of every single model in term of performance evaluation statistics are different. Through this review, it is concluded that the precise prediction will not only lead to notable decreases in penalties but also promote performance of various application fields, e.g., power grid maintenance and operating scheduling as well. Reliable forecasting of RE output and electricity requirement also presents an essential part in defining the optimal extent of the spinning stock required for the stable development and control of the micro-grid with higher renewable energy penetration.

Forecasting capabilities are increasing, and different nations are gradually moving towards the construction of smart grid, which is fully automated energy distribution network that controls and monitors the consumers and nodes, further ensuring a bi-directional flow of information and energy. Much work is still needed in forecasting field to support these networks with accurate knowledge and also support RE integration with the conventional grids.

## Declaration of Competing Interest

There is no conflict of interest for this submission.

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