Time Frames, Variables, and Performance Metrics Consideration in Renewable Energy Prediction Models: A Review

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Abstract

Renewable energy has gained immense attention due to its potential to reduce the world's dependency on fossil fuels and mitigate climate change. As the energy harnessing rate from renewable sources depends on some external parameters like solar radiation, wind speed, direction, and turbulence, the generation rate in such sources comes with a high level of fluctuations. Fluctuations in their output can increase operating costs for the electricity system and be quite challenging for utility companies to always maintain a proper balance between the generation and usage of electricity. To reduce the operation cost and increase the reliability of the system, robust forecasting models are used to predict the generation rate and energy demand. This review paper offers a thorough examination of cutting-edge data-driven forecasting models utilized in forecasting renewable energy generation and demand. The paper organizes previous studies into five distinct groups based on prediction time frame: immediate, very short-term, short-term, medium-term, and long-term. It subsequently assesses the performance of various forecasting models, including three primary categories: time series, machine learning, and ensemble models, concerning predicting energy demand and generation rates across different time frames, using standard performance evaluation metrics. The findings indicate that ensemble models employing neural networks and support vector machines demonstrate notably higher accuracy rates in predicting energy demand and generation rates compared to the other models.

Keywords
Forecasting, Machine Learning, Heuristic Algorithms, Time series, Deep Learning.

1. Introduction
Energy, particularly electrical energy, is essential for social, industrial and economic development for countries. Previously, a major proportion of electricity was produced using only fossil fuels. But, use of fossil fuels worsened environmental issues (Lian et al., 2019) and the swift depletion of this source has led to a global energy crisis. Therefore, renewable energy sources have become increasingly popular in recent years. Renewable sources of energy are considered "clean" as they do not emit greenhouse gases or other pollutants associated with traditional sources of energy (Lv et al., 2022). Utilization of renewable energy offers numerous advantages including reduction of environmental pollution, sustainability, energy security, job creation, and easy energy access for people in remote areas (Lian et al., 2019).

Taking the advantages of clean energy into consideration, the share of renewable sources in electricity generation is getting higher compared to other sources. Despite several advantages, many challenges such as high initial investment cost, unpredictable output, limitation in energy storage, requiring a significant amount of land, and public acceptance are common in utilizing renewable energy (Lian et al., 2019).

As the generation rate of renewable sources is heavily influenced by the unpredictability of external parameters such as weather conditions, solar radiation, and wind speed, the generation rate comes with stochastic characteristics. Fluctuations in outputs from renewable sources can increase operating costs for the electricity system and also pose potential risks to the reliability of the electricity supply. So the unexpected changes in the generation rate can be quite challenging to maintain a proper balance between the generation and usage of electricity at all times, especially in small or isolated electrical grids (Voyant et al., 2017). To overcome these challenges and operate power generation effectively, forecasting the renewable power generation is pivotal(Ostadi et al., 2019).

Besides the application of prediction models by grid operators to maintain the balance between the generation and usage of electricity, such models are also used by generation companies and energy retailers to optimize their bidding on the electricity market (Amin Naseri, 2018, Motamedisedeh et al., 2022). In addition, it is crucial to use a highly accurate model to evaluate the energy demand and generation rate to optimize the optimum capacity of rooftop solar power and an optimal combination of energy resources for remote areas(Ostadi et al., 2020). Overestimation of energy demand or underestimation of the generation rate might lead to an over-design of the system, while underestimation of energy demand or overestimation of the generation rate could lead to an unreliable system (Lian et al., 2019).

Numerous models are presented in the literature to predict the energy demand or generation rate. Fig 1 presents this increasing trend of the number of articles in this context, results from the search of the term "(prediction OR forecast) AND energy AND (demand OR generation)" in the database Scopus. As can be seen, the number of articles related to prediction models has increased dramatically.

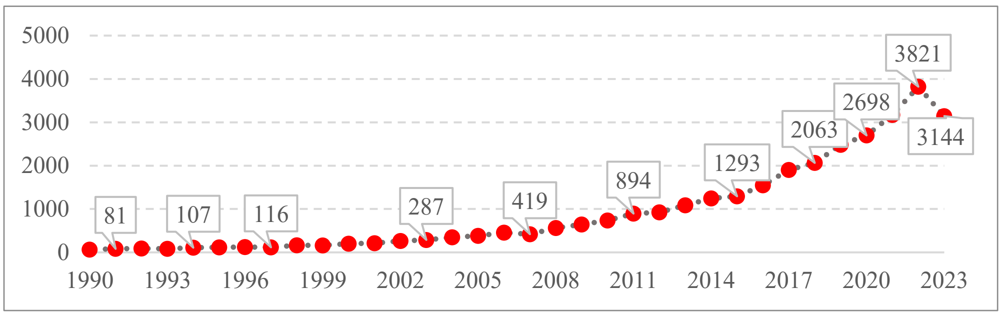

Figure 1: Number of publications on the prediction models for energy demand and generation

To see this research area from a macro perspective, and identify the most frequently used combination, bibliometric analysis has been performed based on the article titles and abstracts in the published papers since 2010. The result is shown by the density maps in Figure 2. Based on the results, to predict the generation rate, PV and wind are the most used sources of energy in the case study. Regression, ensemble, Markov, machine learning, neural network, and hybrid models are the commonly used names in the titles and abstracts of the papers. Among all the countries, China, Turkey, Pakistan, and India are mostly mentioned in the articles. The repetition of the words scheduling, and dispatch indicates that the prediction models come with scheduling and dispatch problems.

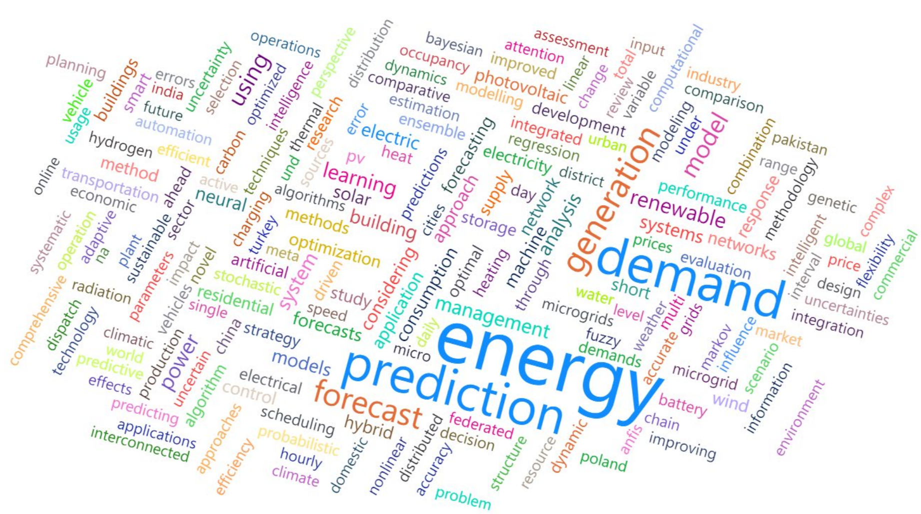

Figure 2: The result of bibliometric analysis based on the titles of the articles.

In this paper, four main characteristics of prediction models for generation rate and energy demand including the prediction time frame, models' variables, model types, and performance measuring parameters are presented by comparing more than 100 recently published articles. In the rest of this article, initially, different prediction time frames are presented. Then, the most used variables in prediction models and model types are provided. Finally, the model's performance evaluation parameters are provided in the last section.

2. Prediction Time Frames

Different prediction time frames are considered in the literature based on their application. Three-time frames, namely immediate (from 15 minutes to 12 hours), very short-term (from 1 to 6 hours), and short-term (from 1 to 3 days) are proposed in literature (Guermoui et al., 2020). Wang et al. (2011) proposed three-time frames as Immediate short-term (to the next 8 hours), short term (for the next day), and long term (for the next multiple days) (Wang et al., 2011). Hossain (2020) considered four different prediction times, as very short-term (1 minute to an hour), short-term (1 hour to a week), medium-term (1 month to a year), and long-term (more than a year) (Hossain, 2020). By considering different articles and the applications of prediction models, the prediction time frame can be categorized into five different groups; immediate, very short term, short term, medium term, and long term. Table 1 presents the application of prediction models in different time frames (Voyant et al., 2017).

Table 1. Application of prediction models based on prediction time frame

Groups	Time Frame	Granularity	Application
Immediate (IM)	15 min to 12 hours	30s to 5 min	Regulation, Real-time distribution
Very Short-Term (VST)	1 to 8 hours	1 hour	Load Tracking, Schedule Updating
Short Term (ST)	Day ahead	1 hour	Load dispatch planning, Operational security in the energy market, Unit Commitment, Schedule
Medium Term (MT)	Multiple days ahead	1 hour	Maintenance planning, Operation management, Operation cost
Long Term (LT)	Month to year	Day	Network development

Figures 3 and 4 present the frequency use of different time frames for the prediction models in general and their applications. Based on the values, the short-term and very short term are the most common prediction time frames in the literature, and the long-term time frame is only used for the prediction of demand.

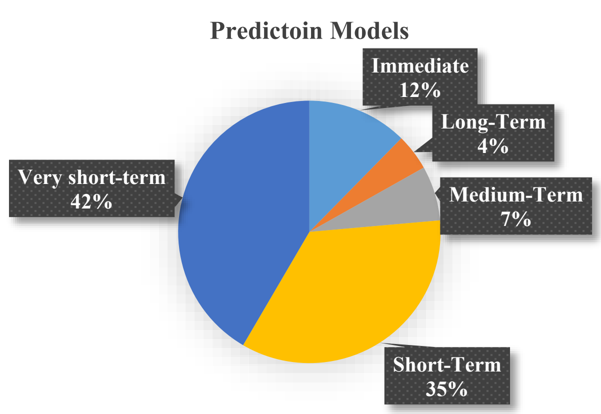

Figure 3. Frequency of timeframes for prediction

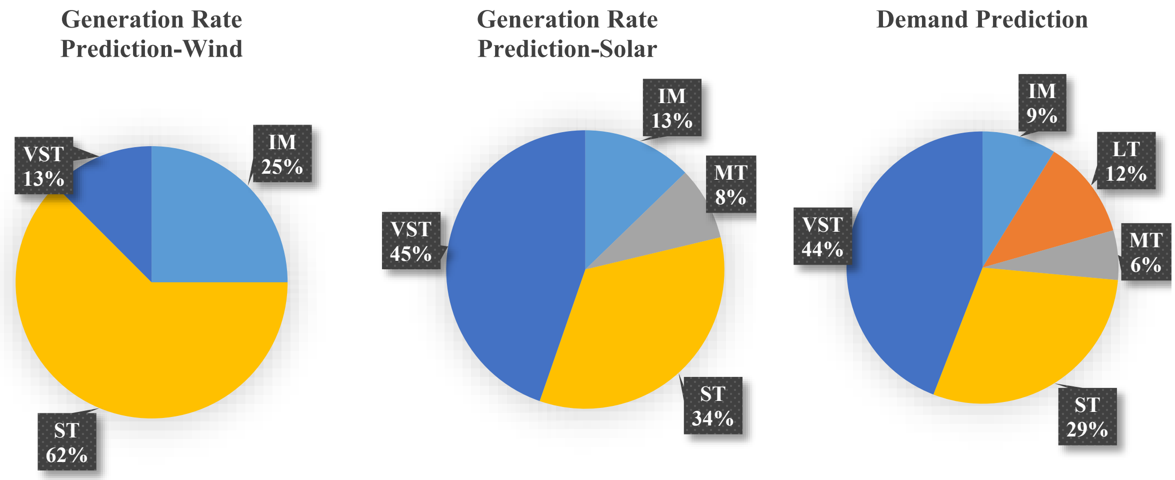

Figure 4. Frequency of timeframes for prediction by application (IM=immediate, LT=long-term, MT=mid-terms=short terms=very short-term)

3. Variables considered in the models:

To predict the generation rate and energy demand utilizing renewable energy-based generators such as solar panels, and wind turbines, different variables need to be considered as shown in Figure 5 (Amasyali and El-Gohary, 2018, Tascikaraoglu and Uzunoglu, 2014, Ahmed et al., 2020, Gupta et al., 2011, Sedeh and Ostadi, 2020).

Among all variables, meteorological factors are the most used in the literature to predict the short- and long-term generation rate. Qing and Niu (2018) evaluate the correlation of meteorological factors like solar radiation, temperature, humidity, and pressure with the energy generation rate by the solar panel (Qing and Niu, 2018). Pedro and Coimbra (2015) and Chu et al. (2015) used such parameters for the prediction of generate rate by solar panels for the next 15 minutes (Pedro and Coimbra, 2015, Chu et al., 2015). Ramsami and Oree (2015) considered meteorological factors such as wind speed and sunshine hours to predict the generation rate by solar panels and wind turbines (Ramsami and Oree, 2015). Gupta et al. (2011) considered different parameters such as wind speed, gusty wind, wind direction, temperature, humidity, pressure, visibility, sunshine hours, rainfall, and season for predicting the wind turbine output (Gupta et al., 2011).

Parameters like date, weekday, holiday type, and lowest and highest temperature are the commonly used variables for the prediction of energy demand (Xuemei et al., 2010). Besides the parameters related to temperature, historical values for solar radiation and humidity is considered in (Li et al., 2009) for the prediction of energy demand in non-residential buildings. Solomon et al. (2011) also considered the dew point, wind speed, and pressure for the proposed prediction model (Solomon et al., 2011). Penya et al. (2011) also considered the day type (holiday or workday), season, and day of the week for the proposed prediction models (Penya et al., 2011).

4. Prediction Model

Different models are available to predict the energy generation and demand in the literature which can be divided into two main general groups: i) physical models (deterministic approach) and ii) data-driven models. Physical models are based on fundamental physical laws and principles, and they are developed using a combination of theoretical analysis and experimental validation. In physical models, the generation rate is estimated using theoretical functions based on the characteristics of the installation location, such as radiation angle and farm layout, as well as meteorological parameters such as pressure and temperature. The energy demand is also estimated based on the installed facilities, their consumption rate, and the simulation of usage time based on the conditions (Voyant et al., 2017).

Data-driven models are prediction models that use statistical and computational techniques to learn patterns and relationships directly from the data. These models are developed without prior knowledge of the underlying physics, or the system being modeled. Data-driven models are trained on large datasets, and their performance is measured by how well they can generalize to new data. Based on the literature the data-driven models can be categorized into three groups time series, machine learning, and ensemble models.

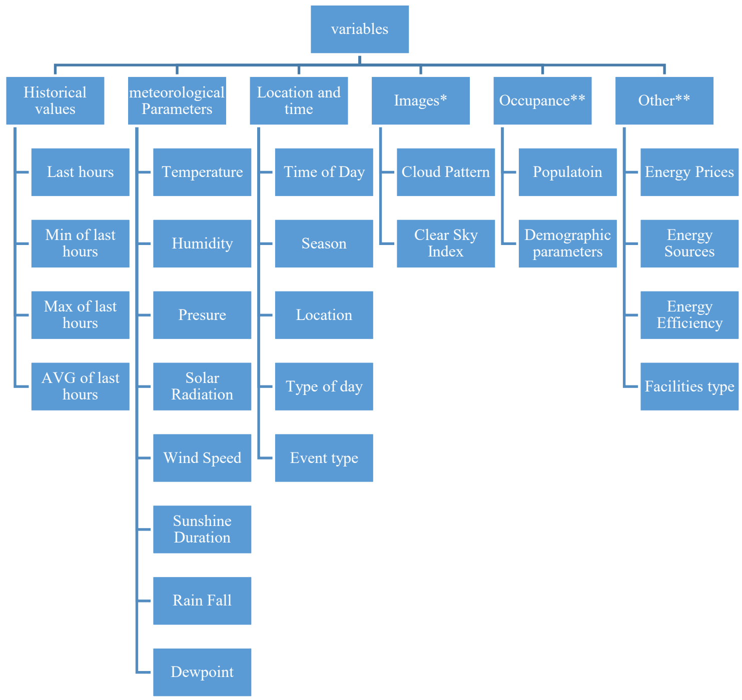

Figure 5. Most common variable in prediction models
* Used for the prediction of generation rate by solar
** use for the energy demand prediction

4.1 Time series model

Time series models are statistical models used to analyze time-series data, which is a sequence of data points measured at uniform time intervals. Time series models can be used to predict future values based on past values and trends observed in the data. These models can help identify patterns and trends in the data and can be used to forecast future values or detect anomalies (Tascikaraoglu and Uzunoglu, 2014). The structure of time series models is relatively straightforward, they can adjust for regional data trends, and such models offer prediction confidence intervals (Tascikaraoglu and Uzunoglu, 2014). on the other hand, a large amount of data is required for using the time series models and they are weak to extract the nonlinear trends (Tascikaraoglu and Uzunoglu, 2014). Autoregression (AR), moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), autoregressive fractionally integrated moving average (ARFIMA) and seasonal autoregressive integrated moving average (SARIMA) are the most common method in this group (Tang et al., 2022, Fathi et al., 2022).

4.2 Machine learning model

Machine learning models are a subset of predictive models that use algorithms to learn patterns from data and make predictions or decisions without being explicitly programmed. In prediction tasks, machine learning models can be used to make predictions based on historical data. The process involves training the model on a set of data to learn the patterns and relationships between the input features and the output variable, and then using the trained model to make predictions on new, unseen data (Tascikaraoglu and Uzunoglu, 2014).

Several machine-learning-based models are proposed in the literature, but there is some conflict about their performance in different research. While Tso and Yau (2007) show the error value for the regression tree is lower than the neural network and the neural network performance is superior to linear regression for short-term prediction, Olaiya and Adeymo (2012) show the error value for both Artificial Neural Network (ANN) and Regression tree is almost equal for the long-term prediction of solar radiation in Nigeria (Tso and Yau, 2007, Olaiya and Adeyemo, 2012). In another case while Demirtas et al. (2012) show the result of the K-Nearest Neighborhood (KNN) is superior to ANN for predicting solar radiation in the immediate time frame, Ferrari et al. (2012) and Lazzaroni et al. (2015) have claimed that the result is the opposite for the Italian market and the error for predicting the solar radiation for the immediate time frame by the ANN is lower than KNN (Demirtas et al., 2012, Ferrari et al., 2012, Lazzaroni et al., 2015). So, the model performance is dependent on different parameters such as the prediction time horizon. Sun et al. (2022) compared the application of Ensemble Models in the prediction of energy demand (Sun et al., 2020).

Deep learning models are another highly accurate prediction model in the literature but their training process of them is time-consuming. Faiq et al. (2023) used long short-term memory (LSTM) to predict the energy demand in a building at Multimedia University, Malacca Campus. Based on the result and by using the RMSE to evaluate the error value, the result of the LTSM model is superior to SVR and Gaussian Process Regression (GPR) (Faiq et al., 2023).
In another application of deep learning models for prediction, Wang et al. (2019) compared the results of Convolutional neural networks (CNN) and LSTM based on the values of MAE, MAPE, and RMSE (Wang et al., 2019). It shows that there is no direct relation between the model performance and the length of historical data used for prediction and after a specific number of records, considering more records will decrease the model performance. Wang et al. (2019) also showed in some cases the result of CNN is higher than LSTM and in some cases, the LTSM proposed a better solution than CNN (Wang et al., 2019). Burrows (1997) compared the result of the Regression tree and Linear regression for the prediction of solar radiation for the next 18 hours and based on the result the regression tree is superior to linear regression (Burrows, 1997).

There are several machine learning models each model comes with its advantages and disadvantages. The ANN-based model does not need the mathematical model and is good for high data error, but needs too much data for training and the training process is time-consuming (Tascikaraoglu and Uzunoglu, 2014). SVM-based models usually come with a low level of error but they need to tun the parameters approximately and comes with complex process(Tascikaraoglu and Uzunoglu, 2014). Bayasian-based models are a good choice for problems with a high level of missing values but are directly related to the user's expertise (Tascikaraoglu and Uzunoglu, 2014).

4.3. Ensemble models

Ensemble models refer to a combination of two or more models to reach a higher accuracy result. The results of models can be combined with a simple average or weighted average based on their accuracy. In complex problems, a machine learning model is used to combine the results of other models.

Based on the literature, combination models come with a higher accuracy rate. Gaston et al. (2010), Prokop et al. (2013), and Yang et al. (2014) showed the combination of ANN and SVM has a better result in comparison to each separate model for the prediction of solar radiation in an immediate time frame in Czech, Spain, and Singapore (Gastón et al., 2010, Prokop et al., 2013, Yang et al., 2014). Dong et al. (2015) used the combination of ANN and SVM to predict the solar radiation in the coming 10 minutes in the USA and based on the result the error for the combined model is lower than the ARMA model (Dong et al., 2015).

In another research, Bouzerdoum (2013) proposed a hybrid model based on the combination of SARIMA and SVM to predict the solar radiation in Italy in the coming 10 minutes and based on the result the hybrid model by the error value of nRMSE equal to9.4% comes with lower error in compare of both separate models (Bouzerdoum et al., 2013).

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5. Performance measuring metrics

Based on the literature, the error evaluation functions can be categorized into three groups; 1) Scale Dependent, 2) Percentage-based, and 3) Scale-free measures as Fig 6.

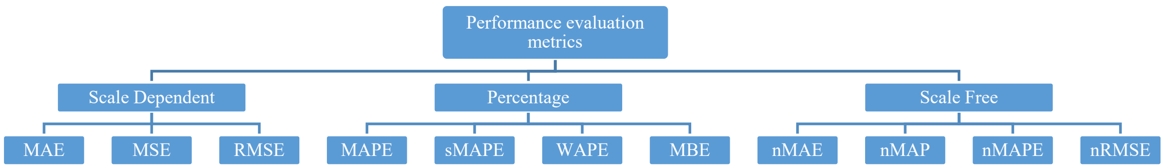

Fig 6. Error evaluation models

Among all of the measures, Mean Absolute Error (MAE) is the simplest one (Xuemei et al., 2010). It interoperates easily but it is dependent on the unit of data and is not good for comparing the performance of prediction models in a different context with different data units (Rodríguez et al., 2018). MAE measures the average of the errors (differences between real values and predicted values) in a set of predictions (Barrera et al., 2020).
As the error grew linearly in the MAE model, Barrera et al. (2020) used the Mean Square Error (MSE) beside the MAE for evaluation of error which in MSE a quadratic function is considered for error changes (Barrera et al., 2020). In MSE, the scale of the result is square of the scale for basic data, so the Root Mean Squared Error (RMSE) is proposed (Rodríguez et al., 2018).

All previous measures are scale-dependent and are not suitable for the evaluation and comparing the performance of prediction models in a different context, so the Mean Absolute Percentage Error (MAPE) is presented for evaluating the error by presenting the error as a percentage of the observed data (Cabrera et al., 2021). Due to the asymmetric characteristic of MAPE, the Symmetric Mean Absolute Percentage Error (SMAPE) is presented to evaluate the error value (Memon et al., 2021).
In all previous functions for evaluation of error the weight of all data is equal, so Weighted Absolute Percentage Error (WAPE) is presented for the situation that the difference in costs of under-forecasting or over-forecasting is negligible (Barrera et al., 2020).
While there is no difference between positive and negative difference between predicted values and actual values in all previous error evaluation functions, Mean Bias Error (MBE) can be calculated to indicate whether the model overestimates or underestimates the power output (Amasyali and El-Gohary, 2018).
Based on the literature, several measurements are defined to evaluate the model performance, and the result of the model will change by changing the performance evaluation measurement. While the result of overestimation varied in comparison to underestimation, it is neglected in the literature. Fig 7, present the frequency application of performance measuring metrics in the literature. Based on the literature the RMSE, nRMSE, and MAPE, are the most used performance evaluation metrics.

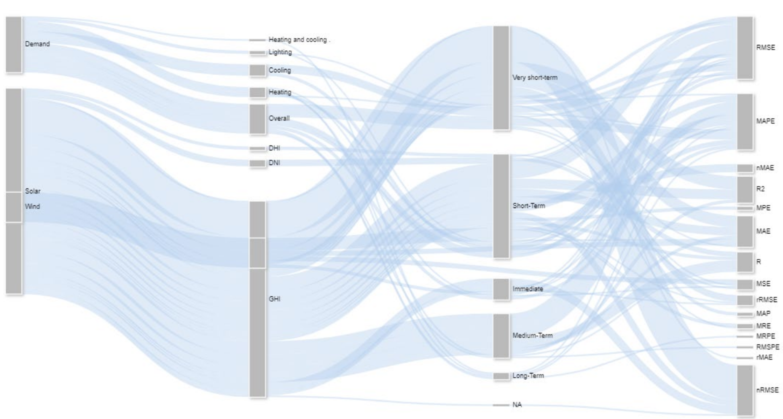

Fig 7. Frequency of performance measurement metrics

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Table 2, summarize the accuracy rate of different models in the literature.

Table 2. Summery of the articles

Area	horizon	Model	Location	Performance Metrics	Authors (year)
Demand	IM	ANN	NR	MSE = 0.15	(Paudel et al., 2014)
	LT	ANN	R	MAPE (%) = 5.06	(Turhan et al., 2014)
		Regression	R	MAPE (%) = 0.36	(Catalina et al., 2013)
	MT	ANN	R	R (%)= 0.83	(Popescu and Ungureanu, 2013)
			NR	RMSPE (%)= 15.7	(Ferlito et al., 2015)
	ST	ANN	NR	RMSE (kWh) = 725	(Wong et al., 2010)
				MAPE (%) = 9.5	(Neto and Fiorelli, 2008)
		MLR	R	MAPE (%) = 12.36	(Iwafune et al., 2014)
	VST	ANN	R	RMSE (kWh)= 1.68	(Chou and Bui, 2014)
			NR	MAPE (%) = 0.81	(Mena et al., 2014)
				MRE (%)= 3.65	(Hou et al., 2006)
		SVM	NR	RMSE (kWh)= 0.02	(Xuemei et al., 2010)
				MAE = 1.94	(Dagnely et al., 2015)
				MAPE (%) = 0.06	(Massana et al., 2015)
		WSVM	NR	RMSE (kWh)= 0.03	(Jinhu et al., 2010)
Solar Generation Rate	IM	Ensemble Model {ANN}	UAE	rRMSE = 9.1	(Alobaidi et al., 2014)
		GA	Singapore	RMSE(Wh/m2) = 52.6	(Wu et al., 2014)
		k-NN	Turkey	nRMSE = 18	(Demirtas et al., 2012)
		Random Forest	Benchmark	nRMSE = 10	(Zamo et al., 2014)
	MT	ANN	Saudi Arabia	MAPE (%) = 10.3	(Mohandes, 2012)
		GA-SA	Iran	MAPE (%) = 0.138	(Mostafavi et al., 2013)
	ST	ANN	Nigeria	nRMSE = 24	(Olaiya and Adeyemo, 2012)
		Ensemble	China	MAE(Mj/m2) = 1.26	(Sun et al., 2015)
		Ensemble Models {SVM}	Italia	MAPE (%) = 6	(De Felice et al., 2015)
		MLP	China	MAE = 0.72	(Akarslan and Hocaoglu, 2016)
		SVM	Australia	MAPE (%) = 12.6	(Deo et al., 2016)
			Iran	RMSE = 0.69	(Shamshirband et al., 2016)
	VST	ANN	Singapore	nRMSE = 20.65	(Dong et al., 2014)
		AR	France	rMAE = 5.34	(Monjoly et al., 2017)
		ARMA	France	nRMSE = 36.59	(Voyant et al., 2014)
		Ensemble {ANN-ARMA}	N/A	NRMSE = 13.7	(Voyant et al., 2013)
		Ensemble {ARMA- NAR}	Algeria	NRMSE = 0.2	(Benmouiza and Cheknane, 2016)
		Ensemble Models {ANN}	Japan	MAPE (%) = 4	(Chaouachi et al., 2009)
		RNN	India	RMSE = 14.96,MAE = 9.6,R2 (%)= 79.12	(Yadav and Behera, 2014)
		SVR	Germany	nRMSE = 6.2	(Wolff et al., 2016)
Wind Generation Rate	IM	LSSVR	N/A	MAPE (%)=9.19	(Zhou and Tong, 2021)
	ST	Ensemble {BA-LSSVM}	N/A	MAPE (%)=1.56	(Wu and Lin, 2019)
		SVM	N/A	MRE=7.97	(Liu et al., 2012)
			N/A	MAE=0.39	(Wang et al., 2021)

Conclusion

In this paper, a review of most commonly published paper for the prediction of energy demand and generation rate by PV and wind is presented. To predict the energy demand and generation rate, different parameters are considered in the literature which can be categorized into groups of historical values, metrological parameters, location, date and time. To predict the energy demand, occupancy related variables are also considered and for the prediction of solar radiation, the sky images are also considered in some research. The predictions are applied for five different time frames, which mostly energy generation is predicted for immediate and very short time frame and in some case the demand is predicted for long time frame. Among all the prediction models, the ANN, SVM, and ensemble related models come with higher accuracy rate in compared to the other models. Additionally, due to the complex characteristic of wind, the prediction of generation rate by wind comes with lower accuracy rate in compared to the prediction of generation rate by solar.

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