Renewable and Sustainable Energy Reviews 108 (2019) 513–538

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Machine-learning methods for integrated renewable power generation: A comparative study of artificial neural networks, support vector regression, and Gaussian Process Regression

Mahdi Sharifzadeh[a,b,*], Alexandra Sikinioti-Lock[a], Nilay Shah[a]

[a] Department of Chemical Engineering, Imperial College London, South Kensington Campus, London SW7 2AZ, United Kingdom
[b] Department of Electronic and Electrical Engineering, University College London, WC1E 7JE, United Kingdom

ARTICLE INFO

Keywords:
Machine-learning
Big data
Renewable wind and solar power
Electricity demand
Artificial neural networks (ANN)
Support vector regression (SVR)
Gaussian process regression (GPR)

ABSTRACT

Renewable energy from wind and solar resources can contribute significantly to the decarbonisation of the conventionally fossil-driven electricity grid. However, their seamless integration with the grid poses significant challenges due to their intermittent generation patterns, which is intensified by the existing uncertainties and fluctuations from the demand side. A resolution is increasing energy storage and standby power generation which results in economic losses. Alternatively, enhancing the predictability of wind and solar energy as well as demand enables replacing such expensive hardware with advanced control and optimization systems. The present research contribution establishes consistent sets of data and develops data-driven models through machine-learning techniques. The aim is to quantify the uncertainties in the electricity grid and examine the predictability of their behaviour. The predictive methods that were selected included conventional artificial neural networks (ANN), support vector regression (SVR) and Gaussian process regression (GPR). For each method, a sensitivity analysis was conducted with the aim of tuning its parameters as optimally as possible. The next step was to train and validate each method with various datasets (wind, solar, demand). Finally, a predictability analysis was performed in order to ascertain how the models would respond when the prediction time horizon increases. All models were found capable of predicting wind and solar power, but only the neural networks were successful for the electricity demand. Considering the dynamics of the electricity grid, it was observed that the prediction process for renewable wind and solar power generation, and electricity demand was fast and accurate enough to effectively replace the alternative electricity storage and standby capacity.

1. Introduction

Nowadays the need to move towards more sustainable technologies and methods is more urgent than ever due to the adverse effects caused by climate change. The International Energy Agency [1] asserts that over 65% of the GHGs (greenhouse gases) emanate from the energy sector, which signifies the need for transformation within this sector. Recent global events such as COP21 have set challenging targets to prevent the alarming impacts of climate change, which will be addressed by the adoption of stringent legislation. While the power sector accounts for 66% of the GHG emissions globally [1], renewable energy resources (RESs) have a burgeoning leading role in its decarbonisation. However, the intermittent generation patterns of solar and wind power due to the meteorological effects have rendered their deep implementation difficult, and further research and measures are required. In an electricity grid, the primary objective is to ensure the balance between supply and demand, in order to avoid power cuts and ensure that all consumers receive the electricity they need. This can be met by installing energy storage units as well as the commitment of stand-by generation capacities, but such an integration raises the costs of the electricity grid.

For this reason, many endeavours have been made in predicting power load as well as electricity generation from RESs, which with sufficient accuracy could minimise operational costs and facilitate their technological penetration [2]. One of the approaches with which this issue is addressed is by enhancing the near-term predictability of the renewable energy systems and incorporating this knowledge into smart control systems that can optimise the power dispatch within an electricity smart grid. Here Big Data analytics is the “enabler” as it can convert real-time data, into “actionable knowledge”. Many studies have been conducted with the view to predicting the renewable energy generation as well as the electricity demand. Extensive reviews can be

* Corresponding author. Department of Electronic and Electrical Engineering, University College London, London, WC1E 7JE, UK.
E-mail address: m.sharifzadeh@ucl.ac.uk (M. Sharifzadeh).

https://doi.org/10.1016/j.rser.2019.03.040
Received 25 July 2018; Received in revised form 19 February 2019; Accepted 19 March 2019
Available online 10 April 2019
1364-0321/

Table 1
Literature concerning wind speed and power forecasting.

Authors	Input (historical data)	Output (predictions)	Forecast horizon	Method	Models used
Ak, Vitelli and Zio [41],	Wind Speed	Wind Speed	Short-term	Statistical	MLP
Masseran [42]	Wind Speed	Wind Speed	Short-term	Statistical	ARIMA ARCH
Shi, Qu and Zeng [15]	NWP, Wind Power	Wind Power	Short-term	Statistical	ARIMA
Alexiadis [43]	Wind Speed, Direction, Pressure, Temperature, Spatial correlation	Wind Speed and Power	Very short-term	Artificial Intelligence	ANN, ARMA
Sideratos and Hatziargyriou [44]	Wind Power, NWP time series	Wind Power	Short-term	Artificial Intelligence	RBF, FLS
Mohandes et al. [45]	Daily Mean Wind Speed	Wind Speed	Long-term	Artificial Intelligence	SVM, MLP
Jursa and Rohrig [46]	Wind Power, NWP time series of multiple areas	Wind Power	Short-term	Artificial Intelligence	ANN/kNN
Ghadi et al. [47]	NWP, SCADA	Wind Power	Short-term	Artificial Intelligence	ICA, ANN
Kramer and Gieseke [48]	Wind Speed	Wind Power	Short-term	Artificial Intelligence	SVR
Han, Li and Liu [49]	Wind Speed Direction, Air Temperature, Air Pressure, Relative Humidity	Wind Power	Short-term	Artificial Intelligence	ANN
Carolin Mabel and Fernandez [50]	Wind Speed, Relative Humidity, Generation Hours Energy Output	Wind Power	Short-term	Artificial Intelligence	ANN
Cellura et al. [51]	Weibull Distribution	Wind Speed	Short-term	Artificial Intelligence	ANN, Universal kriging (UK) estimator
Welch, Ruffing and Venayagamoorthy [52]	Wind Speed, Temperature, Relative Humidity	Wind Speed	Short-term	Artificial Intelligence	ANN (MLP, ELM, SRN)
Ernst et al. [36],	Wind Power, NWP time series of multiple areas	Wind Power	Short-term	Artificial Intelligence	SVM, ANN, ME, NNS (ensemble)
Ramirez-Rosado et al. [53]	NWP, Wind Power	Wind Power	Short-term	Hybrid	MLP/Kalman-ARIMA-FLS
Bin, Haitao and Ting [54]	Historic Wind Speed	Wind Speed	Short-term	Artificial Intelligence	NN, GPR, LS-SVR
Hong, Pinson and Fan [55]	Historic Wind Power	Wind Power	Short-term	Artificial Intelligence	NN, GPR, SVM
Jiang et al. [35]	Historic Wind Speed	Wind Speed	Short-term	Artificial Intelligence	GPR
Chen et al. [34]	NWP	Wind Power	Short/medium terms	Artificial Intelligence	GPR, ANN
Sfetsos [9],	Hourly Wind Speed	Hourly Wind Speed	Short-term	Statistical, Hybrid	NLN, AR, ARMA, ANFIS, RBF
Kusiak, Zheng, and Song [16]	Wind Speed and Power	Wind Speed and Power	Short-term	Hybrid	SVM(speed), kNN(power)
Barbounis and Theocharis [56]	Spatial Correlation, Wind Speed Data	Wind Speed	Very short-term	Hybrid	FNN
Hu et al. [37]	Wind Power	Wind Power	Very short term (15 m)	Hybrid, ensemble	ARIMAX, bagging, QRF, RF, QR-SVM, QR-NN
Barbosa de Alencar et al. [38]	Air Temperature, Air Humidity, Atmospheric Pressure, average wind speed, wind direction	Wind Speed	Very Short/Short./Medium/Long	Hybrid, ensemble	NN, ARIMA
Eseye et al. [57]	NWP	Wind Power	Medium-term	Artificial Intelligence	GA-ANN, BP NN
Najeebullah et al. [58]	Wind Speed, Relative Humidity, Temperature	Wind Power	Medium-term	Hybrid	ANN, SVR
Li et al. [59]	NWP	Wind Power	Short-term	AI	SVM

found for the prediction of electricity demand [3,4], the photovoltaic power generation in Refs. [5,6] and the wind power [7]. Baños et al. [8], reviewed the optimization studies focused on all areas of renewable energy operation. Here, the broad observation is that artificial intelligence methods tend to outperform the respective statistical approaches [9–11]. These application areas are briefly reviewed in the following.

1.1. Predicting power generation from wind energy

Wind power forecasting has had a growing interest in the research community throughout the last decades [12]. Research involving forecasting wind power generation is summarized in Table 1. In Ref. [13] an extensive review is provided on the feature selection methodologies that have used across the literature for wind power prediction. It was additionally shown that feature selection is an important pre-processing technique when using AI techniques.

Two trends can be found in the literature for wind power forecasting in which the wind power is either predicted directly from historical data and wind speed, or indirectly by predicting wind speed and converting the speed to power via power curves. A review was conducted that groups the studies accordingly [14]. Shi et al. [15] conducted a comparative study between predicting the wind power directly from the historical data and indirectly from power curves and found that wind speed data provides better accuracy. They showed that the former method produces more accurate results, which is expected since the correlation between wind speed and power is stochastic and cannot satisfy a deterministic approach. The inability to predict wind power with the use of power curves is also discussed in Refs. [16,17]. Meng et al. [18] applied a hybrid method where wavelet packet decomposition was first applied for pre-processing wind data and their decomposition into time subseries, which are then using for training an artificial neural network (ANN) using a crisscross optimization algorithm. It was observed that the proposed algorithm outperforms other methods for 1–5-h ahead predictions. In addition, outperformed back-propagation and particle swarm optimization in training the ANN parameters. Similarly, Liu et al. [19] applied a hybrid method consisting of wavelet transformation and two neural networks. The decomposed low-frequency sub-layers of wind speed data was applied for training a long short-term memory neural network, and the high-frequency sub-layers were applied for training an Elman neural network. Wang et al. [20] applied a similar hybrid algorithm in which wavelet transform was applied to decompose the signals into various frequency series. The data sets were then applied for training a deep belief network, where the uncertainties was handed by the spine quantile regression. Huai-zhi et al. [21] applied a deep learning based ensemble framework that was a combination of wavelet transform and convolutional neural networks. They demonstrated the success of their approach on case studies from China. Yu et al. [22] proposed a hybrid approach in which the data is decomposed into time series using a Gaussian mixture copula method, and then applied for training Gaussian process regression models. The proposed method showed promise in accommodating seasonality variations, and uncertainties in the wind speed. The performance of linear, non-linear, artificial intelligence and hybrid models for predicting the mean hour-wind speed was examined with comparison to one another in Ref. [9]. More specifically, AR, ARIMA, MLP, RBF, ELM, ANFIS, and NLN models were built and it was concluded that linear models had the largest errors, whereas the non-linear and artificial intelligence (AI) models had approximately close errors with the neural network logic having the lowest. Yu et al. [23] applied an improved neural network structure called Long Short-Term Memory-enhanced forget-gate (LSTM-EFG), combined with Spectral Clustering to extract temporal correlation characteristics for forecasting wind power. The authors reported up to 18.3% higher accuracy compared to conventional LSTM, SVR, and KNN methods with higher computational efficiency. Liu et al. [24] applied a model consisting of three elements; wavelet packet decomposition (WPD) was applied to decompose the original time-series into several sublayers. The high-frequency sublayer was used to train a convolutional neural network (CNN) with a one-dimensional convolution operator. Finally, a convolutional long short term memory network (CNNLSTM) was applied for low-frequency sublayers. The author reported superior performance and robustness against sudden changes in wind speed. Similar studied by Liu et al. [19,25], using the same strategy for decomposing the data into multilayers and training various recurrent neural networks, showed improvements over conventional approaches. Zhu et al. [26] applied convolutional neural networks for 4-h ahead forecast of the data from a wind farm with successful results. Hu and Chen [27] applied a nonlinear hybrid model in which, hysteresis (a biological neural system property) was included in the activation function to improve the performance of an Extreme Learning Machine (ELM) model. In addition, a weighted objective function was optimized using Differential Evolution algorithm (DE) in order to establish the balance between "learning performance" and "model complexity" in a long short term memory neural network (LSTM). The authors reported superior performance over other conventional models for the cases of the 10-min ahead (utmost short term) and 1-h ahead (short term) wind power predictions. Wang and Li [28] developed a model consisting of the three elements of the optimal feature extracting, deep learning and error correction, for wind speed prediction. The feature extraction element consisted of variational mode decomposition, Kullback-Leibler divergence, energy measure, and sample entropy methods. A long short term memory (LSTM) network was applied for deep learning. A generalized auto-regressive conditionally heteroscedastic model was applied for error correction. The authors demonstrated the superior performance of their model over benchmarks using three sets of real data. Wang et al. [29] used k-mean clustering for the classification of numerical weather prediction (NWP) data, which was then applied for training a deep belief network (DBN) consisting of cascading restricted Boltzmann machines (RBMs). The authors validated their model using data from the Sotavento wind farm in Spain. The results demonstrated more than 44% improvement over a back-propagation neural network (BP) and a Morlet wavelet neural network.

(MWNN) benchmark. Zhang et al. [30] studied short-term wind power forecast, using a hybrid model. Singular spectrum analysis was applied to decompose the original data into a trend component and a fluctuation component. The trend component was forecasted using a least squares support vector machine, while the fluctuation component was predicted using a deep belief network (DBN). A locality-sensitive hashing search algorithm was applied to cluster the nearest training samples for further improvement.

Yu et al. [31] developed hybrid models in which, wavelet transform was first adopted to decompose the data into several sub-series. The second element of the model included either a standard recurrent neural network (RNN), a long short term memory (LSTM) neural network, or a gated recurrent unit neural (GRU) network and aimed at extracting "deeper features". The final element consisted of support vector machine (SVM) for prediction. The authors demonstrated the performance of their hybrid methods using real data. Higashiyama et al. [32] applied feature extraction from numerical weather prediction (NWP) data using three-dimensional convolutional neural networks (3D-CNNs) which has the advantage of direction extraction of spatio-temporal features from NWP data. They demonstrated the superior performance of their model against benchmark models. Chen et al. [33] applied a hybrid model based on support vector regression machine (SVRM), Long Short Term Memory neural networks (LSTMs), and an extremal optimization algorithm (EO) for forecasting wind speed. A cluster of LSTMs was applied to explore the implicit information of the wind data. Then, the parameters of the nonlinear SVRM model were optimized using the extremal optimization algorithm. The author demonstrated the performance of their model for the 10min ahead prediction of wind speed data from inner Mongolia, China.

In Ref. [16], between 4 different data mining algorithms, namely support vector regression (SVR), the multilayer perceptron (MLP), and two types of regression trees the accuracy of the SVR was the highest. Chen et al. [34] reported that dynamical GPR (Gaussian Regression Process) outperforms an MLP (Multilayer Perceptron Neural Network). Jiang et al. [35] also observed that GPR displayed good performance in comparison to MLP and SVM (Support Vector Machine) for predicting the wind speed. In the study by Ernst et al. [36], SVM yielded the best predictions out of artificial neural networks (ANN), a mixture of experts (ME) and nearest neighbour search (NNS) for wind power. However, when all the models were incorporated together as an ensemble model the least errors were achieved. It has been observed that the combination of multiple modelling techniques could optimise the performance of the predictions [37,38], since the weaknesses observed in some models may be smoothed by others. Tascikaraoglu and Uzunoglu provide an extensive review of the ensemble methodologies that have been used for wind power forecasting [39]. Finally, accuracy measures and benchmarking techniques used in the literature have been reviewed by Refs. [7,40].

1.2. Predicting power generation from solar energy

With respect to the input selection for solar power forecasting, data from numerical weather predictions (NWP) and historic power production are used in most cases. The research in the field is summarized in Table 2. Bacher et al. applied two autoregressive models for PV power forecasting in which both had an input of the historic power production data, but only one of them used additionally NWP. It was concluded that the model which used the NWP had a better performance particularly for predictions after 2 h, but for very short-term predictions, historical data was the most vital entry [60].

Artificial intelligence and statistical methods have been implemented for solar irradiance and photovoltaic power predictions extensively in various comparative studies, with a view to identifying the methods that fit better to this application. The applied methods are very diverse and include auto-regressive time-series [60], regression trees [61], k-nearest neighbours (kNNs) [62,63], artificial neural networks (ANNs) [64,65], support vector regression [66,67], and Gaussian process regression [68] to name a few. Martín et al. [10] found that multilayer neural networks (MLP) and adaptive neuro-fuzzy inference systems (ANFIS) are superior in predicting the solar energy that is harnessed by solar thermal plants compared to autoregressive statistical models. Salcedo-Sanz et al. [69] studied the prediction of the total daily solar irradiance with a number of various techniques, such as SVR, ELM, Bagged Trees and GPR and found that GPR had a better accuracy than other methods. Fernandez-Jimenez et al. [11] compared various statistical and AI models namely kNN, ANFIS, ARIMA and ANN (MLP, EML, RBF), where data was obtained from two different numerical weather (NWP) prediction programmes. It was shown that the MLP ANN outperformed all the other models followed by ANFIS. Similarly, in Ref. [62] MLP neural networks were successful in making 1 h and 2 h forecasts with the use of historical data of power produced by a PV farm compared to the statistical method ARIMA and the kNN. For small time steps (5 min), Reikard [70] found that ANN provided more accurate forecasts compare to an ARIMA method as well as from a hybrid method of ANN coupled with ARIMA. On the other hand, for larger time steps, the ARIMA was the best method (15, 30, 60 min). This is expected since on higher resolutions the forecast is more data dependent making the ANN the better choice, whereas for lower resolutions the diurnal cycle can be captured more effectively by regression methods. Behera et al. [71] applied a single layer feed-forward whose weights were optimized using a particle swarm algorithm. Sharma and Kakkar [72] applied four machine-learning tools, namely FoBa, leapForward, Spikeslab, Cubist and bagEarthGCV for predicting solar irradiance. The underlying methodologies of these models were an adaptive forward-backward greedy algorithm, regression subset selection algorithm, a spikes and slab algorithm, a rule-based multivariate linear modelling, a multivariate adaptive regression splines algorithm, respectively. The results of Spikeslab and Cubist were reported to be stable and accurate for different time horizons. Tang et al. [64] applied a combination of extreme learning machine and entropy method. They reported that this hybrid algorithm performs better than a generalized regression neural network, and a radial basis function neural network, for short-term photovoltaic power forecast. Similarly, Hossain et al. [73] applied an extreme learning machine (ELM) algorithm for predicting power output from a photovoltaic system. They reported a superior performance compared to SVR and ANN benchmarks. Majumder et al. [74] applied Variational Mode Decomposition and Extreme Learning Machine for predicting solar irradiation. The algorithm was reported robust under noisy conditions and despite the presence of outliers in the historical data. Srivastava and Lessmann [75] studied the forecast of global horizontal irradiance (GHI), a measure of the shortwave radiation received which is often used for PV installation. They applied long short term memory (LSTM) neural networks. The average forecast skill of 52.2% over benchmark was reported. Qing and Niu [76] applied LSTM neural networks for hourly day-ahead solar irradiation prediction from weather data. Using experimental data, they demonstrated 18.34 and 42.9% improvements in root mean square error (RMSE), compared to BPNNs, for two datasets. Alzahrani et al. [77] applied deep recurrent neural networks (DRNNs) for forecasting solar irradiance, using real data from Canada. They demonstrated significant improvements over conventional methods such as support vector regression (SVR) models, and feedforward neural networks (FNNs). Li et al. [78] studied short-term solar power forecast. Using correlation coefficients, they identified the solar radiation intensity, atmospheric temperature, and relative humidity as the most correlated variables with the photovoltaic power output. A deep belief network was applied which showed significant improvements over a base-line backpropagation (BP) neural network. Abdel-Nasser and Mahmoud [79] applied long short-term memory recurrent neural network (LSTM-RNN) to forecast solar power generation. Compared to multiple linear regression (MLR) model, bagged regression trees (BRT), and feedforward neural network models, their LSTM-RNN model showed superior performance. Zhang et al. [80] studied several ANN configuration for short term (in the order of minutes) of photovoltaic power generation, namely multi-layer perceptron (MLP), convolutional neural network (CNN), and long short term memory (LSTM) structures. Image data such as the sun intensity, as well as cloud movement and appearance, was applied to forecast the solar power generation. The authors reported root mean squared error (RMSE) of 7%, 12% and 21% for the MLP, LSTM, and CNN configurations, respectively. Wang et al. [81] applied hybrid deterministic and probabilistic models for forecasting photovoltaic power. The deterministic model consisted of wavelet transform (WT) and deep convolutional neural network (DCNN). WT was applied to decompose original signal into several frequency series which were applied for training the DCNN model. The probabilistic model was developed by extending the deterministic model using spine quantile regression (QR). They demonstrated the outperformance of their method using real data from PV farms in Belgium.

Several of the studies presented in Table 2 have applied various types of artificial neural networks with the view to determining the most suiting one. As mentioned above, Fernandez-Jimenez et al. found that the MLP neural network outperformed ELM and RBF architectures [11]. However, in Ref. [90] ELM networks are suggested for time series data forecasting since they exceeded the performance of both the MLP and RBF neural networks. In addition, in Ref. [52] it was similarly established that recurrent architectures (ELM) provide a better performance than the respective linear ones (MLP). Finally, Shi et al. implemented Support Vector Machines (SVM) along with a data classification algorithm that categorises days as sunny, foggy, cloudy and rainy and found promising results particularly for the two former categories [89].

Table 2
Literature concerning solar irradiance and PV power forecasting.

Authors	Forecast horizon	Method Type	Method	Prediction Output	Input
Ridley, Boland and Lauret [82]	Short-term	Statistical	BIC	Diffuse solar radiation	Hourly/Daily Clearness index, Solar altitude, Apparent solar time, Measure of persistence of global radiation levels
Ruiz-Arias et al. [83]	Short-term	Statistical	AR	Solar Irradiance	Global, diffuse solar radiation
Bacher, Madsen and Nielsen [60],	Short-term	Statistical	AR	PV power	NWP, Past power production
Chen et al. [84],	Medium	Artificial intelligence	RBF ANN	PV power	Past power production, NWP (Solar Irradiance, Temperature, Relative Humidity)
İzgi et al. [85]	Very short-term	Artificial intelligence	MLP ANN	PV power	Past power production, Solar Irradiance, Temperature, Relative Humidity
Mellit and Pavan [86]	Short-term	Artificial intelligence	MLP ANN	Solar Irradiance	Solar Irradiance, Temperature
Mellit, Benghanem and Kalogirou [87]	Short-term	Artificial intelligence	MLP ANN	PV power	Solar Irradiation, Temperature, Relative Humidity
Mellit et al. [88]	Short-term	Artificial intelligence	FNN	Solar Irradiance	Air Temperature, Relative humidity, Direct, Diffuse Global irradiance, Sunshine duration
Martín et al. [10]	Medium	Artificial intelligence	AR, ANN, ANFIS	Solar Thermal Plants	Ground Solar Radiation (hourly), Clearness index, Lost component
Shi et al. [89]	Short-term	Artificial intelligence	SVM with weather classification	PV power	NWP, Past power production
Yona et al. [90]	Short-term	Artificial intelligence	ANN (MLP, RBF, ELM)	PV power	Global Solar Radiation, Temperature, Atmospheric pressure, Humidity, Cloud amount, Wind speed, and Rainfall
Ding, Wang and Bi [91]	Short-term	Artificial intelligence	ANN	PV power	Past power production, Meteorological Data
Salcedo-Sanz et al. [69]	Short-term	Artificial Intelligence	ELM, SVR, GPR, Bagged Trees	Solar Irradiance	NWP
Sfetsos and Coonick [92]	Short-term	Artificial intelligence, Hybrid	ANN (MLP, ELM, RBF), ANFIS, ARMA	PV power	Solar Radiation, Time indicator
Reikard [70]	Short-term	Artificial intelligence, Hybrid	ARIMA, ANN, ARIMA-ANN	Solar Irradiance	Solar Irradiation, Temperature, Relative Humidity, Cloud cover
Mellit et al. [93]	Medium	Artificial intelligence, Hybrid	ANFIS, ANN (MLP, RBF)	Mean monthly clearness indexes, daily solar radiation	Latitude, Longitude, Altitude
Fernandez-Jimenez et al. [11]	Short-term	Hybrid	kNN, ANN (MLP, RBF,ELM), ANFIS, ARIMA	PV power	Year moment, Past power production, NWP (×2) [Solar power surface sensible heat flux, Surface latent heat flux, Surface downward shortwave radiation, Surface downward longwave radiation, Top outgoing shortwave radiation, Top outgoing longwave radiation, Temperature]
Pedro and Coimbra [62]	Short-term	Hybrid	GA-ANN, ANN, ARIMA, kNN	PV power	Past power production

Table 3
Literature concerning demand forecasting.

Authors	Forecast horizon	Method Type	Method	Input
Taylor [100]	Short-Term	Statistical	ARMA, EXS	Historic Load Data
Taylor, de Menezes and McSharry [101]	Short-Term	Statistical	EXS, PCA	Historic Load Data
Taylor and Buizza [102]	Short-Term	Statistical	ARMA	Historic Load Data, NWPs, Weather data
Gould et al. [103]	Short\Medium Term	Statistical	EXS	Historic Load Data
Al-Hamadi and Soliman [104]	Short-Term	Statistical	Kalman Filtering	Historic Load & Weather Data, Current Weather Data
Taylor and Mcsharry [105]	Short-Term	Statistical	ARIMA, AR, EXS, PCA	Historic Load Data
Taylor [95]	Very short-term	Statistical	ARIMA, AR, EXS, PCA	Historic Load Data
Villalba and Alvarez [106]	Short-Term	Artificial Intelligence	ANN	Historic Load Data
Wang et al. [107]	Short-Term	Artificial Intelligence	ε-SVR	Historic Load Data
Zheng, Zhu and Zou [108]	Short-Term	Artificial Intelligence	SVM	Historic Load Data
Badri, Ameli and Motie Birjandi [109]	Short-Term	Artificial Intelligence	ANN, FLS	Historic Load Data
Ho et al. [110]	Short-Term	Artificial Intelligence	ES	Historic Load & Weather Data
Galarniotis et al. [111]	Short-Term	Artificial Intelligence	ELM, FIR	Historic Load Data
Hong, Pinson, and Fan [55]	Short-Term	Artificial Intelligence	ANN, GPR	Historic Load Data, Temperature
Shu and Luonan [112]	Short-Term	Hybrid	SOM-SVM	Historic Load Data
Zhang and Dong [113]	Short-Term	Hybrid	ANN-Wavelet	Historic Load Data
Song et al. [114]	Short-Term	Hybrid	FLS	Historic Load Data

1.3. Predicting power demand

Predicting electricity load has been the focus of intense research too. The conducted research is inherently multifaceted, and include input selection, predictive model type and structure, training algorithm, dynamic learning, and the implications of electricity deregulation for the price [94]. Table 3 summarizes the research in the field. Broadly speaking, the prediction horizon can be divided into very short-term, short-term, mid-term and long-term, each with a different set of decision variables (Table 1). Amongst these, short-term (hours to a day) prediction of electricity demand has significant implication for the optimal operation of electricity grids, as it has similar time-scale when significant fluctuations occur during stochastic wind and solar power generation. Overall, with regard to the inputs used for demand forecasting, historical load data is essential and in some cases, meteorological information is utilised. The former is of greatest significance in very short-term forecasting (10–30 min), whereas for greater time intervals the weather data becomes increasingly important [95]. For instance, Drezga and Rahman studied the optimal variables selection for short-term load forecast using the so-called phase-space embedding method. The input variables applied for training the neural network included electricity load, temperature, as well as daily and half-daily cycles, at different time intervals. They demonstrated that with appropriate selection of only 15 inputs, high accuracy could be achieved for predicting power load on working days and weekends [96]. Sovann et al. [97] applied Autocorrelation (ACF), partial autocorrelation (PACF), and cross-correlation (CCF) in order to identify the best-suited input variables for the neural network-based forecast of electricity load. They reported that a combination of time indicators, lagged load, and weather variables such as dry bulb and dew point temperature provided the best performance. Tao et al. [98], proposed a method based on correlation clustering. The idea is that assigning consumers with similar demand behaviour can improve the overall demand forecast. Recently, nonconventional variables were proposed for power consumption prediction. For instance, Vinagre et al. [99] demonstrated that solar radiation serves as a good indicator of energy consumption for in a building.

The examples of the machine-learning methods applied for load forecast include time series [115], linear regression [116], moving average [117], wavelet transforms [118], support vector regression (SVR) [119], Gaussian process regression (GPR) [120], Fuzzy models [121], Artificial Neural Networks (ANNs) [94], and expert systems [122,123]. Artificial neural networks have been broadly used for demand forecasting. Hippert et al. [124] presented a review of the load forecasting methods. In Refs. [111,125], a comparative study was conducted with regard to the MLP, FIR and ELM neural networks. It was established that ELM and FIR are more capable in forecasting time series than MLP, with the latter of the two producing the best results. It should be mentioned that neural networks outperform FL models due to their ability to compute nonlinearity in the data [109]. Support Vector Machines and Regression have also been extensively used in load forecasting [107,108,112]. Support vector regression was applied to a smoothed and pre-processed dataset of the load corresponding to East China, the results of which were further developed in order to account for the seasonal variations [107]. Three different Support Vector Machines were compared in Ref. [108], namely a Gaussian wavelet SVM, a conventional Gaussian SVM and a Morlet wavelet SVM, and it was found that the former had a superior performance both in accuracy and speed. Hong et al. [55] reported a forecasting competition where several techniques were considered in order to forecast the load for a number of different horizons by using historical data and temperature information. Amongst the various methods developed, GPR was found the best in terms of accuracy. Almeshaiei and Soltan [117] proposed a method based on decomposition and segmentation of the electricity time series for daily load forecast. They demonstrated their method on a case study from Kuwaiti electric network. Outliers in historical load data could severely degrade the accuracy of forecast. With the view of overcoming this challenges, Zhang et al. [126] proposed a method based on spatial-temporal feature clustering, and demonstrated its effectiveness. What is more, the volume of data has an impact on the accuracy of the forecasting models; when sufficient data on load was provided that could represent not only the weekly and daily patterns but also the respective annual ones, the accuracy of the statistical model used (ARMA) increased significantly [100]. With a view to establishing the most suitable statistical methods, a comparative study was carried out by Taylor and McSharry and it was found that exponential smoothing outperformed the ARIMA, AR, and PCA models [105]. Coelho et al. [121] proposed a hybrid model with adaptive parameter update using an evolutionary bio-inspired optimization algorithm. They described the method computationally efficient and accurate for predicting short-term electricity load. Hong [127] applied a hybrid method consisting of recurrent neural networks (RNNs), support vector regression (SVR), chaotic artificial bee colony algorithm. Such hybrid algorithm offers several desirable functionalities such as seasonal classification and adjustment, recurrent calculations, and chaotic sequence to enable seasonal and monthly electricity forecast. Dedinec et al. [128] applied a deep belief network (DBN) consisting of multiple layers of restricted Boltzmann machines for forecasting electricity load. The author demonstrated the performance of their method using real data from the Macedonian system operator (MEPSO), which showed between 8.6% and 21% reduction in the absolute percentage error (MAPE) compared to a typical feed-forward multi-layer perceptron neural network. Shi et al. [129] applied a deep learning algorithm for the two power load forecast scenarios of aggregated demand in New England, and 100 individual households in Ireland. They reported up to 23% improvements in the aggregated case, and 5% improvement in the disaggregated case compared to a "shallow neural network" benchmark.

Hernández et al. [130] applied a multi-agent architecture based on multi-layer perceptrons (MLP) neural network, in the context of virtual power plants for collaborative load forecast. Javed et al. [131] proposed a multiple load forecasting model which combines individual time-series into a single model, using ANNs and SVMs. They demonstrated that such aggregated model is superior for predicting short-term demand. Critical reviews of demand forecasting, dynamic pricing and demand side management is recently presented by Khan et al. [4], Raza et al. [94], and Hernandez et al. [132].

A close research area is concerned with the electricity price forecasting. In a deregulated market, this price is closely related to the deficit and surplus between supply and demand. By the emergence of renewable power from wind and solar, the electricity supply-demand balance has become more and more uncertain. Therefore, the electricity price forecast has been the subject of intensive research. While a comprehensive review of these methods is beyond the scope of this article, Weron and Nowotarski have provided extensive reviews and recent updates [133,134] for electricity price forecasting. More recent studies have focused on hybrid methods. Yang et al. [135] applied the kernel extreme learning machine (KELM) and autoregressive moving average (ARMA) for forecasting electricity price. The parameters of KELM are optimized using a particle swarm optimization algorithm and therefore, the overall framework is self-adaptive. The performance of the method was demonstrated on a few case studies from the US, Spain, and Australia. Inspired by the field of chemical reaction optimization, Abedinia et al. [136] proposed a combinatorial neural network (CNN) framework, in which the parameters of CNN are optimized by a stochastic search algorithm. Wang et al. [137] developed a hybrid framework based on empirical mode decomposition, variational mode decomposition, and neural networks. The developed method proved efficient for multi-step prediction of the electricity prices in several case studies from France and Australia. Amjady and Daraeepour [138] proposed that due to the interrelation between the electricity demand and price, it is more effective to forecast them simultaneously. They applied mutual information (MI) for the selection of inputs, and a cascaded neuro-evolutionary algorithm for learning. Ghasemi et ai [139], for forecasting electricity price and load. They applied a hybrid algorithm in which Conditional Mutual Information (CMI) and adjacent features were applied for input selection. The input signals were decomposed into several terms using Flexible Wavelet Packet Transform (FWPT). Finally, nonlinear least square support vector machine (NLSSVM) and autoregressive integrated moving average (ARIMA) were applied for learning.

The above-mentioned artificial neural network models fall in the category of deterministic machine-learning methods. In the recent years, the deterministic methods are developed further to include the confidence intervals of predictions too, known as probabilistic forecasting methods. The probabilistic forecasting methods could be based on scenario with assigned probability, or in the form of probabilities of quantiles, intervals, or density functions [140]. While presenting a thorough review of these methods is not in the scope of the present publication, interested readers are referred to recent reviews by Hong and Fan [140], Zhang et al. [141], and van der Meer and Munkhammar [142].

Finally, it should be noted that the application of forecasting method is gaining wide-spread acceptance in power and energy industry. Examples of lateral application include occupancy prediction of office buildings [143], State of charge estimation for electric vehicle [144] the estimation of energy consumption in buildings using solar data [145], and forecasting the of district heating consumption [146], security assessment of power systems [147], and restoring microgrids after fault occurrence [148].

Despite the broad research in the literature, a comprehensive analysis where the performance of all the key machine-learning algorithms is compared against a consistent set of data is missing. The key contribution of this study is to exhaustively compare the three machine-learning methods of ANN, GPR, and SVR against a comprehensive set of solar, wind and demand data, hence illustrating the challenges that need to be overcome and quantifying the performance of each method.

In the first part of this publication, an introduction was presented that puts the research in context. The next section outlines the methodology that was followed throughout this research, starting with the data pre-processing steps that were required prior to performing any prediction, and continuing with the exact procedures with which the predictive models were tuned and built. The third section will present the results and is split into five categories, namely wind power prediction, solar power prediction, electricity demand prediction and the comparison of results. The final section summarizes the observations and proposes future research directions.

2. Methodology

The research methodology is presented in two parts. The first part describes the data acquisition and pre-processing. The second part reports the employed machine-learning algorithms and their implementation methods. More details are provided in the online Supplementary Materials.

2.1. Data pre-processing

As the objective of this research was to develop data-driven models that can produce relatively accurate predictions for the wind power, solar power, and electricity demand, the acquisition, and processing of data is one of the most important aspects of the present research, to which special attention is paid. In the next subsections the data that was used in this study will be introduced, followed by an elaboration on the procedures that were implemented with regard to its processing. More specifically, the topics of normalisation, cleaning, time series data clustering, and correlation analysis will be covered. The former two are procedures which are more often than not implemented with every data training technique, and are to large extent common for data pre-processing. Data clustering was required specifically for the electricity demand, in order to construct the training datasets. Finally, the correlation analysis was one of the most important parts of the present research, as it provided an insight for the lags that were used by the predictive NARX models.

Table 4 summarizes different inputs available in the present study, for each type of model training and validation, more specifically, the data used for wind power prediction included the wind power, the wind speed at 10 m above ground level at the specific location, and the

Table 4
Inputs used for wind power, solar power, and electricity demand forecasting.

Input Vectors	Wind Power Prediction	Solar Power Prediction	Electricity Demand Prediction
Hourly Variable	✓	✓	✓
Seasonal Variable	✓	✓	✓
Wind Power (KW)	✓		
Solar Power (KW)		✓	
Electricity Energy [Wmin]			✓
Temperature (°C)	✓	✓	
Wind Speed at 10 m $\left(\frac{m}{s}\right)$	✓		
Direct irradiance (KW)		✓	
Diffuse irradiance(KW)		✓	

Table 5
The option used for the ninja renewables simulations.

Required details for simulation	Values
Latitude [°]	51.379
Longitude [°]	1.441
Wind turbine capacity [kW]	1
Wind Turbine Hub Height [m]	58
Wind Turbine Model	Vestas V80 2000
Solar panel capacity [kW]	1
Solar Azimuth [°]	164.3853
Solar Pitch [°]	38.67047

temperature. For the solar power prediction, the inputs include direct and diffuse irradiance, as well as the temperature. Finally, the only information applied for the demand is the hourly measurement of consumed electrical energy per household.

The wind and solar data were acquired from the ninja renewables website [149] and the details that were input can be observed in Table 5. Here, the location shown corresponds to a southeast location of the UK, namely Canterbury. For the wind simulations, one of the most commonly used onshore wind turbines was used, a Vestas V80 [150,151]. The dataset covered the years from 1985 to 2014.

The demand data used for this study was hourly measurements of electrical energy of 1157 households which was made available by Hildebrand Technology. Based on a confidentiality agreement, the data did not have any information with regard to the location of the households, and it was not possible to associate any meteorological information to it. The period covered by the dataset was from the 1st June of 2013 until the 30th of May 2016 and the electrical energy was measured in [$Wmin$]. The electricity demand data was clustered with a view to extracting representative consumer patterns which were used as an input in the predictive data-driven methods.

Normalisation is particularly important for most machine-learning methods; as non-normalised data can result in computationally ill-conditioned calculations. A representative example of this is with neural networks with a sigmoid activation function, for which, if the values of t are large, the gradient of $f(t)$ will become very small. This makes the training procedure unproductive and inefficient. The algorithm that was chosen for the classification of the demand data was the K-Spectral Centroid, which is a partitioning method based on the k-means approach that classifies data with regard to their shapes. The MATLAB code was available from the Stanford Network Analysis Project (SNAP) [152].

2.2. Forecasting methods

In forecasting a time series with a data-driven approach, there are three types of architectures that can be used, namely the input-output approach (I—O), the non-linear autoregressive (NAR) and the nonlinear autoregressive with exogenous inputs (NARX). The main difference between these architectures is the type of data each method accepts as inputs. The former uses any kind of input except the past value of the target series. The second approach uses only the past values of the target series, and finally the latter uses both the target's previous values as well as exogenous inputs. It can be easily seen that the NARX procedure outperforms the former two when the exogenous inputs are correlated to the targets, as it carries more information about the system. These three main types of models are listed in the following.

$$y(t+p) = f(x(t),\ x(t-1),\ldots,x(t-d_x)) \tag{1}$$

$$y(t+p) = f(y(t),\ y(t-1),\ldots,y(t-d_y)) \tag{2}$$

$$y(t+p) = f(x(t),\ x(t-1),\ldots,x(t-d_x), y(t),\ y(t-1),\ldots,y(t-d_y)) \tag{3}$$

where $y(t)$ is the output time series of the dependent variable that is predicted (in this case wind power output, solar power output and electricity demand), $f(\cdot)$ represents the "black box" model used for prediction. $x(t)$ is the input time series (independent variable). d_y and d_x are the feedback and input delays which correspond to the number of past values of the target or the inputs, respectively, that are used for the prediction of the future value. p represents the number of steps ahead for which the future behaviour is being predicted ($p \geq 1$).

The present research examines the performance of artificial neural networks (ANN), support vector regression (SVR) and Gaussian process regression (GPR) for predicting power generation from wind and solar energy, as well as the stochastic behaviour of electricity demand. These methods were chosen for various reasons that were associated with either their proven good performance (ANN, SVR) or their potential to provide high accuracy forecasts and black-box models in other applications (GPR).

2.2.1. Artificial neural networks

Artificial neural networks (ANNs) are developed in analogies with the architecture of the human brain, enabling it to interpret a great amount of data and transform them into actionable knowledge [153]. The thorough survey of literature presented earlier, suggests that for the prediction of time series, dynamical neural networks are most efficient as they can be trained and tuned to predict time-dependent data. Amongst the various developments of dynamical neural networks, the Non-linear AutoRegressive model with exogenous inputs (NARX) neural network has gained great popularity in the research community [154–159].

In order to obtain a neural network that is both accurate and effective in terms of computational cost, there are many parameters that are required to be tuned and many options that need to be selected. More specifically, prior to training a NARX neural network, the two key parameters of the autoregressive model, namely the input (d_x) and feedback (d_y) delays need to be determined as well as the number of neurons in the hidden layer. Upon finding the optimal architecture, the next step is to find the appropriate training method. As will be seen in the results section, a fully connected ANN with a single hidden layer would suffice for accurate modelling of power generation from wind and solar energy, as well as electricity demand. While detailed comparison of various ANN methods is beyond the scope of the present study, the research results are generalizable in the sense that more complex neural network architectures could also achieve a similar or better performance. The overall procedure that was followed in the present research, in order to build the NARX models for every one of the three prediction studies (wind, solar and demand forecasting) is depicted in Fig. 1. It should be noted that in principle, the optimal values of the input delays, the feedback delays and the number of neurons in the hidden layer are all interrelated. However, simultaneous optimization of these structural parameters poses a formidable bi-level optimization problem, as they are indeed hyper-parameters, and their values must be fixed before the training process could start. Nevertheless, as will be shown in Results section, even under the simplifying assumption that they could be optimized independently, excellent results can be achieved. The artificial neural networks were implemented using the Neural Network Toolbox™, and the Optimization Toolbox™ (for the case of the genetic algorithm) in MATLAB. The options for stochastic gradient descent (SGD) were activated in order to manage the computational costs.

Neural networks are highly efficient in predicting empirical data. It is shown that for a sufficiently large number of neurones, even only one hidden layer suffices to simulate any nonlinear function from a compact input set [160–162]. Therefore, in order to minimise the training effort and without loss of generality, the neural networks designed in this research consisted of a single layer. Then the number of neurons in the hidden layer of the neural network were optimized until no further improvement was achieved. In order to set the input and feedback

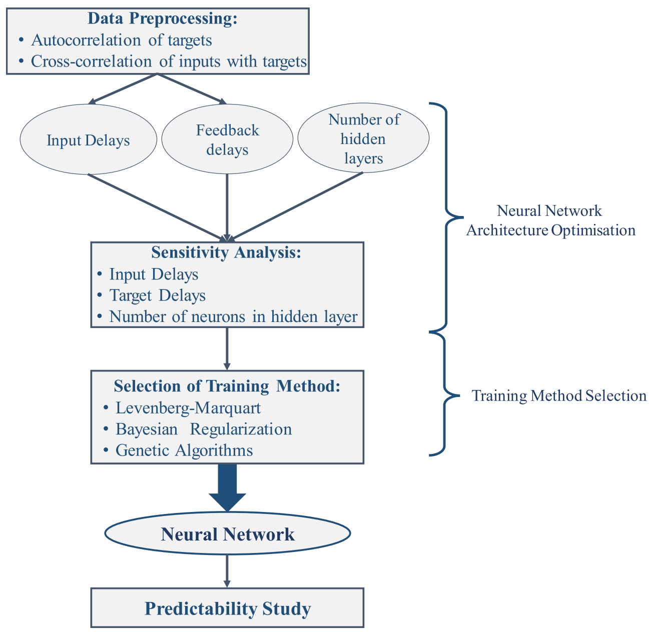

Fig. 1. Framework for tuning NARX neural network parameters and selecting the training method.

delays, a correlation analysis was performed on the data, and then through a trial and error procedure, the best performing delays were selected for each model [154,157]. It should be noted that artificial neural networks often suffer the two problems of overfitting and premature convergence to local solutions. In order to tackle these issues, the ANN model was first trained with a Genetic Algorithm (GA), and then its solution was applied as the initial guess for the Levenberg-Marquardt and Bayesian Regularization methods. The justification is that GA is a stochastic global optimization algorithm and is efficient in handling local solutions, while the role of the other two methods is to refine the solution. In order to handle the overfitting issues, prior to the training procedures, the available data was split into three subsets, namely the training set (typically 70%), the validation set (15%) and finally the testing set (15%). The training algorithm uses the training set to update the weights and biases of the neural network by minimising the mean squared error. At the same time, however, an additional mean squared error is calculated which corresponds to the validation data. In the beginning of the training procedure, both of these errors drop, but as the neural network becomes more and more tuned to the training data, the validation error will start increasing. From the moment this happens, the training algorithm runs for a predetermined number of times. If by the time it has ran for this number of steps, the validation error does not decrease, the training terminates and the weights and biases that correspond to the lowest validation error (that occurred during those iterations) are returned. The testing data is utilised after the training is completed, in order to examine the network's performance. This procedure is referred to as early stopping, since the training algorithm terminates prior to reaching the optimal point [163].

2.2.2. *Support vector regression (SVR)*

Support vector machines are a renowned classification algorithm, which categorise data accurately, do not have any difficulty with the number of dimensions of data and require only a small training sample, but they are computationally demanding if caution is not taken [164]. By applying minor alterations this method can be also implemented for regression purposes [165,166]. Support Vector Machines and ε-SVR are applicable to static problems, and therefore, the black box models that can be built through this method can only be used for simulation. In order to make step-ahead predictions further modifications need to be made, in order to build a NARX architecture for the SVR that could give a dynamic effect to the model. In the present research, a toolbox developed in KU Leuven was employed, which is based on the Least Squared Support Vector Regression (LS-SVR) methodology, and allows the development of a dynamical model [167,168].

2.2.3. *Gaussian Process Regression (GPR)*

Gaussian Process Regression (GPR) is a non-parametric probabilistic kernel model. This machine-learning method has gained more and more ground in the literature over the past few years [169]. This method not only can be applied for prediction, but also can provide the confidence interval for each point in the prediction which quantifies the uncertainty of the forecast. Essentially, a Gaussian process is generalisation of the respective probability distribution. The Gaussian distribution takes an input vector and computes its probability whose characteristics are a mean and variance. The probability of an input time series vector, for each time step, is computed. Therefore instead of having a mean and variance that are scalars, the GPR model calculates a mean and covariance vector [169–171]. It should be mentioned that the GPR, similarly to SVR, cannot dynamically predict ahead as it is not a dynamic algorithm. For this purpose, a toolbox developed by Stepančič and Kocijan [172] was applied in this study that can build a NARX architecture and allows predictions to be made for any time horizon.

3. Results and discussion

This section presents the results. It is divided into four sections which correspond to the three different types of predictions that were conducted, namely wind power, solar power, and electricity demand forecasting, followed by the last section in which a comparison of the different models and datasets is made. For each type of prediction, the structure of the results begins with firstly demonstrating the various features of the data and follows with evaluating the performance of the various predictive analytics methods. The various inputs used for each case of wind power, solar power, and electricity consumption forecasting are given in Table 6. It should be mentioned that throughout this paper a prediction time step is equivalent to an hour. Moreover, the term "model" is used to denote the black box model that is fed by the inputs of the present time and predicts the response of the system at the present time, meaning that no forecasting takes place.

3.1. *Wind power forecast*

3.1.1. *Data pre-processing*

In Table 7 the maximum absolute value for each cross-correlation is given, in order to quantify the dependence of wind power with regard to each input. It can be seen that wind power is directly dependent on wind speed (Fig. 2b), whereas the correlation with hourly (time) variable is weak (Fig. 2e). This is expected since wind speed is the driving force of the turbines, and even though wind is a result of the

Table 6
Inputs used for wind power, solar power, and electricity demand forecasting.

Input Vectors	Wind Power Prediction	Solar Power Prediction	Electricity Demand Prediction
Hourly Variable	✓	✓	✓
Seasonal Variable	✓	✓	✓
Wind Power (KW)	✓		
Solar Power (KW)		✓	
Electricity Energy [Wmin]			✓
Temperature (°C)	✓	✓	
Wind Speed at 10 m $\left(\frac{m}{s}\right)$	✓		
Direct irradiance (KW)		✓	
Diffuse irradiance(KW)		✓	

Table 7
Maximum absolute cross-correlations for input data used for wind power prediction.

Input	Maximum absolute correlation
Hourly variable	−0.026563
Seasonal variable	−0.205345
Wind Speed	0.979487
Temperature	−0.206958

temperature gradients caused by solar irradiance, the time of the day seems to have an indirect and random interrelationship with power. However, it can be seen that the time of the year (Fig. 2d) as well as the temperature (Fig. 2c) influence the wind power.

3.1.2. Forecasting wind power with artificial neural networks (ANN)

For the implementation of neural networks, firstly a sensitivity analysis was conducted with which the delays of the network as well as the number of hidden neurons were determined. Moreover, the response of the selected neural network was tested for a number of different time horizons. In order to select the most fitting value for each instance, two factors were taken into consideration. Firstly, the mean square error (MSE) of the neural network's response with regard to the testing data for the 1-h ahead prediction was taken into consideration, which is depicted in the vertical axis of Fig. 3a–c. Secondly, the error's autocorrelation and cross-correlation with each input were calculated as graphically presented in Fig. 2d–f for each simulation, and the simulation for which the most of the correlations that were within limits was selected. In particular, especially for the neural networks whose response did not significantly change, the second factor was utilised to make a selection.

Fig. 3a–c shows that there is a point beyond which the performance of the neural network did not significantly change, as the input delays, the feedback delays and the number of neurons in the hidden layer increased. Therefore, the aforementioned second factor was taken into consideration and the characteristics of the neural network that were chosen were 10 input delays, 12 feedback delays and 10 neurons within the hidden layer.

With regard to the predictability analysis, different neural networks were developed for each time horizon. The accuracy as well as the regression values of these neural networks are given in Table 8, and are represented in Fig. 3. d.

As expected, the accuracy and the fitting capability of the model drops as the time horizon of the prediction increases, since the model is given no knowledge for the interval between the current state and the time horizon of the prediction. This can also be observed in Fig. 3e and f, where the response of the neural network is given for all the predicted time horizons that were tested. The cooler colours denote the shorter time horizons and it can be observed that they are closer to the target series (black line). It seems that the neural network's response becomes less smooth as we move along to longer prediction steps. The forecasting errors of the ANN models for predicting the wind power

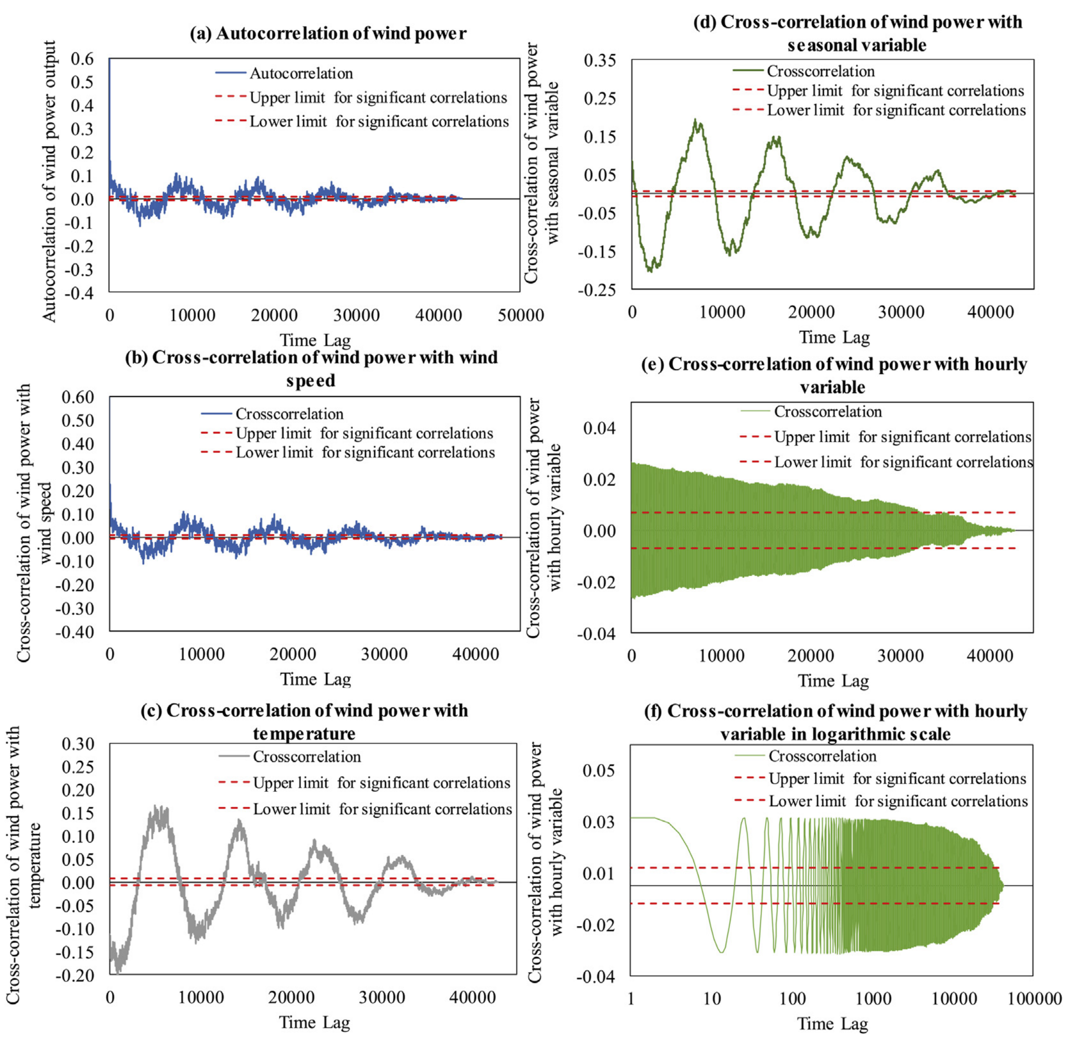

Fig. 2. Cross-correlations for input data applied for the wind power prediction.

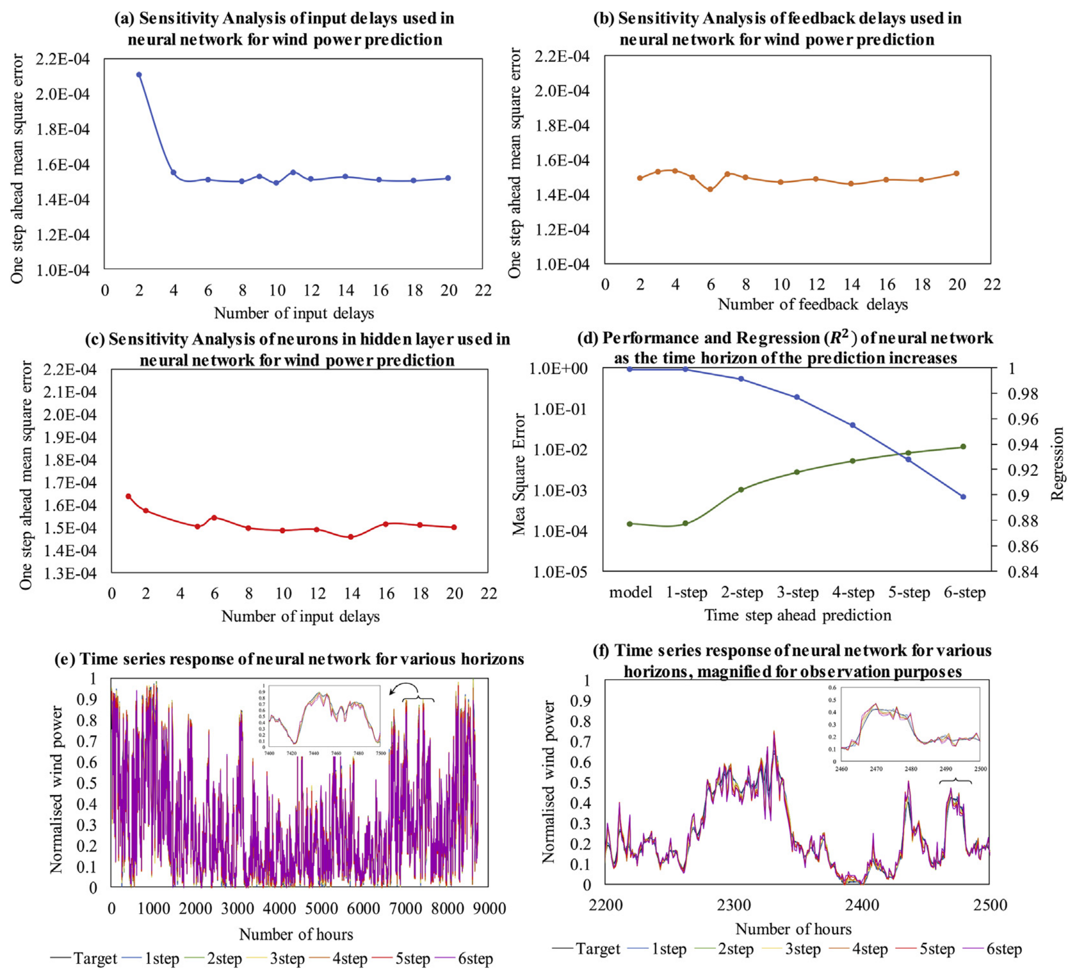

Fig. 3. The sensitivity analysis and performance of ANN for wind power prediction.

Table 8
Regression and MSE values for various time horizons regarding wind power prediction with neural networks.

Time horizon	Regression (R^2)	Mean Square Error
model	0.99874	1.4473E-04
1-step	0.99874	1.4560E-04
2-step	0.9914	9.9105E-04
3-step	0.97675	2.7000E-03
4-step	0.95477	5.1000E-03
5-step	0.92761	0.0081
6-step	0.89807	0.0113

generation are reported in the second column of Table 9.

3.1.3. Forecasting wind power with support vector regression

As the SVR machine-learning method is stationary, it cannot be directly implemented to a time series problem that will be built to forecast. For this reason, a different toolbox from the default respective one in MATLAB (ε-SVR) was utilised that could use a NARX architecture in conjunction with LS-SVR for time series forecasting.

The sensitivity analysis that took place for tuning the SVR was done for the MATLAB toolbox (ε-SVR) in which the three available kernel functions were tried, namely the linear, the polynomial and the radial basis function (RBF). Upon testing the various available kernels, it was found that the RBF was more suited for this case.

In Table 10, the performance indicator is given for all the time horizons for which predictions were conducted. As mentioned earlier, the Model (ε-SVR) is stationary, i.e., with an input at a given time provides the response of the system for the same time. As can be seen in Fig. 4 a, the Model (ε-SVR) has a much greater error than when the LS-SVR predicts 1 h ahead. This observation should be attributed to the fact that the ε-SVR does not have an autoregressive architecture, which means that to make a prediction this method uses only the input that is specific to that particular time, and does not use the past values of the target series at all. The time-series responses for each time horizon are given in Fig. 4. b, and magnified in Fig. 4. c, for various time steps. Similar to the neural networks, as the time horizon of the prediction increases, the accuracy of the model decreases.

Table 9
The performance of ANN training algorithms for wind power generation, solar power generation and electricity demand.

	Training error for wind power prediction	Training error for solar power prediction	Training error for electricity demand
Levenberg-Marquardt	0.000147	0.00032439	0.000846
Bayesian Regularization	0.00014342	0.00026489	0.000747
Genetic Algorithm	0.0108	0.0252	0.0364

Table 10
MSE values for various time horizons regarding wind power prediction with SVR.

Time horizon	Mean Square Error (Testing)
Model (ε-SVR)	0.000797
1-step (NARX LS-SVR)	0.0000503
2-step (NARX LS-SVR)	0.0024
3-step (NARX LS-SVR)	0.0062
4-step (NARX LS-SVR)	0.0093

3.1.4. Forecasting wind power with Gaussian Regression Process

The sensitivity analysis conducted for the GPR included the establishment of the best kernel function that could be used to predict the response of the wind power as it was given an input vector that included the hourly variable, the seasonal variable, the wind speed and the temperature. The kernels that were tested are the ones listed as well as the performance of the model for each one of the cases is listed in Table 11. The best testing performance was provided by the kernel Matern 32, although the best training performance was given from ARD Matern 32. It can be observed that there is a trend in the listed performances which signifies that the ARD kernels give a good training performance, but their testing performance is degraded, whereas the others have the opposite effect except for the squared exponential that seems to have a similar training and testing performance. Since it is sought to have good generalisation in the designed models, the testing performance is prioritised and therefore for wind power prediction the kernel Matern 32 was selected. Finally, in Fig. 5 the response of the GPR model for wind power prediction is represented and it can be noticed that overall the GPR captures the data very well and the target series lies always within the confidence intervals. Furthermore, it seems that there is more uncertainty associated with the time the wind power reaches local maxima and minima.

Table 11
Training and Testing Performance of GPR for various kernel functions for wind power prediction.

Kernel function	Training Performance (MSE)	Testing Performance (MSE)
Squared exponential	8.0220E-04	8.2141E-04
Matern 32	8.2351E-04	7.5198E-04
Matern 52	8.0885E-04	7.9520E-04
ARD Squared Exponential	7.8194E-04	8.4339E-04
ARD Matern 32	7.8154E-04	8.4127E-04
ARD Matern 52	7.8162E-04	8.4274E-04

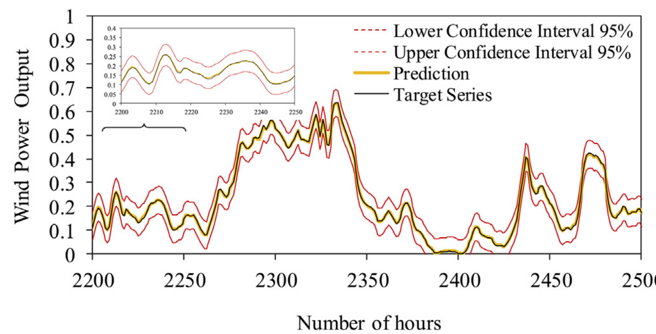

Fig. 5. Time series response of GPR for wind power prediction (present time) magnified for observation purposes.

3.2. Solar power forecast

3.2.1. Data pre-processing

The methodology and the steps required for solar power prediction are identical to the respective ones conducted for wind power prediction. This is due to the fact that the data were acquired from the same source, and therefore the same pre-processing steps were needed. However, due to the discontinuous nature of solar power, the results gained from this dataset were quite different.

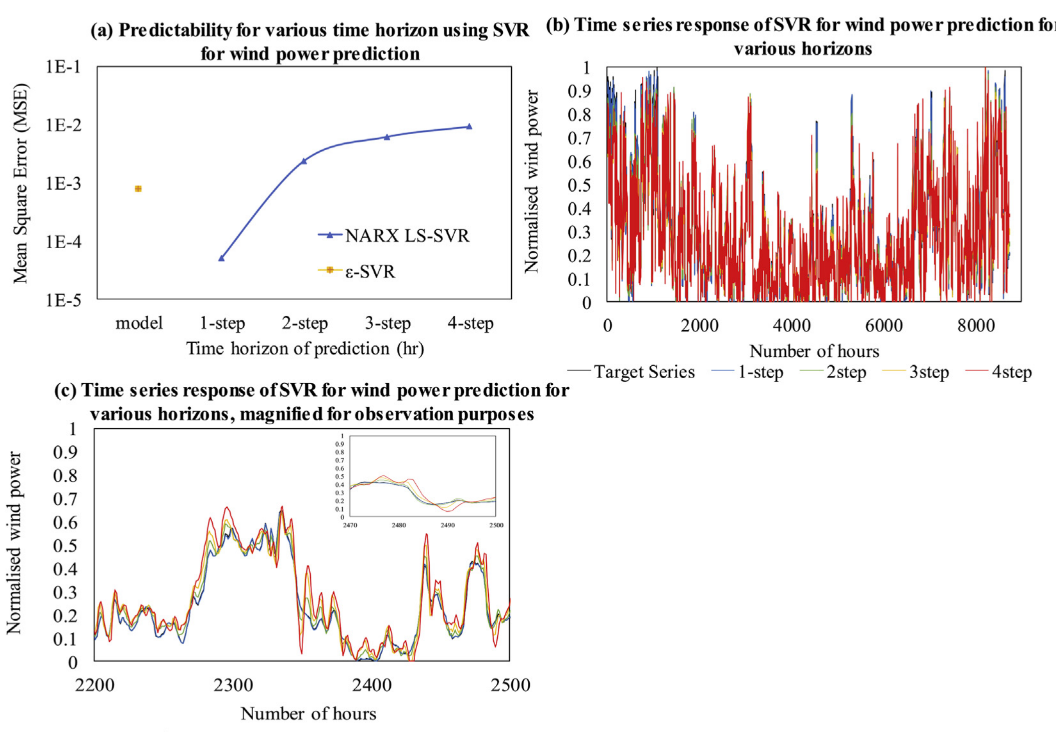

Fig. 4. The sensitivity analysis and performance of the SVR for wind power prediction.

Table 12
Maximum absolute cross-correlations for input data used for solar power prediction.

Input	Maximum absolute correlation
Hourly variable	0.612193
Seasonal variable	0.241428
Direct Irradiance	0.963682
Diffuse Irradiance	0.812037
Temperature	0.432654

In Table 12 the maximum absolute cross-correlations of the solar power with each respective input are given. It should be noted that the reason the autocorrelation is not included in this table is that its maximum value is always 1 and corresponds to the zero-time lag (Fig. 6 a). Equivalently to wind power, the two variables that seem to be related more closely to the solar power output are the direct and diffuse irradiance (Fig. 6. b). The temporal variables and temperature have an entirely different relation, though. The time of the day has a greater effect on the solar power output than the time of the year, which is expected as the photovoltaics have a discontinuous response; they produce energy during daylight only (Fig. 6c-f).

3.2.2. Forecasting solar power with artificial neural networks

The framework in Fig. 1 was followed to establish the ANN's architecture. More specifically, the feedback delays (Fig. 7 a) were first studied, followed by the input delays (Fig. 7. b), and the number of neurons within the hidden layer (Fig. 7. c). By allowing these parameters to take various values a nonlinear response can be observed, which is distinctively different from respective sensitivity analyses conducted for the case of wind power. In addition, it should be mentioned that even though in Fig. 7. c it seems that if the number of neurons was increased, the accuracy of the ANN could further improve, this was not pursued since the model became very computationally expensive when the number of hidden neurons took a value over 14. The parameters that were selected for the neural network's architecture were 12 input delays, 12 feedback delays and 14 neurons within the hidden layer.

With a view to generating predictions for various future time horizons, six different NARX neural networks were constructed. The performance of each of these networks is listed in Table 13. It can easily be identified that the accuracy of the neural network decreases as the time horizon increases. This trend can be observed additionally from the response of the neural networks for the various time horizons which is visualized in Fig. 7. d. The 1-h ahead closely follows the target series and shows a very good performance, followed by the 2-h ahead prediction, which although in general, it captures the target series well, there are some instances for which it did not converge to the desired value. From 3 h and further, although for some days a satisfactory accuracy is achieved, there are numerous instances for which the

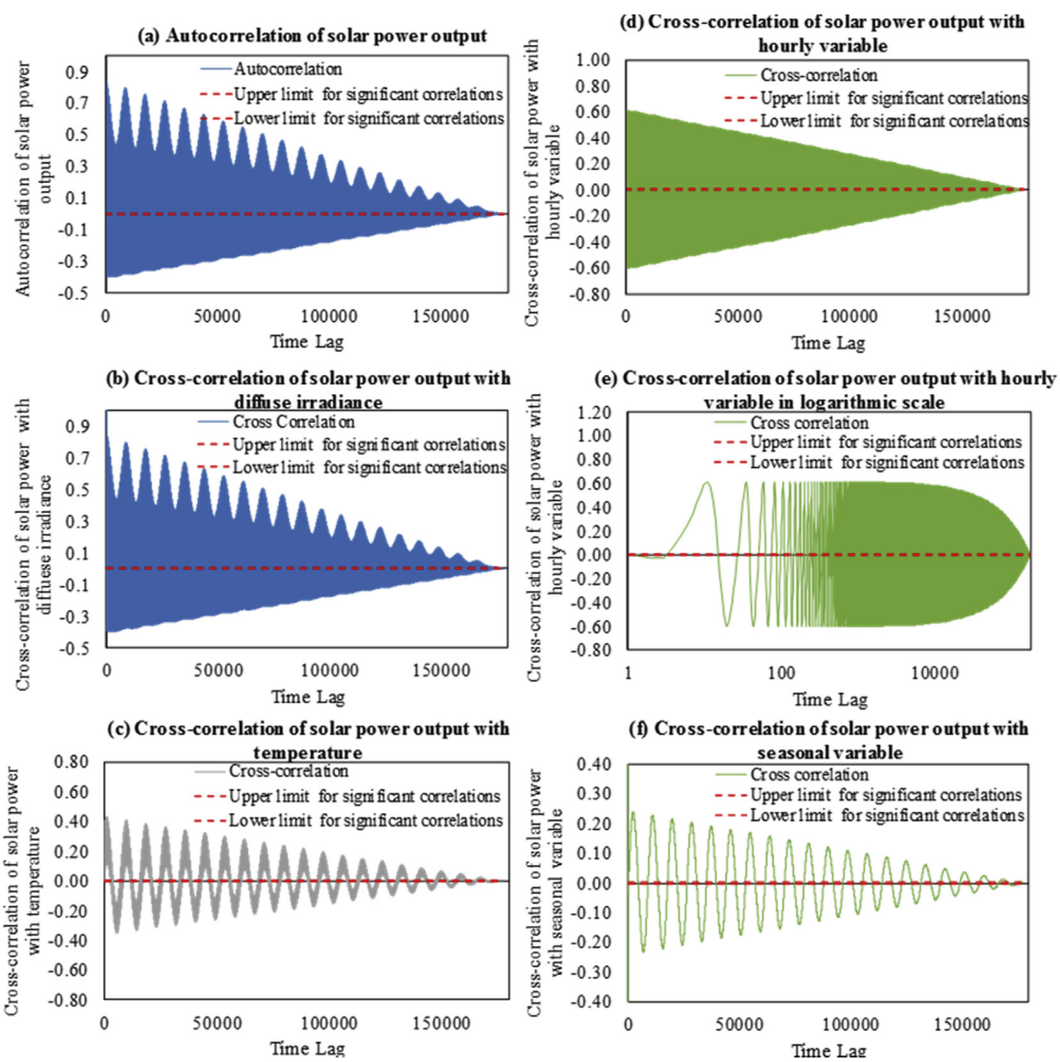

Fig. 6. Cross-correlations for input data applied for the solar power prediction.

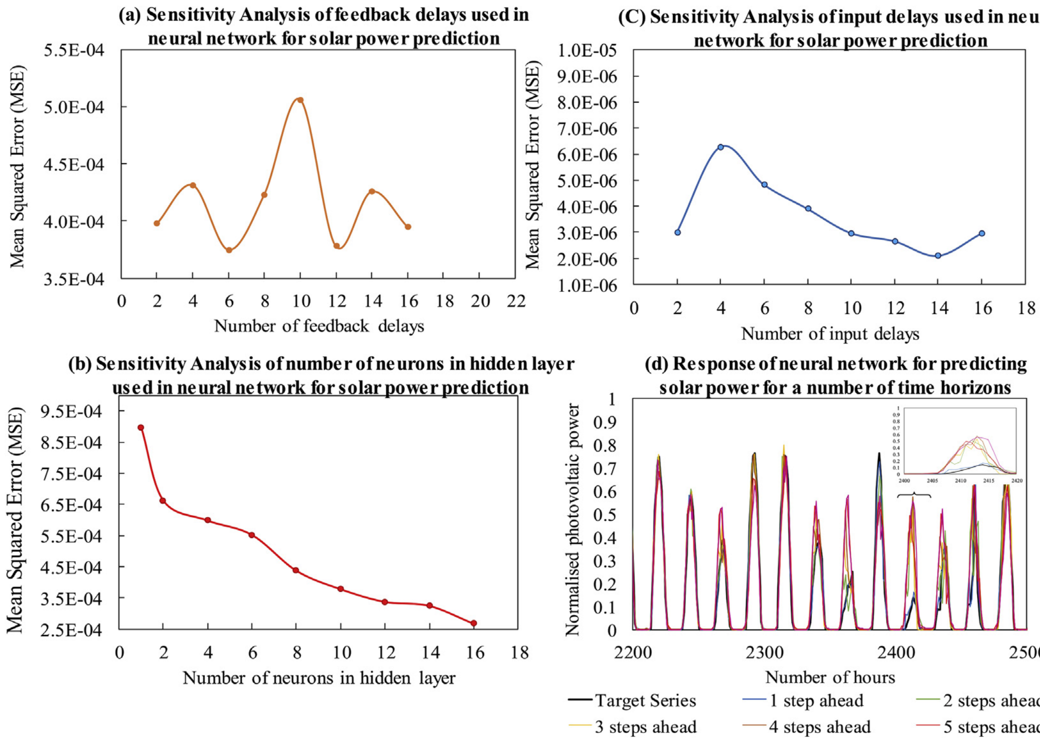

Fig. 7. The sensitivity analysis and performance of ANN for solar power prediction.

Table 13
MSE values for various time horizons regarding solar power prediction with neural networks.

Time horizon	Mean Square Error
model	0.00031467
1-step	0.00032632
2-step	0.0028
3-step	0.0037
4-step	0.0047
5-step	0.0061
6-step	0.0065

Table 14
MSE values for various time horizons regarding solar power prediction with SVR.

Time horizon	Mean Square Error (Testing)
Model (ε-SVR)	0.0015
1-step (NARX LS-SVR)	0.000002025
2-step (NARX LS-SVR)	0.0049
3-step (NARX LS-SVR)	0.0182
4-step (NARX LS-SVR)	0.0356
5-step (NARX LS-SVR)	0.0551

predictions show a 200% error of solar power production which can be problematic if these models are used in an actual practice. The forecasting errors of the ANN models for predicting the solar power generation are reported in the third column of Table 9.

3.2.3. Forecasting solar power with support vector regression

Similar to the case of wind data, a sensitivity analysis in the MATLAB toolbox (ε-SVR) was conducted in order to establish the most fitting kernel function out of the choices of linear, polynomial and radial basis function (RBF). The polynomial kernel did not converge and did not manage to capture the underlying pattern of the solar dataset. The linear kernel provided an error of 0.0114 but did not terminate due to reaching the maximum number of iterations and finally, the RBF which was deemed to be most suitable, converged with the performance of 0.0015.

The solar power was forecasted for a number of time horizons with the NARX LS-SVR method by applying the RBF kernel and setting the delays for the input vector and the target to 12. The performances for each corresponding time horizon is given in Table 14, and depicted in Fig. 8 a, where it can be seen that for one step ahead prediction a significant accuracy is accomplished. The reason for this is that the model that predicts the present response has a greater error is identical to the respective one given for wind power, that is to say, the ε-SVR does not have an autoregressive architecture. In Fig. 8. b, the response of the time series for all the time horizons simulated are provided and similarly to the case of wind, as it moves towards larger prediction horizons, the model tends to lose its accuracy. One striking observation, though is that the accuracy does not seem to drop for all time steps equivalently, as in the case of wind, but mostly for the days for which a small amount of solar power is produced (Fig. 8. c). The reason behind this phenomenon is in contrast to the wind power case, the solar power is discontinuous. Therefore when the model is asked to predict 5 h ahead at dawn it has no knowledge of whether the solar irradiance will be limited throughout the day. This leads to the model giving a prediction that has an average pattern over all the training data. On the other hand, when performing 1-h ahead predictions the model can adjust its response if the day is cloudy, as it receives all the respective information with only 1 h delay. This is the reason for which when moving from the one step ahead prediction towards longer time horizons, the error increases by approximately the power of 3.

3.2.4. Forecasting solar power with Gaussian Regression Process (GPR)

In order to tune the GPR for the prediction of solar power, a sensitivity analysis was conducted in order to establish the best kernel function. From Table 15, it can be seen that the Matern 52 kernel outperformed all others, and this function was therefore selected to build the final GPR model. The response of the built model is depicted in Fig. 9 a for all the testing data (the year 2014), and in Fig. 9. b a total of 500 h, with a view to providing a higher resolution. Even though

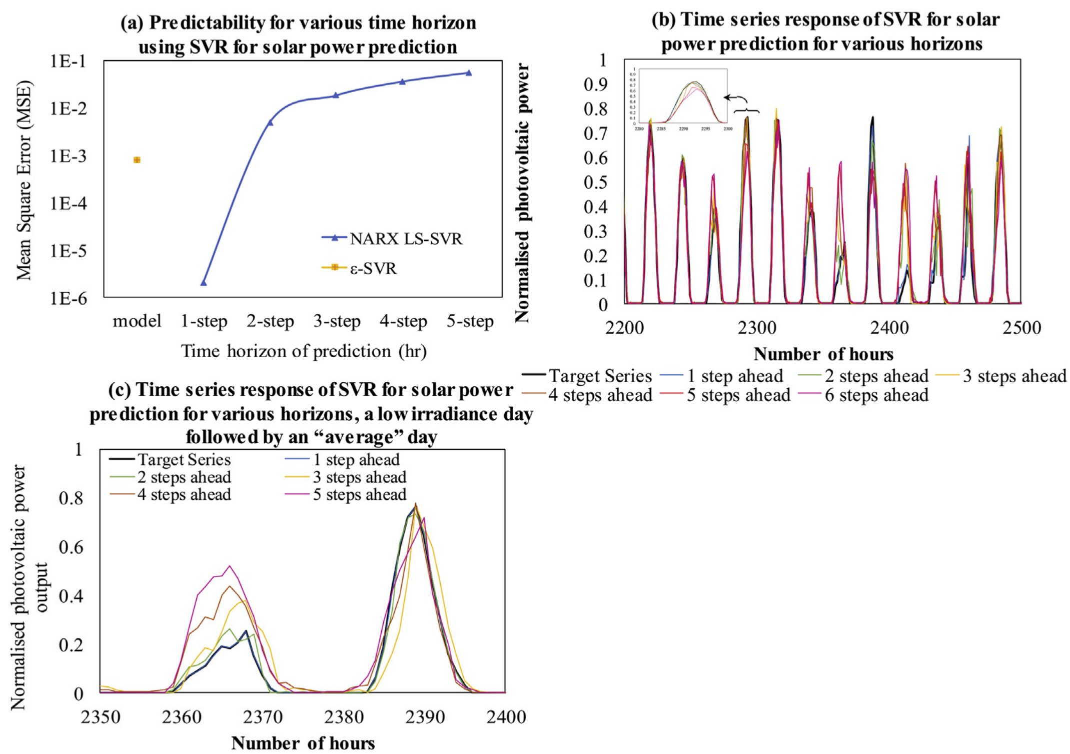

Fig. 8. The sensitivity analysis and performance of SVR for solar power prediction.

Table 15
Sensitivity analysis for appropriate kernel function selection for solar power prediction.

Kernel function	Training Performance	Testing Performance
Squared exponential	1.5598E-05	3.3E-03
Matern 32	9.2948E-06	3.2E-03
Matern 52	6.4625E-06	1.9E-03
ARD Squared Exponential	7.9675E-06	2.2E-03
ARD Matern 32	1.2948E-05	3.5E-03
ARD Matern 52	8.7765E-06	2.1E-03

there are some instances where the prediction is not exactly fitted to the target series (as was mostly for the case of the wind), the model gives satisfactory results and the target series for almost the entirety of the time steps lies within the confidence intervals.

3.3. Electricity demand forecast

3.3.1. Data pre-processing

3.3.1.1. Time series data clustering. The case of electricity demand prediction was quite different from the respective wind and solar power for several reasons. Firstly, owing to the fact that the dataset provided was in a disaggregated form and included the hourly electricity consumption of 1157 households located around the world, the dataset required clustering. Secondly, this data had no other inputs associated with it, due to privacy considerations. Finally, as this dataset was received from actual measurement units that were installed in the households there are additional errors and uncertainties affiliated with the data, such as instrument failures.

In order to perform the data clustering, the K-Spectral Centroid analysis was performed, which is a data clustering technique that categorises time series data according to their shape [152]. As this is a partitioning data technique the number of clusters needed to be set

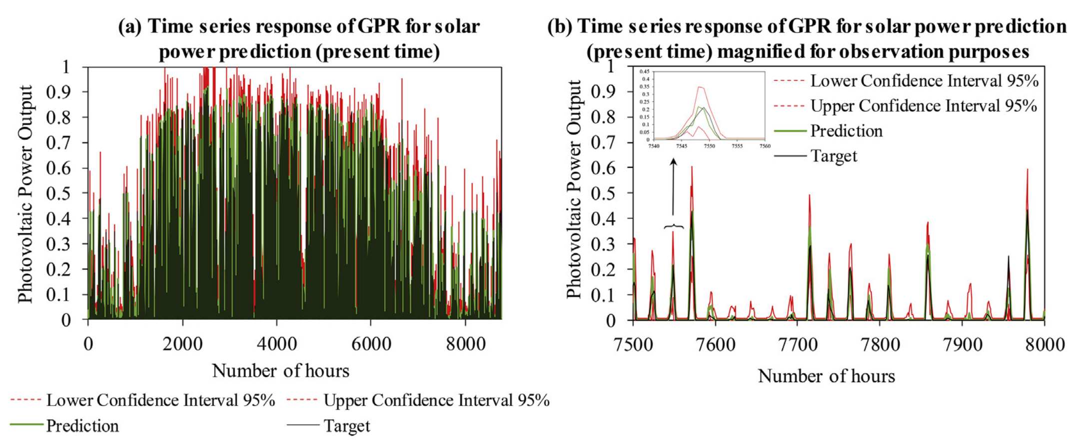

Fig. 9. (a) Time series response of GPR for solar power prediction (present time) and (b) Time series response of GPR for solar power prediction (present time) magnified for observation.

Table 16
Number of households that correspond to each cluster, for each simulation.

Total number of clusters	2	3	4	5	6	7	8	10
cluster 1	220	166	240	164	225	164	124	95
cluster 2	390	407	144	125	105	97	76	46
cluster 3		37	192	120	60	51	36	96
cluster 4			34	167	104	111	57	31
cluster 5				34	84	94	88	90
cluster 6					32	66	116	58
cluster 7						27	81	90
cluster 8							32	48
cluster 9								26
cluster 10								30
Total:	610	610	610	610	610	610	610	610

prior to executing the algorithm. In this study, the number of clusters for which this algorithm was run are $K = \{2,3,4,5,6,7,8,10\}$. Beyond 10 clusters the households were thought to be poorly split as there were only 610 households to be divided and some of the clusters were comprised of very few households.

In Table 16 the numbers of houses that correspond to each cluster for each value of K are given. It can be seen that overall for all cases, each cluster has a sufficient amount of information. In Fig. 10a-c, the division of the data can be observed for different numbers of clusters for k = 2,3,5. Over the various clusters, for all cases, there is at least one of the patterns that has a distinctly different behaviour compared to the rest, as it seems to be shifted by 6 months. These patterns that seem to have a six-month lag correspond to households in the southern hemisphere since during the warmer months of the southern hemisphere, the northern hemisphere experiences colder temperatures and vice versa. This observation stands due to the positive correlation between the electricity consumption and the temperature.

The number of clusters that was selected was five which is graphically represented in Fig. 10. c. The reasoning behind this decision is:

- The wind and solar data that correspond to a specific location in the UK and therefore the selected electricity demand pattern should at least correspond to the northern hemisphere
- The majority of households in the dataset are located in the northern hemisphere

As can be observed from Fig. 10. c there are two distinct patterns that correspond to the northern hemisphere; Pattern 1 and Pattern 2. Finally, Pattern 1 was chosen because a larger number of households were within that specific cluster and also its pattern seems to be closer to what is expected from a household. Pattern 2 maintains large values throughout the winter there are some instances were little variation is observed, whereas Pattern 1 seems to have a daily pattern in conjunction with a seasonal variation.

3.4. Data autocorrelations

For electricity demand prediction although no other data was associated with it, for the predictive analytics two inputs were included, specifically the hourly and seasonal variables. By introducing these variables, it was hoped that the training of the models would be facilitated. This statement has proven to stand, as from Table 17 it can be observed that the maximum cross-correlations of each of the inputs can be considered to be significant, especially for the hourly variable.

Similar to the case of solar power, the autocorrelation of demand shows both a yearly and daily repetition and the values do not decrease as steeply as for the case of wind power (Fig. 11 a). The dependence of the demand on the time of the day and year is represented in the cross-correlation graphs depicted in Fig. 11a-c. A noteworthy characteristic of all the graphs in this section is that they are not entirely symmetrical as opposed to the wind and solar data. This is due to the fact that this dataset is a result of actual measurements and therefore has the stochasticity associated with them.

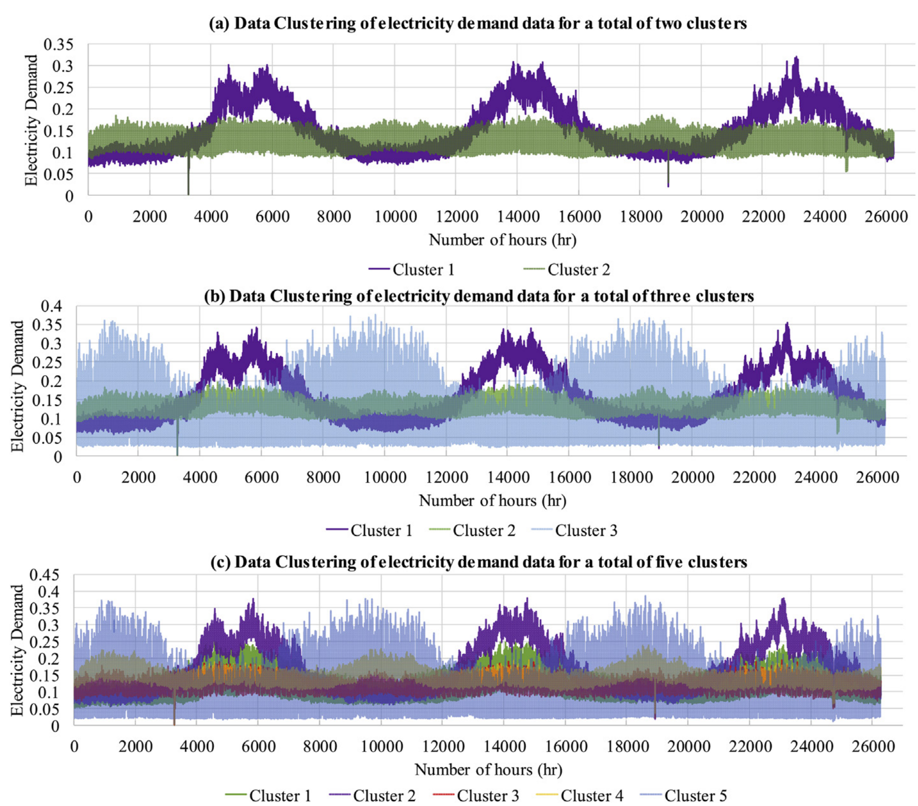

Fig. 10. Data Clustering of electricity demand data for the total of (a) two (b) three, and (c) five clusters.

Table 17
Maximum absolute cross-correlations for input data used for electricity demand prediction.

Input	Maximum absolute correlation
Hourly variable	0.622855
Seasonal variable	0.29743

3.4.1. Forecasting electricity demand with artificial neural networks

As mentioned earlier, the demand data had no inputs associated with it, but during the pre-processing procedure, the hourly and seasonal variables were introduced to the electricity demand dataset with an aim to facilitate each of the predictive analytics methods in identifying the temporal dependence of the data. Before continuing with the identification of the optimal parameters of the NARX network it was deemed necessary to examine whether these exogenous inputs would improve the network's performance resulting in a NARX (nonlinear autoregressive method with exogenous inputs) architecture, or whether it would be preferred to only use the past values of the electricity demand as an input (NAR, nonlinear autoregressive method). The results of this analysis are depicted in Fig. 12 a where it can be clearly seen that the temporal variables drastically improve the performance of the neural network especially for low feedback delays. For this reason, the NARX architecture was selected and a sensitivity analysis of the input and feedback delays as well as the number of neurons in the hidden layer was conducted. The results are depicted in Fig. 12a-c for each parameter, respectively. The performance of the neural network constantly improved until a certain point, as the number of input and feedback delays increased. The optimal values were identified 22 and 24 for the former and latter respectively. However, the number of neurons in the hidden layer did not seem to affect the performance of the network, and therefore the respective value was maintained at 12.

From the three predictive analytics methods used in this research, neural networks were the only ones that managed to achieve an overall good response for forecasting electricity demand which is depicted in Fig. 12. d. The performance of the neural networks for each time horizon respectively is enlisted in Table 18. As expected the accuracy of the model drops as the time horizon of the prediction increases. The forecasting errors of the ANN models for predicting the electricity demand are reported in the fourth column of Table 9.

3.4.2. Support vector regression

Following the same approach as for the previous cases, the MATLAB toolbox of SVR was employed to study the response of the model for each of the three kernels, namely the linear, polynomial and the RBF. Similarly, it was found that the RBF kernel outperformed both others, and it was this kernel that was used therefore for the NARX LS-SVR. The testing performance of all the models computed are given in Table 19 and are graphically represented in Fig. 13 a.

The way with which the error increases for the case of electricity demand is remarkably different from the case of solar and wind prediction, since it does not seem to increase as steeply when the time horizon rises. This can be explained with Fig. 13. b where it can be observed that overall the SVR failed to be trained successfully. Even though the right part of the response of Fig. 13a-b shows promising results for a part of the data, at some point the model decays to a value. This signifies that perhaps the training data may not have been sufficient to make the model sensitive to the seasonal variations, or that after the data clustering the dataset should have been cleaned and any potential outliers ought to have been smoothed out. Nonetheless, it should be mentioned that the good response shown for parts of the forecasts displays the potential of SVRs to be used for this particular application.

3.4.3. Gaussian Regression Process (GPR)

The Gaussian Regression Process, similar to SVR, was found also not to be able to capture the underlying patterns of the dataset of electricity demand. In Table 20, the performances retrieved from trying the various available kernels from the respective MATLAB toolbox can be seen. The training performances of all kernels other than the squared exponential and the ARD squared exponential were particularly high. The kernel that was selected was the squared exponential and the response of the model for the whole testing dataset is displayed in Fig. 14 a where it can be observed the model for a large part of the dataset does not follow the target series. In Fig. 14. b, an area in which a good fitting was achieved is depicted and as for the method SVR, it is noted that this

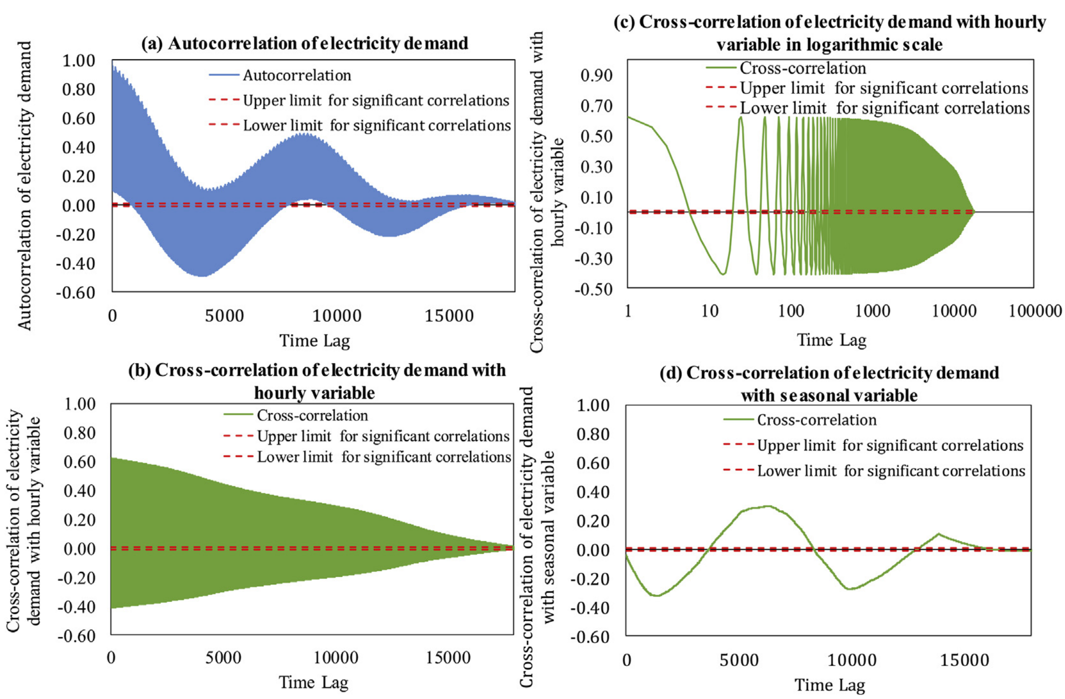

Fig. 11. Cross-correlations for input data applied for the solar power prediction.

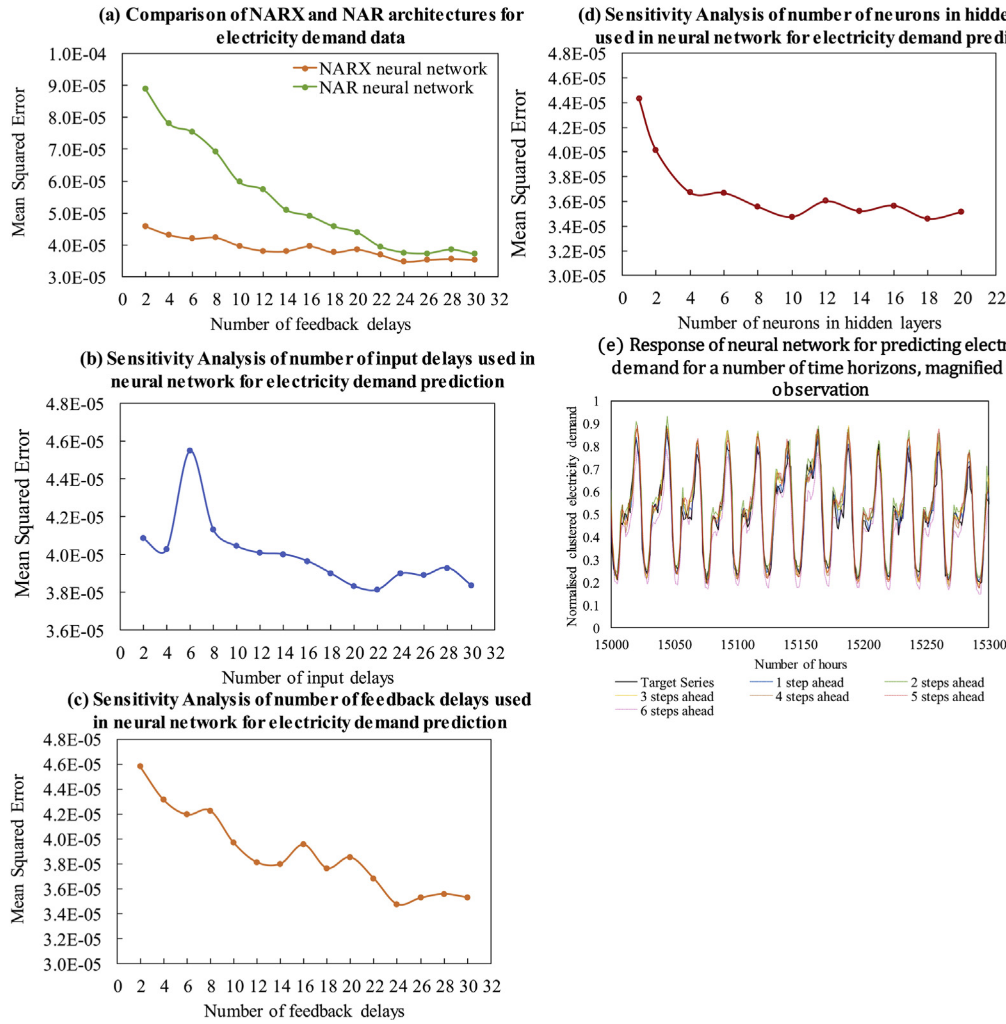

Fig. 12. The sensitivity analysis and performance of ANN for electricity demand prediction.

Table 18
MSE values for various time horizons regarding solar power prediction with neural networks.

Time horizon	Mean Square Error
model	0.00079575
1-step	0.00084579
2-step	0.000931306
3-step	0.001427005
4-step	0.001738486
5-step	0.00186682
6-step	0.001882147

Table 19
MSE values for various time horizons regarding electricity demand prediction with SVR.

Time horizon	Mean Square Error (Testing)
Model (ε-SVR)	0.0037
1-step (NARX LS-SVR)	0.000677
2-step (NARX LS-SVR)	0.000931
3-step (NARX LS-SVR)	0.0012
4-step (NARX LS-SVR)	0.0014
5-step (NARX LS-SVR)	0.0017

method has the potential of reaching a good accuracy.

3.5. Comparison of the prediction methods for wind and solar power as well as demand

In this section, all methods and types of predictions will be compared, with a view to summarise all the results presented above and to acquire an insight on the gains and limitations of each method tested. The comparison will be conducted on two levels. Firstly, the most suitable method will be identified for each type of prediction, and secondly the datasets will be compared for each machine-learning technique. Fig. 15a–c depict the comparison of the models by graphing the mean square error of each model with the time horizon for which it was simulated while Fig. 15e and f illustrate how each method has performed with regard to each dataset. The following points can be concluded:

- NARX LS-SVR outperforms NARX NN when the time horizon of the prediction is one, for all types of predictions.
- NARX NNs are found to be more robust for the case of wind power and solar power predictions as their decrease in accuracy is smaller than NARX LS-SVR. The opposite is observed for electricity demand.
- ε-SVR and GPR have similar errors for the cases of wind and solar power prediction. This signifies that if a NARX GPR is implemented it is possible to gain satisfactory results.
- The poor performance of the GPR as well as of the ε-SVR (for wind

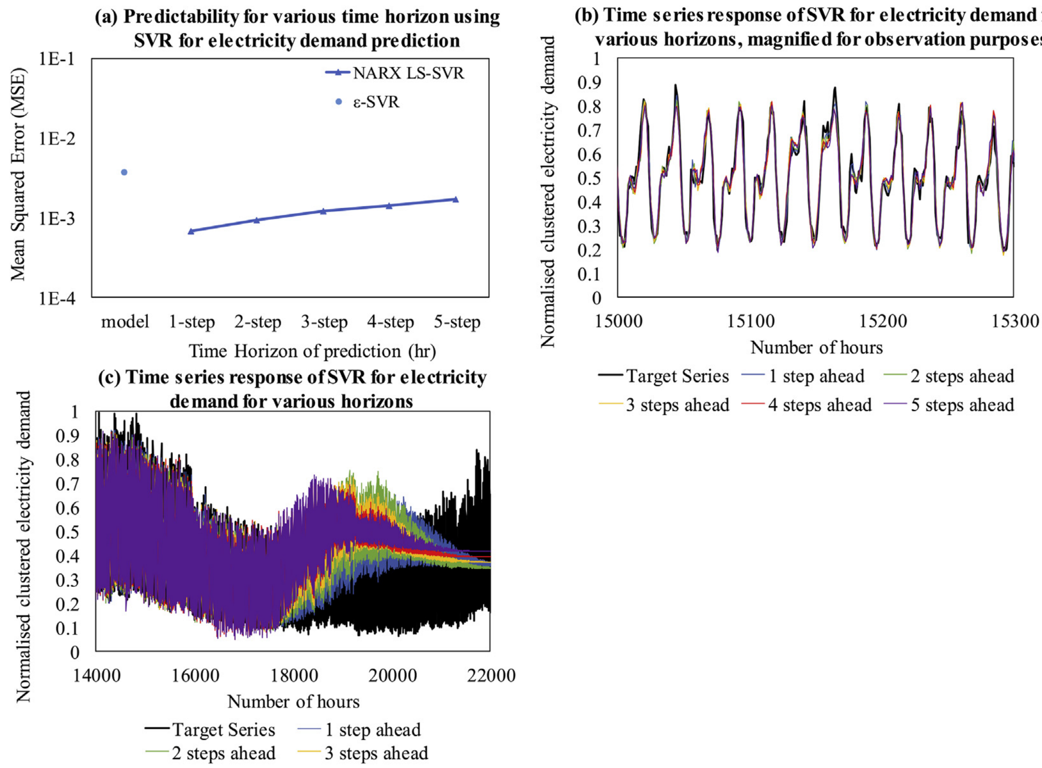

Fig. 13. The sensitivity analysis and performance of SVR for solar power prediction.

Table 20
Sensitivity analysis for appropriate kernel function selection for electricity demand prediction.

Kernel function	Training Performance	Testing Performance
Squared exponential	0.0106	0.0106
Matern 32	1.0302	0.0105
Matern 52	1.0301	0.0105
ARD Squared Exponential	0.0106	0.0106
ARD Matern 32	1.0298	0.0104
ARD Matern 52	1.0299	0.0105

and solar power) is attributed to the fact that these models are not autoregressive, and utilise the target series only for supervised training and not as an input.

- When looking at the electricity demand data, as time horizons of the predictions increase, the accuracy of the models does not drop as in the respective cases of wind and solar power prediction. This denotes that the initial error of the model is significant and the new error introduced by the predicting for longer periods of time, contributes only slightly to the overall error.
- Fig. 15d and e are similar which means that the wind and solar dataset behave in a similar manner with regard to the various predictive models.

The best performing method built in this research was the NARX LS-SVR for 1-h ahead solar power prediction and the worst performing method was the GPR model for the case of demand. Even though the SVR and GPR models did not provide satisfactory results for the electricity demand prediction, it was shown that during some periods, the models managed to capture the underlying patterns of the data. This demonstrates that these particular methods are capable of potentially performing these predictions, however, certain measures must be taken in order to accomplish the desired outcome:

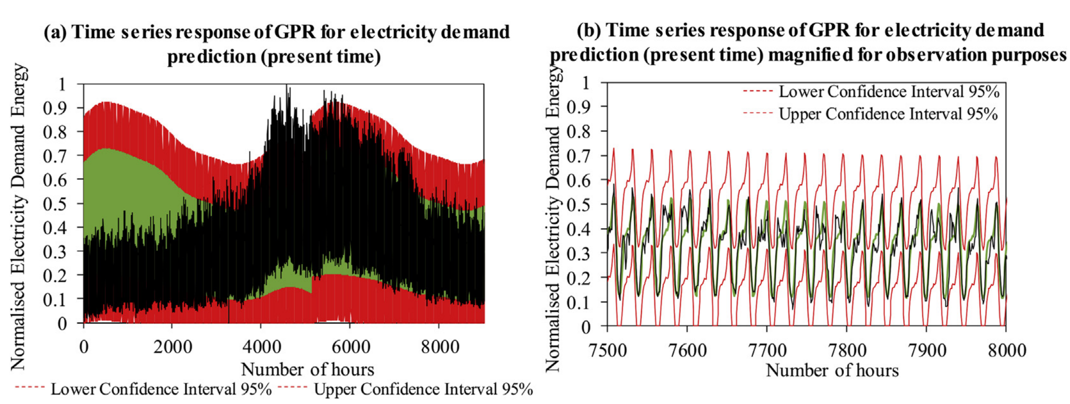

Fig. 14. (a) Time series response of GPR for electricity demand prediction (present time), (b) Time series response of GPR for electricity demand prediction (present time) magnified for observation purposes.

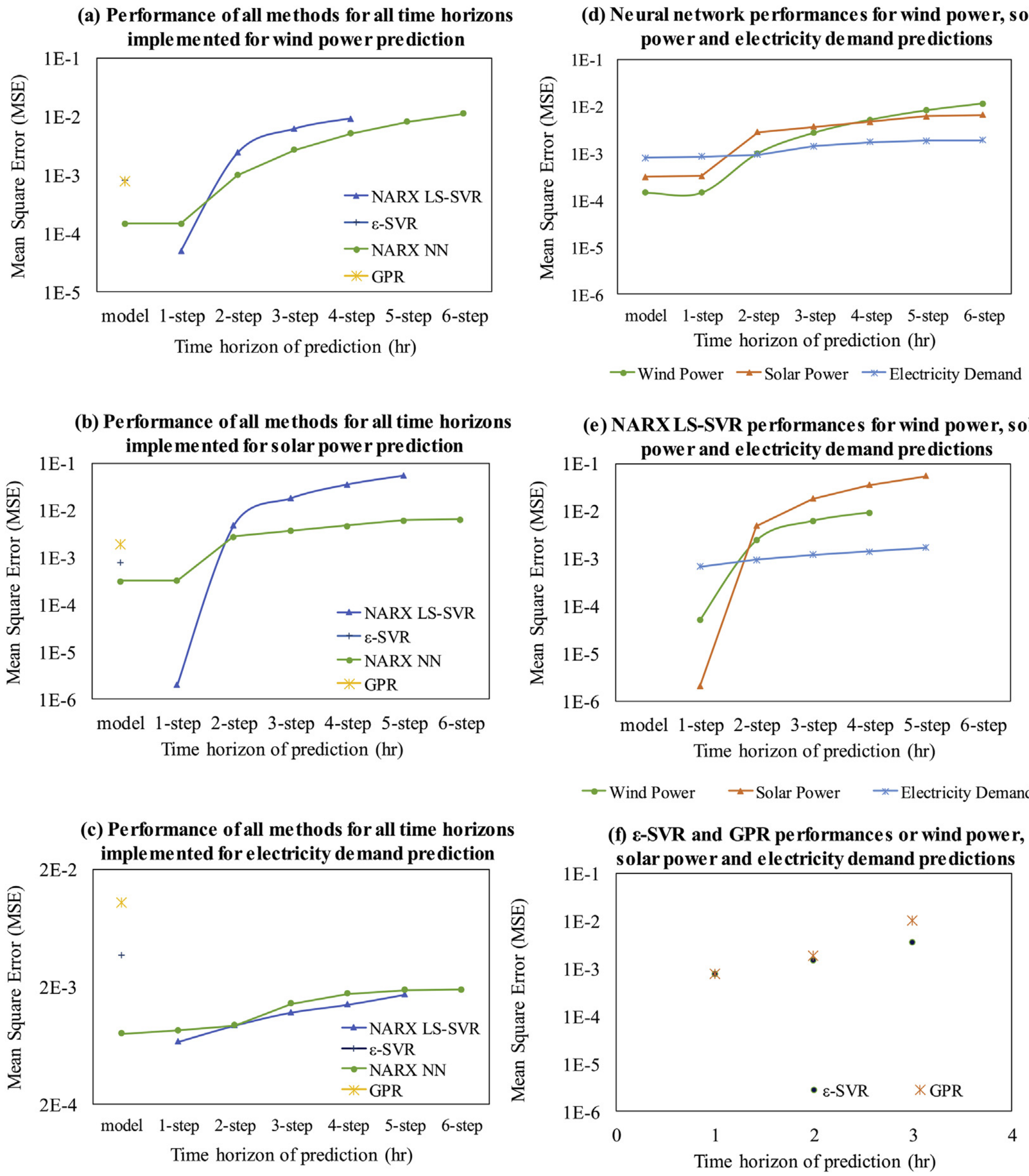

Fig. 15. Comparison of the prediction methods for wind and solar power as well as demand.

- More training data should be used with a view to provide the model more chances to understand the seasonal variation of demand.
- The initial dataset of the 1157 households needs to be cleaned more thoroughly and include a step were the outliers of the dataset are smoothed out. It is suggested the data is clustered and the resulting centroids should be checked for outliers, and return to the initial data to perform smoothing with a view to cluster it again in order to ensure that the outliers did not affect the classification of the data.
- The clustering of the data should be evaluated with further criteria other than the Silhouette coefficient
- Additional exogenous inputs should be introduced wherever possible. An example would be to include a variable that denotes weekdays and weekends.
- If the steps above do not provide any significant improvements, a modelling tool could be used to extract data with a view to establish whether the uncertainty and noise carried in the electricity demand dataset is related to the failure of the prediction models.
- Finally, in Table 21 and Table 22 the mean square error of all the models is given. The green highlighting denotes the method which has the best accuracy for each time horizon.

Table 21
Performance of all dynamic models.

Time	Wind Power		Solar Power		Electricity Demand	
Horizon	ANN	SVR	ANN	SVR	ANN	SVR
1 h	1.46E-04	5.03E-05	3.26E-04	2.03E-06	8.46E-04	6.7E-04
2 h	9.91E-04	2.4E-03	2.8E-03	4.9E-03	9.31E-04	9.31E-04
3 h	2.7E-03	6.2E-03	3.7E-03	1.82E-02	1.43E-03	1.2E-03
4 h	5.1E-03	9.3E-03	4.7E-03	3.56E-02	1.74E-03	1.4E-03
5 h	8.1E-03		6.1E-03	5.51E-02	1.87E-03	1.7E-03
6 h	1.13E-02		6.5E-03		1.88E-03	

Table 22
Performance of all non-dynamic models.

Method	Wind Power	Solar Power	Electricity Demand
NN	1.45E-04	3.15E-04	7.97E-04
ε-SVR	7.97E-04	1.50E-03	
GPR	7.82E-04	1.90E-03	1.04E-02

3.6. Error analysis and denormalization

With an aim to quantify the efficacy of the forecasting methods and the results of the predictive analysis, we selected the best performing method for each of the time horizons and compared the error distributions with those of a naive model, for wind power, solar power as well as electricity demand. Moreover, with a view to assessing the impact of the mean errors to the forecasted values in a real-world application, the ranges of uncertainty have been extrapolated to dimensional units. For the error analysis and specifically for the extrapolation of the error, the following assumptions were made:

- Any fatigue factors or correlations to the age of the solar panels/wind turbines is ignored.
- It is assumed that the predictive models are not influenced by the wind turbine model or the photovoltaic types, respectively.
- Effects with regards to the interactions between the wind turbines are ignored.
- In the calculation of the mean capacity factor, no corrections were made to consider the periods in which the wind turbines or solar photovoltaics are non-operational due to maintenance or other reasons.
- When extrapolating to calculate the expected generated energy along with the threshold of uncertainty, any smoothing effects that may happen due to aggregation is ignored.
- The geographical variations in the wind and solar availability, as well as electricity demand was formulated according to a recent publication [173]. In that contribution, the availability of wind and solar energy was clustered accordingly into various geographical zones, and the demand was considered according to its demographical distribution.

The results of error percentage are shown in Fig. 16(a–c) respectively, and denormalised in the following sections. A comparison is also made with a naive model, for the sake illustration and clarification. The box plots (also known as box and whisker diagram) in Fig. 16, show six elements of the error distribution namely, the minimum and maximum error, the first quartile, median, and third quartile, as well as the mean percentage errors for each stochastic variable.

3.6.1. Error calculation of predictive models

The metric used for the error distribution analysis is the normalised root squared which is calculated as follows:

$$nrse = \frac{\sqrt{(y_{act} - y_{pr})^2}}{y_{act}} \tag{4}$$

where *nrse* stands for normalised root square error. y_{act} and y_{pr} are the values of the actual and predicted performance respectively.

Table 23
The mean percentage error of naive and predictive model for wind power.

Time horizon (hr)	1 step	2 step	3 step	4 step	5 step	6 step
Naive Model	1.76%	3.38%	4.82%	6.12%	7.27%	8.31%
Predictive model	1.88%	2.05%	2.04%	2.61%	3.17%	3.73%

Table 24
The capacity of and electricity generated from onshore wind farms in the UK [174].

Total generated energy from onshore wind farms in the UK for 2017	29088 GWh
Total onshore wind farm capacity at the end of 2017	12847 MW
Total onshore wind farm capacity at the end of 2016	10880 MW

3.6.2. Naive models

Naive models are used as a benchmark for comparison with the predictive models. Typically, it is expected that the predictive models outperform the naive models. For this work, two naive approaches were taken. For wind power which as prementioned (Table 7) has a low correlation with the time of day, for the naive approach, it is assumed that the energy produced at a given time horizon will be the same as the one at a given time earlier. More specifically:

$$y_{pr} = y_{t-i} \tag{5}$$

where y_{pr} is the resulting value of the naive model and y_{t-i} is the actual energy value at i hours before t.

On the other hand, solar power and electricity demand have a strong correlation to the time of day. Therefore, for the naive model, it is more appropriate to assume that the value at a given time horizon is the same as that of the respective time of the previous day.

$$y_{pr} = y_{t-24} \tag{6}$$

It is noted that whereas for wind power there are 6 naive models, for

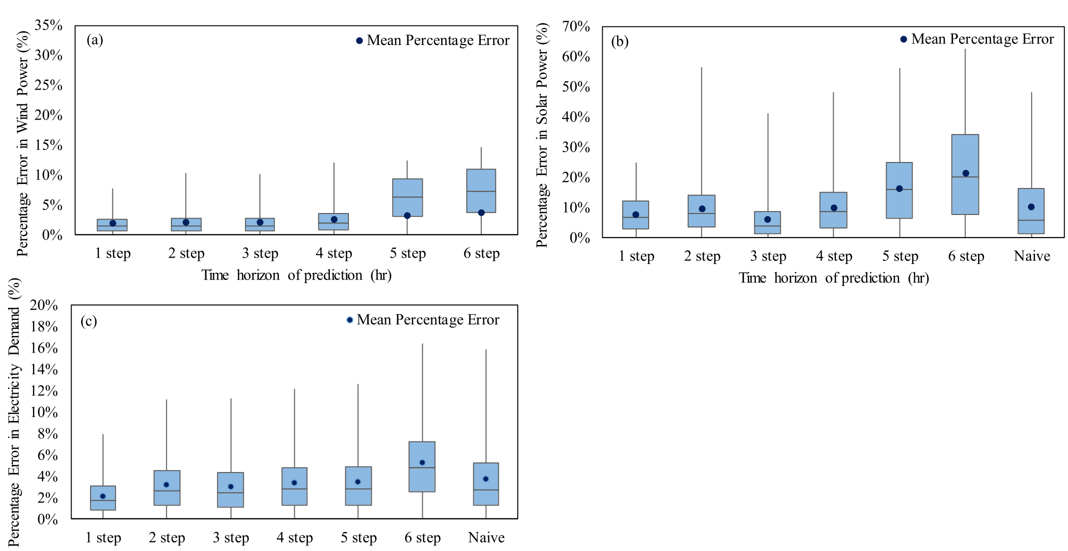

Fig. 16. Box plot of percentage error distributions of (a) the wind power forecasting, (b) the solar power forecasting, (c) the electricity demand forecasting.

Table 25
The mean percentage error of naive and predictive model for wind power generation for an hour.

	Model Type	1 step	2 step	3 step	4 step	5 step	6 step
Wind Turbine [KWh]	Naive Model	610.4 ± 10.7	610.4 ± 20.6	610.4 ± 29.4	610.4 ± 37.3	610.4 ± 44.3	610.4 ± 50.7
Wind Turbine [KWh]	Predictive model	610.4 ± 11.5	610.4 ± 12.5	610.4 ± 12.4	610.4 ± 15.9	610.4 ± 19.3	610.4 ± 22.8
UK (2017) [MWh]	Naive Model	3921 ± 69.0	3921 ± 132.5	3921 ± 189.0	3921 ± 240.0	3921 ± 285.1	3921 ± 325.8
UK (2017) [MWh]	Predictive model	3921 ± 73.7	3921 ± 80.4	3921 ± 80.0	3921 ± 102.3	3921 ± 124.3	3921 ± 146.3

Table 26
Mean percentage error of naive and predictive model for solar power.

Model Type	Mean percentage error
1 step	7.86%
2 step	9.66%
3 step	6.10%
4 step	10.17%
5 step	16.48%
6 step	21.41%
Naive	10.38%

Table 29
Mean percentage error of naive and predictive model for electricity demand.

Model Type	Mean percentage error
1 step	2.10%
2 step	3.13%
3 step	3.00%
4 step	3.31%
5 step	3.40%
6 step	5.20%
Naive	3.67%

Table 27
The capacity of and electricity generated from solar photovoltaic farms in the UK [174].

Total generated energy from onshore wind farms in the UK for 2017	11525 GWh
Total onshore wind farm capacity at the end of 2017	12776 MW
Total onshore wind farm capacity at the end of 2016	11912 MW

solar power and electricity demand only a single naive model is required.

3.6.3. Wind power

3.6.3.1. Error denormalization and distribution analysis. In order to calculate the error of the wind prediction models in dimensional units, the output of the models is denormalised. The output of the wind forecasting models is the dimensionless power of a wind turbine. The data used for this research - as described in Section 2.1, Table 4 - involved a particular model of a wind turbine at a hypothetical 1 kW capacity. By denormalising the predictors' output and by looking at the error distributions of each of the predicted time horizons, Fig. 16a shows the percentage error of the expected wind power of a wind turbine for a given time horizon. It should be noted that for the extraction of these, graphs outliers have been removed (errors that are greater or less that 3 standard deviations). The number of data points that were omitted for each case was at most 1.8%. In addition, the error distributions were calculated for the best performing model in each time horizon (see Table 21). In Table 23, the respective results of the naive model can be seen. It is evident that as the time horizon increases the errors of the naive approach become increasing larger than the errors of the predictive forecasting methods. This means that the predictive models developed in this work add greater value in the increasing time horizons.

3.6.3.2. .Quantification of errors in dimensional units. In this section, the uncertainty of the wind power predictions will be quantified for a Vestas V80 2000 wind turbine and will be extrapolated at a national level (UK). The range of uncertainty will be given for the generated energy that corresponds to the mean capacity factor of a wind turbine in the UK. The mean capacity factor of onshore wind farms can be estimated with the following calculation:

$$cf_{wind} = \frac{Generated\ Energy_{2017}}{Capacity_{2017}*24*365} \tag{7}$$

where $Generated\ Energy_{2017}$ refers to the total power generated from onshore wind farms in 2017 and $Capacity_{2017}$ is the total capacity of onshore wind farms in 2017. Since the capacity of wind power is ever increasing and therefore not a constant value throughout the year, we assume that the new onshore wind farms in 2017 where introduced to the grid evenly across the year.

$$Capacity_{2017} = TotalCapacity_{2017} - \left(\frac{TotalCapacity_{2017} - TotalCapacity_{2016}}{2}\right) = 30.52\% \tag{8}$$

Using the values in Table 24 [174] the mean capacity factor is estimated to be 30.52%. In Table 25, the estimated generated energy for a given hour of a Vestas V80 2000 wind turbine, and of the entire UK onshore wind farm fleet have been calculated.

3.6.4. Solar power

3.6.4.1. Error denormalization and distribution analysis. In a similar manner to wind power, the outputs of the solar prediction models are denormalised and the percentage root squared error distribution is calculated (Table 26 and Fig. 16b). It should be noted that for the error distribution analysis, only values during daylight were considered. It can be seen that the naive approach outperforms the predictive models for time horizons greater than 4 h. This indicates that better forecasting performances may have been achieved if the energy produced on the previous day at the same time was used as an input.

3.6.4.2. Quantification of errors in dimensional units. In this section, the

Table 28
Mean percentage error of naive and predictive model for solar power for an hour.

	1 step	2 step	3 step	4 step	5 step	6 step	Naive
Solar Farm [MWh]	21.3 ± 1.68	21.3 ± 2.06	21.3 ± 1.3	21.3 ± 2.17	21.3 ± 3.51	21.3 ± 4.56	21.3 ± 2.21
UK (2017) [MWh]	1362 ± 107	1362 ± 132	1362 ± 83	1362 ± 139	1362 ± 225	1362 ± 292	1362 ± 141

Table 30
Mean percentage error of the naive and predictive models for the electricity consumption of an average household without electricity heating.

	1 step	2 step	3 step	4 step	5 step	6 step	Naive
Household consumption during peak time for 1hr [Wh]	600 ± 12.59	600 ± 18.79	600 ± 18	600 ± 19.84	600 ± 20.41	600 ± 31.21	600 ± 22.01

uncertainty of the solar power predictions will be quantified for a solar power farm of 200 MW, and will be extrapolated at a national level (UK). Similar to the section above, the mean capacity factor is estimated to be 10.66%, given the values of Table 27. The mean percentage error of naive and predictive model are reported in Table 28.

3.6.5. Electricity demand

3.6.5.1. Error denormalization and distribution analysis. The output of the electricity demand models is the normalised energy spent in a household for a given hour. The distribution of the percentage error is presented in Fig. 16c, and the mean values of the error are given in Table 29. As in the case of solar power generation, it can be observed that the performance of the naive model is relatively good. This indicates that for the 6 h ahead prediction, better forecasting performances could be achieved if the energy produced on the previous day at the same time was used as an input.

3.7. Quantification of errors in dimensional units

With a view to quantifying the errors in dimensional units for domestic electricity demand, the energy usage will be extrapolated to that of an average household in the UK. According to Ref. [175] looking at the average hourly load curves of households without electricity heating the peak load typically reaches 600 W (Table 30).

4. Conclusions

This research has successfully implemented predictive analytics methods that forecast the wind power, the solar power and the electricity demand of households. Moreover, the uncertainty of these predictions is quantified by the mean square error for the case of neural networks and support vector regression, as well as confidence intervals for the Gaussian process regression method. It is believed that from the knowledge acquired by these data-driven models, an optimal investment and usage of energy storage units could be achieved, which would result in achieving an economically feasible solution that allows an even higher level of penetration of renewable energy sources within electricity grids.

Finally, it should be mentioned that there are many additional opportunities and issues that need to be addressed, when looking at the future of the energy sector. For example, demand-side response, where incentives are given to customers to use electricity at off-peak hours has shown to have a very beneficial effect in managing and controlling the load of the electricity grid. With the increase of electric vehicles, demand-side response can gain an even greater role in the electricity distribution system. The batteries of the cars that are interconnected to the grid in an event of a frequency drop can provide electricity to the grid instead of charging, thus avoiding the immediate conventional plant response [176]. All these opportunities should be integrated within a predictive control system for a smart grid and it is evident that the results of such research can be immediately applicable and can facilitate and contribute to the transition of the energy sector to modern and sustainable technologies.

Acknowledgment

The authors would like to gratefully acknowledge the data supplied from the Hildebrand Limited, and Ninja Renewables online database.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rser.2019.03.040.

Abbreviations

ANFIS Adaptive Neuro Fuzzy Inference System
ANN Artificial Neural Networks
AR AutoRegressive
ARCH AutoRegressive Conditional Heteroskedasticity model
ARIMA AutoRegressive Integrated Moving Average
ARMA AutoRegressive Moving Average
BIC Bayesian Information Criterion
BP Back Propagation Neural Network
BR Bayesian Regularization
ELM Elman Recurrent Neural Network
EXS Exponential Smoothing
FIR Finite Impulse Response Neural Network
FLS Fuzzy Logic Systems
FNN Fuzzy Neural Network
GA Genetic Algorithm
GHGs Greenhouse gases
GPR Gaussian Regression Process
ICA Imperialist Component Algorithm
IEA International Energy Agency
I—O Input-Output model
kNN k-Nearest Neighbour
LM Levenberg-Marquart
LS-SVR Least Squared Support Vector Regression
MA Moving Average
ME Mixture of Experts
MLP Multilayer Perceptron Neural Network
MPC Model Predictive Control
NAR Nonlinear AutoRegressive model
NARX Nonlinear AutoRegressive model with eXogenous inputs
NLN Neural Logic Network
NNS Nearest Neighbour Search
NWP Numerical Weather Prediction
PCA Principal Component Analysis
PV PhotoVoltaic
SCADA Supervisory Control and Data Acquisition
QR Quantile Regression
QRF Quantile Random Forest
RBF Radial Base Function Neural Network
RES renewable energy resources
RF Random Forest
SRN Simultaneous Recurrent Neural Network
SVM Support Vector Machines
SVR Support Vector Regression

References

[1] International Energy Agency. Energy and climate change. Paris, France: IEA; 2015. https://doi.org/10.1038/479267b.
[2] Tayal D. Achieving high renewable energy penetration in Western Australia using data digitisation and machine learning. Renew Sustain Energy Rev 2017;80:1537–43. https://doi.org/10.1016/j.rser.2017.07.040.
[3] Suganthi L, Samuel AA. Energy models for demand forecasting—a review. Renew Sustain Energy Rev 2012;16:1223–40. https://doi.org/10.1016/j.rser.2011.08.014.

[4] Khan AR, Mahmood A, Safdar A, Khan ZA, Khan NA. Load forecasting, dynamic pricing and DSM in smart grid: A review vol. 54. Elsevier; 2016. https://doi.org/10.1016/j.rser.2015.10.117.
[5] Mellit A, Kalogirou S a. Artificial intelligence techniques for photovoltaic applications: a review. Prog Energy Combust Sci 2008;34:574–632. https://doi.org/10.1016/j.pecs.2008.01.001.
[6] Inman RH, Pedro HTC, Coimbra CFM. Solar forecasting methods for renewable energy integration. Prog Energy Combust Sci 2013;39:535–76. https://doi.org/10.1016/j.pecs.2013.06.002.
[7] Jung J, Broadwater RP. Current status and future advances for wind speed and power forecasting. Renew Sustain Energy Rev 2014;31:762–77. https://doi.org/10.1016/j.rser.2013.12.054.
[8] Baños R, Manzano-Agugliaro F, Montoya FG, Gil C, Alcayde A, Gómez J. Optimization methods applied to renewable and sustainable energy: a review. Renew Sustain Energy Rev 2011;15:1753–66. https://doi.org/10.1016/j.rser.2010.12.008.
[9] Sfetsos A. A comparison of various forecasting techniques applied to mean hourly wind speed time series. Renew Energy 2000;21:23–35. https://doi.org/10.1016/S0960-1481(99)00125-1.
[10] Martín L, Zarzalejo LF, Polo J, Navarro A, Marchante R, Cony M. Prediction of global solar irradiance based on time series analysis: application to solar thermal power plants energy production planning. Sol Energy 2010;84:1772–81. https://doi.org/10.1016/j.solener.2010.07.002.
[11] Fernandez-Jimenez LA, Muñoz-Jimenez A, Falces A, Mendoza-Villena M, Garcia-Garrido E, Lara-Santillan PM, et al. Short-term power forecasting system for photovoltaic plants. Renew Energy 2012;44:311–7. https://doi.org/10.1016/j.renene.2012.01.108.
[12] Costa A, Crespo A, Navarro J, Lizcano G, Madsen H, Feitosa E. A review on the young history of the wind power short-term prediction. Renew Sustain Energy Rev 2008;12:1725–44. https://doi.org/10.1016/j.rser.2007.01.015.
[13] Salcedo-Sanz S, Cornejo-Bueno L, Prieto L, Paredes D, García-Herrera R. Feature selection in machine learning prediction systems for renewable energy applications. Renew Sustain Energy Rev 2018;90:728–41. https://doi.org/10.1016/j.rser.2018.04.008.
[14] Zheng ZW, Chen YY, Huo MM, Zhao B. An overview: the development of prediction Technology of wind and photovoltaic power generation. Energy Procedia 2011;12:601–8. https://doi.org/10.1016/j.egypro.2011.10.081.
[15] Shi J, Qu X, Zeng S. Short-term wind power generation forecasting: direct versus indirect arima-based approaches. Int J Green Energy 2011;8:100–12. https://doi.org/10.1080/15435075.2011.546755.
[16] Kusiak A, Zheng H, Song Z. Short-term prediction of wind farm power: a data mining approach. IEEE Trans Energy Convers 2009;24:125–36. https://doi.org/10.1109/TEC.2008.2006552.
[17] Sánchez I. Short-term prediction of wind energy production. Int J Forecast 2006;22:43–56. https://doi.org/10.1016/j.ijforecast.2005.05.003.
[18] Meng A, Ge J, Yin H, Chen S. Wind speed forecasting based on wavelet packet decomposition and artificial neural networks trained by crisscross optimization algorithm. Energy Convers Manag 2016;114:75–88. https://doi.org/10.1016/J.ENCONMAN.2016.02.013.
[19] Liu H, Mi X, Li Y. Wind speed forecasting method based on deep learning strategy using empirical wavelet transform, long short term memory neural network and Elman neural network. Energy Convers Manag 2018;156:498–514.
[20] Wang HZ, Wang GB, Li GQ, Peng JC, Liu YT. Deep belief network based deterministic and probabilistic wind speed forecasting approach. Appl Energy 2016;182:80–93. https://doi.org/10.1016/J.APENERGY.2016.08.108.
[21] Wang H, Li G, Wang G, Peng J, Jiang H, Liu Y. Deep learning based ensemble approach for probabilistic wind power forecasting. Appl Energy 2017;188:56–70.
[22] Yu J, Chen K, Mori J, Rashid MM. A Gaussian mixture copula model based localized Gaussian process regression approach for long-term wind speed prediction. Energy 2013;61:673–86. https://doi.org/10.1016/J.ENERGY.2013.09.013.
[23] Yu R, Gao J, Yu M, Lu W, Xu T, Zhao M, et al. LSTM-EFG for wind power forecasting based on sequential correlation features. Future Gener Comput Syst 2019;93:33–42. https://doi.org/10.1016/J.FUTURE.2018.09.054.
[24] Liu H, Mi X, Li Y. Smart deep learning based wind speed prediction model using wavelet packet decomposition, convolutional neural network and convolutional long short term memory network. Energy Convers Manag 2018;166:120–31. https://doi.org/10.1016/j.enconman.2018.04.021.
[25] Liu H, Mi X, Li Y. Smart multi-step deep learning model for wind speed forecasting based on variational mode decomposition, singular spectrum analysis, LSTM network and ELM. Energy Convers Manag 2018;159:54–64. https://doi.org/10.1016/j.enconman.2018.01.010.
[26] Zhu A, Li X, Mo Z, Wu H. Wind power prediction based on a convolutional neural network. Int conf circuits, devices syst ICCDS 2017 2017;2017–janua:131–5 2017. https://doi.org/10.1109/ICCDS.2017.8120465.
[27] Hu YL, Chen L. A nonlinear hybrid wind speed forecasting model using LSTM network, hysteretic ELM and Differential Evolution algorithm. Energy Convers Manag 2018;173:123–42. https://doi.org/10.1016/j.enconman.2018.07.070.
[28] Wang J, Li Y. Multi-step ahead wind speed prediction based on optimal feature extraction, long short term memory neural network and error correction strategy. Appl Energy 2018;230:429–43. https://doi.org/10.1016/j.apenergy.2018.08.114.
[29] Wang K, Qi X, Liu H, Song J. Deep belief network based k-means cluster approach for short-term wind power forecasting. Energy 2018;165:840–52. https://doi.org/10.1016/j.energy.2018.09.118.
[30] Zhang Y, Le J, Liao X, Zheng F, Li Y. A novel combination forecasting model for wind power integrating least square support vector machine, deep belief network, singular spectrum analysis and locality-sensitive hashing. Energy 2018;168:558–72. https://doi.org/10.1016/j.energy.2018.11.128.
[31] Yu C, Li Y, Bao Y, Tang H, Zhai G. A novel framework for wind speed prediction based on recurrent neural networks and support vector machine. Energy Convers Manag 2018;178:137–45. https://doi.org/10.1016/j.enconman.2018.10.008.
[32] Higashiyama K, Fujimoto Y, Hayashi Y. Feature extraction of NWP data for wind power forecast by using 3d-convolutional neural network. 12th int renew energy storage conf, vol. 155. 2018. p. 350–8. https://doi.org/10.1016/J.EGYPRO.2018.11.043.
[33] Chen J, Zeng GQ, Zhou W, Du W, Lu K Di. Wind speed forecasting using nonlinear-learning ensemble of deep learning time series prediction and extremal optimization. Energy Convers Manag 2018;165:681–95. https://doi.org/10.1016/j.enconman.2018.03.098.
[34] Chen N, Qian Z, Nabney IT, Meng X. Wind power forecasts using Gaussian processes and numerical weather prediction. IEEE Trans Power Syst 2014;29:656–65. https://doi.org/10.1109/TPWRS.2013.2282366.
[35] Jiang X, Dong B, Xie L, Sweeney L. Adaptive Gaussian process for short-term wind speed forecasting. 2010.
[36] Ernst B, Oakleaf B, Ahlstrom ML, Lange M, Moehrlen C, Lange B, et al. Predicting the wind. IEEE Power Energy Mag 2007;5:78–89. https://doi.org/10.1109/MPE.2007.906306.
[37] Hu J, Heng J, Tang J, Guo M. Research and application of a hybrid model based on Meta learning strategy for wind power deterministic and probabilistic forecasting. Energy Convers Manag 2018;173:197–209. https://doi.org/10.1016/j.enconman.2018.07.052.
[38] Barbosa de Alencar D, de Mattos Affonso C, Limão de Oliveira R, Moya Rodríguez J, Leite J, Reston Filho J. Different models for forecasting wind power generation: case study. Energies 2017;10:1976. https://doi.org/10.3390/en10121976.
[39] Tascikaraoglu A, Uzunoglu M. A review of combined approaches for prediction of short-term wind speed and power. Renew Sustain Energy Rev 2014;34:243–54. https://doi.org/10.1016/j.rser.2014.03.033.
[40] Foley AM, Leahy PG, Marvuglia A, McKeogh EJ. Current methods and advances in forecasting of wind power generation. Renew Energy 2012;37:1–8. https://doi.org/10.1016/j.renene.2011.05.033.
[41] Ak R, Vitelli V, Zio E. An interval-valued neural network approach for prediction uncertainty quantification. IEEE Trans Neural Networks Learn Syst 2015;26:2787–800. https://doi.org/10.1109/TNNLS.2015.2396933.
[42] Masseran N. Modeling the fluctuations of wind speed data by considering their mean and volatility effects. Renew Sustain Energy Rev 2016;54:777–84. https://doi.org/10.1016/j.rser.2015.10.071.
[43] Alexiadis MC, Dokopoulos PS, Sahsamanoglou HS, Manousaridis IM. Short-term forecasting of wind speed and related electrical power. Sol Energy 1998;63:61–8. https://doi.org/10.1016/S0038-092X(98)00032-2.
[44] Sideratos G, Hatziargyriou ND. An advanced statistical method for wind power forecasting. Power Syst IEEE Trans 2007;22:258–65. https://doi.org/10.1109/tpwrs.2006.889078.
[45] Mohandes MA, Halawani TO, Rehman S, Hussain AA. Support vector machines for wind speed prediction. Renew Energy 2004;29:939–47. https://doi.org/10.1016/j.renene.2003.11.009.
[46] Jursa R, Rohrig K. Short-term wind power forecasting using evolutionary algorithms for the automated specification of artificial intelligence models. Int J Forecast 2008;24:694–709. https://doi.org/10.1016/j.ijforecast.2008.08.007.
[47] Ghadi MJ, Gilani SH, Afrakhte H, Baghramian A. A novel heuristic method for wind farm power prediction: a case study. Int J Electr Power Energy Syst 2014;63:962–70. https://doi.org/10.1016/j.ijepes.2014.07.008.
[48] Kramer O, Gieseke F. Short-term wind energy forecasting using support vector regression. Soft comput model ind environ appl 6th int conf SOCO 2011, vol. 87. 2011. p. 271–80. https://doi.org/10.1007/978-3-642-19644-7_29.
[49] Han S, Li J, Liu Y. Tabu search algorithm optimized ANN model for wind power prediction with NWP. Energy Procedia 2011;12:733–40. https://doi.org/10.1016/j.egypro.2011.10.099.
[50] Carolin Mabel M, Fernandez E. Analysis of wind power generation and prediction using ANN: a case study. Renew Energy 2008;33:986–92. https://doi.org/10.1016/j.renene.2007.06.013.
[51] Cellura M, Cirrincione G, Marvuglia A, Miraoui A. Wind speed spatial estimation for energy planning in {Sicily}: {A} neural kriging application. Renew Energy 2008;33:1251–66. https://doi.org/10.1016/j.renene.2007.08.013.
[52] Welch RL, Ruffing SM, Venayagamoorthy GK. Comparison of feedforward and feedback neural network architectures for short term wind speed prediction. Proc int jt conf neural networks 2009. p. 3335–40. https://doi.org/10.1109/IJCNN.2009.5179034.
[53] Ramirez-Rosado IJ, Fernandez-Jimenez LA, Monteiro C, Sousa J, Bessa R. Comparison of two new short-term wind-power forecasting systems. Renew Energy 2009;34:1848–54. https://doi.org/10.1016/j.renene.2008.11.014.
[54] Bin S, Haitao Y, Ting L. Short-term wind speed forecasting based on Gaussian process regression model. CSEE; 2012.
[55] Hong T, Pinson P, Fan S. Global energy forecasting competition 2012. Int J Forecast 2014;30:357–63. https://doi.org/10.1016/j.ijforecast.2013.07.001.
[56] Barbounis TG, Theocharis JB. Locally recurrent neural networks for wind speed prediction using spatial correlation. Inf Sci (Ny) 2007;177:5775–97. https://doi.org/10.1016/j.ins.2007.05.024.
[57] Eseye AT, Zhang J, Zheng D, Ma H, Jingfu G. Short-term wind power forecasting using a double-stage hierarchical hybrid GA-ANN approach. 2017 IEEE 2nd int. Conf. Big data anal. (ICBDA) IEEE; 2017. p. 552–6. https://doi.org/10.1109/ICBDA.2017.8078695.
[58] Najeebullah Zameer A, Khan A, Javed SG. Machine Learning based short term wind power prediction using a hybrid learning model. Comput Electr Eng 2015;45:122–33. https://doi.org/10.1016/j.compeleceng.2014.07.009.
[59] Li C, Lin S, Xu F, Liu D, Liu J. Short-term wind power prediction based on data mining technology and improved support vector machine method: A case study in Northwest China vol. 205. Elsevier Ltd; 2018. https://doi.org/10.1016/j.jclepro.2018.09.143.
[60] Bacher P, Madsen H, Nielsen HA. Online short-term solar power forecasting. Sol Energy 2009;83:1772–83.
[61] Troncoso A, Salcedo-Sanz S, Casanova-Mateo C, Riquelme JC, Prieto L. Local

models-based regression trees for very short-term wind speed prediction. Renew Energy 2015;81:589–98. https://doi.org/10.1016/J.RENENE.2015.03.071.
[62] Pedro HTC, Coimbra CFM. Assessment of forecasting techniques for solar power production with no exogenous inputs. Sol Energy 2012;86:2017–28.
[63] Pedro HTC, Coimbra CFM, David M, Lauret P. Assessment of machine learning techniques for deterministic and probabilistic intra-hour solar forecasts. Renew Energy 2018;123:191–203.
[64] Tang P, Chen D, Hou Y. Entropy method combined with extreme learning machine method for the short-term photovoltaic power generation forecasting. Chaos, Solit Fractals 2016;89:243–8. https://doi.org/10.1016/J.CHAOS.2015.11.008.
[65] Paoli C, Voyant C, Muselli M, Nivet M-L. Forecasting of preprocessed daily solar radiation time series using neural networks. Sol Energy 2010;84:2146–60. https://doi.org/10.1016/J.SOLENER.2010.08.011.
[66] Lauret P, Voyant C, Soubdhan T, David M, Poggi P. A benchmarking of machine learning techniques for solar radiation forecasting in an insular context. Sol Energy 2015;112:446–57. https://doi.org/10.1016/J.SOLENER.2014.12.014.
[67] Bouzerdoum M, Mellit A, Massi Pavan A. A hybrid model (SARIMA–SVM) for short-term power forecasting of a small-scale grid-connected photovoltaic plant. Sol Energy 2013;98:226–35. https://doi.org/10.1016/J.SOLENER.2013.10.002.
[68] Sheng H, Xiao J, Cheng Y, Ni Q, Wang S. Short-term solar power forecasting based on weighted Gaussian process regression. IEEE Trans Ind Electron 2018. https://doi.org/10.1109/TIE.2017.2714127.
[69] Salcedo-Sanz S, Casanova-Mateo C, Munoz-Mari J, Camps-Valls G. Prediction of daily global solar irradiation using temporal Gaussian processes. IEEE Geosci Remote Sens Lett 2014;11:1936–40. https://doi.org/10.1109/LGRS.2014.2314315.
[70] Reikard G. Predicting solar radiation at high resolutions: a comparison of time series forecasts. Sol Energy 2009;83:342–9. https://doi.org/10.1016/j.solener.2008.08.007.
[71] Behera MK, Majumder I, Nayak N. Solar photovoltaic power forecasting using optimized modified extreme learning machine technique. Eng Sci Technol an Int J 2018;21:428–38. https://doi.org/10.1016/J.JESTCH.2018.04.013.
[72] Sharma A, Kakkar A. Forecasting daily global solar irradiance generation using machine learning. Renew Sustain Energy Rev 2018;82:2254–69. https://doi.org/10.1016/J.RSER.2017.08.066.
[73] Hossain M, Mekhilef S, Danesh M, Olatomiwa L, Shamshirband S. Application of extreme learning machine for short term output power forecasting of three grid-connected PV systems. J Clean Prod 2017;167:395–405.
[74] Majumder I, Dash PK, Bisoi R. Variational mode decomposition based low rank robust kernel extreme learning machine for solar irradiation forecasting. Energy Convers Manag 2018;171:787–806. https://doi.org/10.1016/J.ENCONMAN.2018.06.021.
[75] Srivastava S, Lessmann S. A comparative study of LSTM neural networks in forecasting day-ahead global horizontal irradiance with satellite data. Sol Energy 2018;162:232–47. https://doi.org/10.1016/J.SOLENER.2018.01.005.
[76] Qing X, Niu Y. Hourly day-ahead solar irradiance prediction using weather forecasts by LSTM. Energy 2018;148:461–8. https://doi.org/10.1016/j.energy.2018.01.177.
[77] Alzahrani A, Shamsi P, Dagli C, Ferdowsi M. Solar irradiance forecasting using deep neural networks. Procedia Comput Sci 2017;114:304–13. https://doi.org/10.1016/j.procs.2017.09.045.
[78] Li LL, Cheng P, Lin HC, Dong H. Short-term output power forecasting of photovoltaic systems based on the deep belief net. Adv Mech Eng 2017;9:1–13. https://doi.org/10.1177/1687814017715983.
[79] Abdel-Nasser M, Mahmoud K. Accurate photovoltaic power forecasting models using deep LSTM-RNN. Neural Comput Appl 2017:1–14. https://doi.org/10.1007/s00521-017-3225-z.
[80] Zhang J, Verschae R, Nobuhara S, Lalonde J-FF. Deep photovoltaic nowcasting. Sol Energy 2018;176:267–76. https://doi.org/10.1016/j.solener.2018.10.024.
[81] Wang H, Yi H, Peng J, Wang G, Liu Y, Jiang H, et al. Deterministic and probabilistic forecasting of photovoltaic power based on deep convolutional neural network. Energy Convers Manag 2017;153:409–22. https://doi.org/10.1016/j.enconman.2017.10.008.
[82] Ridley B, Boland J, Lauret P. Modelling of diffuse solar fraction with multiple predictors. Renew Energy 2010;35:478–83. https://doi.org/10.1016/j.renene.2009.07.018.
[83] Ruiz-Arias JA, Alsamamra H, Tovar-Pescador J, Pozo-Vázquez D. Proposal of a regressive model for the hourly diffuse solar radiation under all sky conditions. Energy Convers Manag 2010;51:881–93. https://doi.org/10.1016/j.enconman.2009.11.024.
[84] Chen C, Duan S, Cai T, Liu B. Online 24-h solar power forecasting based on weather type classification using artificial neural network. Sol Energy 2011;85:2856–70. https://doi.org/10.1016/j.solener.2011.08.027.
[85] İzgi E, Öztopal A, Yerli B, Kaymak MK, Şahin AD. Short–mid-term solar power prediction by using artificial neural networks. Sol Energy 2012;86:725–33. https://doi.org/10.1016/j.solener.2011.11.013.
[86] Mellit A, Pavan AM. A 24-h forecast of solar irradiance using artificial neural network: application for performance prediction of a grid-connected PV plant at Trieste, Italy. Sol Energy 2010;84:807–21. https://doi.org/10.1016/j.solener.2010.02.006.
[87] Mellit A, Benghanem M, Kalogirou SA. Modeling and simulation of a stand-alone photovoltaic system using an adaptive artificial neural network: proposition for a new sizing procedure. Renew Energy 2007;32:285–313. https://doi.org/10.1016/j.renene.2006.01.002.
[88] Mellit A, Eleuch H, Benghanem M, Elaoun C, Pavan AM. An adaptive model for predicting of global, direct and diffuse hourly solar irradiance. Energy Convers Manag 2010;51:771–82. https://doi.org/10.1016/j.enconman.2009.10.034.
[89] Shi J, Lee WJ, Liu Y, Yang Y, Wang P. Forecasting power output of photovoltaic systems based on weather classification and support vector machines. IEEE Trans Ind Appl 2012;48:1064–9. https://doi.org/10.1109/TIA.2012.2190816.
[90] Yona A, Senjyu T, Saber AY, Funabashi T, Sekine H, Kim CH. Application of neural network to one-day-ahead 24 hours generating power forecasting for photovoltaic system. 2007 int conf intell syst appl to power syst ISAP 2007. p. 7–12. https://doi.org/10.1109/ISAP.2007.4441657.
[91] Ding M, Wang L, Bi R. An ANN-based approach for forecasting the power output of photovoltaic system. Procedia Environ Sci 2011;11:1308–15. https://doi.org/10.1016/j.proenv.2011.12.196.
[92] Sfetsos A, Coonick AAH. Univariate and multivariate forecasting of hourly solar radiation with artificial intelligence techniques. Sol Energy 2000;68:169–78. https://doi.org/10.1016/S0038-092X(99)00064-X.
[93] Mellit A, Kalogirou SA, Shaari S, Salhi H, Hadj Arab A. Methodology for predicting sequences of mean monthly clearness index and daily solar radiation data in remote areas: application for sizing a stand-alone PV system. Renew Energy 2008;33:1570–90. https://doi.org/10.1016/j.renene.2007.08.006.
[94] Raza MQ, Khosravi A. A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. Renew Sustain Energy Rev 2015;50:1352–72.
[95] Taylor JW. An evaluation of methods for very short-term load forecasting using minute-by-minute British data. Int J Forecast 2008;24:645–58. https://doi.org/10.1016/j.ijforecast.2008.07.007.
[96] Drezga I, Rahman S. Input variable selection for ann-based short-term load forecasting. IEEE Trans Power Syst 1998. https://doi.org/10.1109/59.736244.
[97] Sovann N, Nallagownden P, Baharudin Z. A method to determine the input variable for the neural network model of the electrical system. 2014 5th. Int. Conf. Intell. Adv. Syst. Technol. Converg. Sustain. Futur. ICIAS 2014 - proc 2014. https://doi.org/10.1109/ICIAS.2014.6869491.
[98] Tao S, Li Y, Xiao X, Yao L. Load forecasting based on short-term correlation clustering. IEEE Innov. Smart Grid Technol. - Asia 2017:1–7. https://doi.org/10.1109/ISGT-Asia.2017.8378416.
[99] Vinagre E, De Paz JF, Pinto T, Vale Z, Corchado JM, Garcia O. Intelligent energy forecasting based on the correlation between solar radiation and consumption patterns. 2016 IEEE symp. Ser. Comput. Intell. SSCI 2016 2017. https://doi.org/10.1109/SSCI.2016.7849853.
[100] Taylor JW. Triple seasonal methods for short-term electricity demand forecasting. Eur J Oper Res 2010;204:139–52. https://doi.org/10.1016/j.ejor.2009.10.003.
[101] Taylor JW, de Menezes LM, McSharry PE. A comparison of univariate methods for forecasting electricity demand up to a day ahead. Int J Forecast 2006;22:1–16. https://doi.org/10.1016/j.ijforecast.2005.06.006.
[102] Taylor JW, Buizza R. Using weather ensemble predictions in electricity demand forecasting using weather ensemble predictions in electricity demand forecasting. Int J Forecast 2003;19:57–70. https://doi.org/10.1016/S0169-2070(01)00123-6.
[103] Gould PG, Koehler AB, Ord JK, Snyder RD, Hyndman RJ, Vahid-Araghi F. Forecasting time series with multiple seasonal patterns. Eur J Oper Res 2008;191:207–22. https://doi.org/10.1016/j.ejor.2007.08.024.
[104] Al-Hamadi HM, Soliman SA. Short-term electric load forecasting based on Kalman filtering algorithm with moving window weather and load model. Electr Power Syst Res 2004;68:47–59. https://doi.org/10.1016/S0378-7796(03)00150-0.
[105] Taylor JW, Mcsharry PE. Short-term load forecasting Methods : an evaluation based on european data. IEEE Trans Power Syst 2008;22:2213–9. https://doi.org/10.1109/TPWRS.2007.907583.
[106] Villalba SA, Alvarez C. Hybrid demand model for load estimation and short term load forecasting in distribution electric systems. Power Deliv IEEE Trans 2000;15:764–9. https://doi.org/10.1109/61.853017.
[107] Wang J, Zhu W, Zhang W, Sun D. A trend fixed on firstly and seasonal adjustment model combined with the ??-SVR for short-term forecasting of electricity demand. Energy Policy 2009;37:4901–9. https://doi.org/10.1016/j.enpol.2009.06.046.
[108] Zheng Y, Zhu L, Zou X. Short-term load forecasting based on Gaussian wavelet SVM. Energy Procedia 2011;12:387–93. https://doi.org/10.1016/j.egypro.2011.10.052.
[109] Badri A, Ameli Z, Motie Birjandi A. Application of artificial neural networks and fuzzy logic methods for short term load forecasting. Energy Procedia 2012;14:1883–8. https://doi.org/10.1016/j.egypro.2011.12.1183.
[110] Ho K-L, Hsu Y-Y, Chen C-F, Lee T-E, Liang C-C, Lai T-S, et al. Short term load forecasting of Taiwan power system using a knowledge-based expert system. IEEE Trans Power Syst 1990;5:1214–21. https://doi.org/10.1109/59.99372.
[111] Galarniotis AI, Tsakoumis AC, Fessas P, Vladov SS, Mladenov VM. Using Elman and FIR neural networks for short term electric load forecasting. SCS. 2003. Int. Symp. Signals, circuits syst. Proc. (Cat. No.03EX720), vol. 2. IEEE; 2003. p. 433–6. https://doi.org/10.1109/SCS.2003.1227082.
[112] Shu F, Luonan C. Short-term load forecasting based on an adaptive hybrid method. Power Syst IEEE Trans 2006;21:392–401. https://doi.org/10.1109/TPWRS.2005.860944.
[113] Zhang B-L, Dong Z-Y. An adaptive neural-wavelet model for short term load forecasting. Electr Power Syst Res 2001;59:121–9. https://doi.org/10.1016/S0378-7796(01)00138-9.
[114] Song K, Baek Y, Hong DH, Jang G. Short-term load forecasting for the holidays using. IEEE Trans Power Syst 2005;20:96–101. https://doi.org/10.1109/TPWRS.2004.835632.
[115] Marín FJ, Sandoval F. Short-term peak load forecasting: statistical methods versus artificial neural networks. Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 1997. https://doi.org/10.1007/BFb0032594.
[116] Saber AY, Alam AKMR. Short term load forecasting using multiple linear regression for big data. 2017 IEEE symp. Ser. Comput. Intell. SSCI 2017 - proc. 2018. https://doi.org/10.1109/SSCI.2017.8285261.
[117] Almeshaiei E, Soltan H. A methodology for electric power load forecasting. Alexandria Eng J 2011;50:137–44. https://doi.org/10.1016/j.aej.2011.01.015.
[118] Bessec M, Fouquau J. Short-run electricity load forecasting with combinations of stationary wavelet transforms. Eur J Oper Res 2018;264:149–64. https://doi.org/10.1016/J.EJOR.2017.05.037.

[119] Hong W-C. Hybrid evolutionary algorithms in a SVR-based electric load forecasting model. Int J Electr Power Energy Syst 2009;31:409–17. https://doi.org/10.1016/J.IJEPES.2009.03.020.
[120] Yang Y, Li S, Li W, Qu M. Power load probability density forecasting using Gaussian process quantile regression. Appl Energy 2018;213:499–509. https://doi.org/10.1016/J.APENERGY.2017.11.035.
[121] Coelho VN, Coelho IM, Coelho BN, Reis AJR, Enayatifar R, Souza MJF, et al. A self-adaptive evolutionary fuzzy model for load forecasting problems on smart grid environment. Appl Energy 2016;169:567–84. https://doi.org/10.1016/J.APENERGY.2016.02.045.
[122] Rahman S, Hazim O. A generalized knowledge-based short-term load-forecasting technique. IEEE Trans Power Syst 1993. https://doi.org/10.1109/59.260833.
[123] Srinivasan D. Parallel neural network-fuzzy expert system strategy for short-term load forecasting : system implementation and performance evaluation. IEEE Trans Power Syst 1999. https://doi.org/10.1109/59.780934.
[124] Hippert HS, Pedreira CE, Souza RC. Neural networks for short-term load forecasting: a review and evaluation. IEEE Trans Power Syst 2001;16:44–55. https://doi.org/10.1109/59.910780.
[125] Tsakoumis AC, Vladov SS, Mladenov VM. Electric load forecasting with multilayer perceptron and Elman neural network. 6th semin neural netw appl electr eng 2002. https://doi.org/10.1109/NEUREL.2002.1057974.
[126] Zhang W, Mu G, Yan G, An J. A power load forecast approach based on spatial-temporal clustering of load data. Concurr Comput Pract Exp n.d. 2018;0:e4386. https://doi.org/10.1002/cpe.4386.
[127] Hong W-CC. Electric load forecasting by seasonal recurrent SVR (support vector regression) with chaotic artificial bee colony algorithm. Energy 2011;36:5568–78. https://doi.org/10.1016/j.energy.2011.07.015.
[128] Dedinec A, Filiposka S, Dedinec A, Kocarev L. Deep belief network based electricity load forecasting: an analysis of Macedonian case. Energy 2016;115:1688–700. https://doi.org/10.1016/j.energy.2016.07.090.
[129] Shi H, Xu M, Ma Q, Zhang C, Li R, Li F. A whole system Assessment of novel deep learning approach on short-term load forecasting. Energy Procedia 2017;142:2791–6. https://doi.org/10.1016/j.egypro.2017.12.423.
[130] Hernandez L, Baladron C, Aguiar J, Carro B, Sanchez-Esguevillas A, Lloret J, et al. A multi-agent system architecture for smart grid management and forecasting of energy demand in virtual power plants. IEEE Commun Mag 2013. https://doi.org/10.1109/MCOM.2013.6400446.
[131] Javed F, Arshad N, Wallin F, Vassileva I, Dahlquist E. Forecasting for demand response in smart grids: an analysis on use of anthropologic and structural data and short term multiple loads forecasting. Appl Energy 2012. https://doi.org/10.1016/j.apenergy.2012.02.027.
[132] Hernandez L, Baladron C, Aguiar JM, Carro B, Sanchez-Esguevillas AJ, Lloret J, et al. A survey on electric power demand forecasting: future trends in smart grids, microgrids and smart buildings. IEEE Commun Surv Tutorials 2014. https://doi.org/10.1109/SURV.2014.032014.00094.
[133] Nowotarski J, Weron R. Recent advances in electricity price forecasting: a review of probabilistic forecasting. Renew Sustain Energy Rev 2018;81:1548–68.
[134] Weron R. Electricity price forecasting: a review of the state-of-the-art with a look into the future. vol. 30. 2014. https://doi.org/10.1016/j.ijforecast.2014.08.008.
[135] Yang Z, Ce L, Lian L. Electricity price forecasting by a hybrid model, combining wavelet transform, ARMA and kernel-based extreme learning machine methods. Appl Energy 2017;190:291–305. https://doi.org/10.1016/j.apenergy.2016.12.130.
[136] Abedinia O, Amjady N, Shafie-Khah M, Catalão JPSPS. Electricity price forecast using Combinatorial Neural Network trained by a new stochastic search method. Energy Convers Manag 2015;105:642–54.
[137] Wang D, Luo H, Grunder O, Lin Y, Guo H. Multi-step ahead electricity price forecasting using a hybrid model based on two-layer decomposition technique and BP neural network optimized by firefly algorithm. Appl Energy 2017;190:390–407. https://doi.org/10.1016/J.APENERGY.2016.12.134.
[138] Amjady N, Daraeepour A. Mixed price and load forecasting of electricity markets by a new iterative prediction method. Electr Power Syst Res 2009;79:1329–36. https://doi.org/10.1016/J.EPSR.2009.04.006.
[139] Ghasemi A, Shayeghi H, Moradzadeh M, Nooshyar M. A novel hybrid algorithm for electricity price and load forecasting in smart grids with demand-side management. Appl Energy 2016;177:40–59.
[140] Hong T, Fan S. Probabilistic electric load forecasting: a tutorial review. Int J Forecast 2016;32:914–38. https://doi.org/10.1016/j.ijforecast.2015.11.011.
[141] Zhang Y, Wang J, Wang X. Review on probabilistic forecasting of wind power generation. Renew Sustain Energy Rev 2014;32:255–70. https://doi.org/10.1016/j.rser.2014.01.033.
[142] van der Meer DW, Widén J, Munkhammar J. Review on probabilistic forecasting of photovoltaic power production and electricity consumption. Renew Sustain Energy Rev 2018;81:1484–512. https://doi.org/10.1016/j.rser.2017.05.212.
[143] Peng Y, Rysanek A, Nagy Z, Schlüter A. Using machine learning techniques for occupancy-prediction-based cooling control in office buildings. Appl Energy 2018;211:1343–58. https://doi.org/10.1016/J.APENERGY.2017.12.002.
[144] Zahid T, Xu K, Li W, Li C, Li H. State of charge estimation for electric vehicle power battery using advanced machine learning algorithm under diversified drive cycles. Energy 2018;162:871–82. https://doi.org/10.1016/J.ENERGY.2018.08.071.
[145] Fu X, Zhang X. Estimation of building energy consumption using weather information derived from photovoltaic power plants. Renew Energy 2019;130:130–8. https://doi.org/10.1016/J.RENENE.2018.06.069.
[146] Saloux E, Candanedo JA. Forecasting district heating demand using machine learning algorithms. Energy Procedia 2018;149:59–68. https://doi.org/10.1016/J.EGYPRO.2018.08.169.
[147] Tomin NV, Kurbatsky VG, Sidorov DN, Zhukov AV. Machine learning techniques for power system security assessment. IFAC-PapersOnLine 2016;49:445–50. https://doi.org/10.1016/J.IFACOL.2016.10.773.
[148] Karim M Al, Currie J, Lie T-T. A machine learning based optimized energy dispatching scheme for restoring a hybrid microgrid. Electr Power Syst Res 2018;155:206–15. https://doi.org/10.1016/J.EPSR.2017.10.015.
[149] Staffell I, Pfenninger S. Renewables.ninja. 2015.
[150] Staffell I. Wind Turbine Power Curves 2012:1–6.
[151] Staffell I, Green R. How does wind farm performance decline with age? Renew Energy 2014;66:775–86. https://doi.org/10.1016/j.renene.2013.10.041.
[152] Yang J, Leskovec J. Patterns of temporal variation in online media. Time 2011;468:177–86. https://doi.org/10.1145/1935826.1935863.
[153] Kalogirou S a. Artificial neural networks in renewable energy systems applications: a review. Renew Sustain Energy Rev 2001;5:373–401. https://doi.org/10.1016/S1364-0321(01)00006-5.
[154] Soman PC. An adaptive NARX neural network approach for financial time series prediction. 2008.
[155] Lin T, Horne BG, Tiňo P, Giles CL. Learning long-term dependencies in NARX recurrent neural networks. IEEE Trans Neural Netw 1996;7:1329–38. https://doi.org/10.1109/72.548162.
[156] Xie H, Tang H, Liao YH. Time series prediction based on narx neural networks: an advanced approach. Proc 2009 int conf mach learn cybern, vol. 3. 2009. p. 1275–9. https://doi.org/10.1109/ICMLC.2009.5212326.
[157] Li Z, Best M. Structure optimisation of input layer for feed-forward NARX neural network. Int J Model Identif Control 2016;25:217. https://doi.org/10.1504/IJMIC.2016.075814.
[158] Tao C, Shanxu D, Changsong C. Forecasting power output for grid-connected photovoltaic power system without using solar radiation measurement. 2nd IEEE int symp power electron distrib gener syst 2010. p. 773–7. https://doi.org/10.1109/PEDG.2010.5545754.
[159] Siegelmann HT, Horne BG, Giles CL. Computational capabilities of recurrent NARX neural networks. IEEE Trans Syst Man Cybern B Cybern 1997;27:208–15. https://doi.org/10.1109/3477.558801.
[160] Hornik K. Approximation capabilities of multilayer feedforward networks. Neural Network 1991;4:251–7. https://doi.org/10.1016/0893-6080(91)90009-T.
[161] Cybenko G. Correction: approximation by superpositions of a sigmoidal function. Math Control Signals, Syst 1989;2:303–14. https://doi.org/10.1007/BF02134016.
[162] Erb RJ. Introduction to backpropagation neural network computation. Pharm Res An Off J Am Assoc Pharm Sci 1993;10:165–70. https://doi.org/10.1023/A:1018966222807.
[163] Beale MH, Hagan MT, Demuth HB. Neural network Toolbox™ user's guide with MATLAB. 2015. https://doi.org/10.1016/j.neunet.2005.10.002.
[164] Wu X, Kumar V, Ross Quinlan J, Ghosh J, Yang Q, Motoda H, et al. Top 10 algorithms in data mining vol. 14. 2008. https://doi.org/10.1007/s10115-007-0114-2.
[165] Sayad S. Real time data mining. Self-Help Publishers; 2011.
[166] Cortes C, Vapnik V. Support-vector networks. Mach Learn 1995;20:273–97. https://doi.org/10.1007/BF00994018.
[167] Suykens J, Van Gestel T, De Brabanter J, De Moor B, Vandewalle J. Least squares-support vector machines, toolbox for matlab/C v1.8. 2011.
[168] Suykens J, Van Gestel T, De Brabanter J, Vandewalle J. Least squares support vector machines. Singapore: World Scientific; 2002.
[169] Rasmussen CE, Williams CKI. Gaussian processes for machine learning vol. 14. MIT Press; 2006. https://doi.org/10.1142/S0129065704001899.
[170] Kocijan J, Ažman K, Grancharova A. The concept for Gaussian process model based system identification toolbox. Proc 2007 int conf comput syst technol - CompSysTech '07 2007. p. 1. https://doi.org/10.1145/1330598.1330647.
[171] Greiger A. Gaussian Processes for Machine Learning. An introduction to Gaussian Processes, (scaled) GPLVMs, (balanced) GPDMs and their applications to 3D people tracking. 2007.
[172] Stepančič M, Kocijan J. Gaussian-Process-Model-based system-identification toolbox for matlab, GPdyn. [n.d].
[173] Sharifzadeh M, Lubiano-Walochik H, Shah N. Integrated renewable electricity generation considering uncertainties: the UK roadmap to 50% power generation from wind and solar energies. Renew Sustain Energy Rev 2017;72:385–98. https://doi.org/10.1016/j.rser.2017.01.069.
[174] BEIS. Digest of UK Energy Statistics (DUKES): renewable sources of energy. DUKES chapter 6: statistics on energy from renewable sources. UK National Statistics; 2018.
[175] Intertek Testing & Certification Ltd. Household electricity survey. A study of domestic electrical product usage. 2012.
[176] Kennel F, Gorges D, Liu S. Energy management for smart grids with electric vehicles based on hierarchical MPC. Ind Informatics, IEEE Trans 2013;9:1528–37. https://doi.org/10.1109/TII.2012.2228876.