Review of Machine-learning Methods for Integrated Renewable Power Generation: A Comparative Study of Artificial Neural Networks, Support Vector Regression, and Gaussian Process Regression

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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 power and wind was fast and accurate enough to effectively replace the alternative electricity storage and standby capacity.

Keywords

Machine-learning, Big Data, Renewable Wind and Solar Power, Electricity demand, Artificial Neural Networks (ANN), Support Vector Regression (SVR), Gaussian Process Regression (GPR).

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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 found for the prediction of electricity demand [3,4], the photovoltaic power generation in [5], [6] and the wind power [7]. Baños et al., [8] reviewed the optimisation 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 [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 [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 to 5-hour 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 [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 for decompose the original time-series into several sublayers. The high frequency sublayer was 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 the wind speed. Similar studied by Liu et al. [19,25], using the same strategy for decomposing the data to multilayers and training various recurrent neural networks, which showed improvements over conventional approaches. Zhu et al. [26] applied convolutional neural networks for four-hours ahead forecast of 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 ten-minute ahead (utmost short term) and one-hour ahead (short term) wind power predictions. Wang and Li [28] developed a model consisting of the three elements of 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 demonstrated the superior performance of the 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 forecaster, 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 three hybrid models include wavelet transform is firstly 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 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 wind data. Then, the parameters of the nonlinear SVRM model were optimized using the extremal optimization algorithm. The demonstrated the performance of their model for 10min ahead prediction of wind speed data from inner Mongolia, China.

In [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 [7,40].

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 (15m)	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

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 two hours, 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 [62] MLP neural networks were successful in making 1 hour and 2 hour 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 minutes), 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 forecasting global horizontal irradiance (GHI), a measure of shortwave radiation received used for PV installation, using a long short term memory (LSTM) neural network. 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 coefficient, 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 should significant improvements over a base-line back propagation (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 a 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, cloud movement and appearance, was applied to forecast the solar power generation. The authors report 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 for decomposing 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.

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 (x2) [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

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 [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 [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].

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** summarises 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 minutes), 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.

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

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 [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 [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% to 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 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 aggerated 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 thorough review of these methods are 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 10m above ground level at the specific location, and the 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.

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 10m $(\frac{m}{s})$	✓		
Direct irradiance (KW)		✓	
Diffuse irradiance (KW)		✓	

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 from1985 to 2014.

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

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 architecture 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.

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

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

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

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]. A thorough survey of literature 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 details comparison of various ANN methods are beyond the scope of the present study, the research are generalizable in the sense that more complex neural network architectures could also gain 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 **Figure 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.

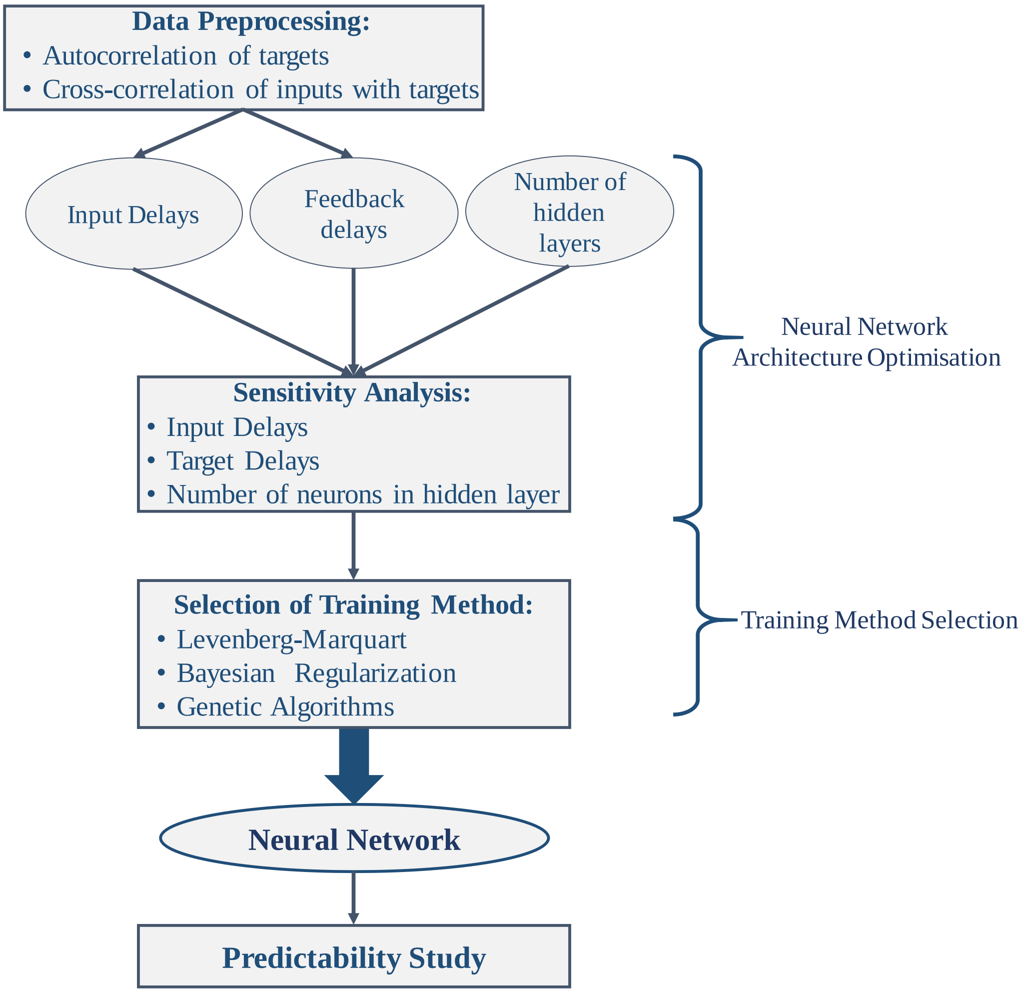

Figure 1. Framework for tuning NARX neural network parameters and selecting the training method

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 minimize 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 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.

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 10m $(\frac{m}{s})$	✓		
Direct irradiance (KW)		✓	
Diffuse irradiance (KW)		✓	

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 (**Figure 2b**), whereas the correlation with hourly (time) variable is weak (**Figure 2e**). This is expected since wind speed is the driving force of the turbines, and even though wind is a result of the 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 (**Figure 2d**) as well as the temperature (**Figure 2c**) influence the wind power.

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

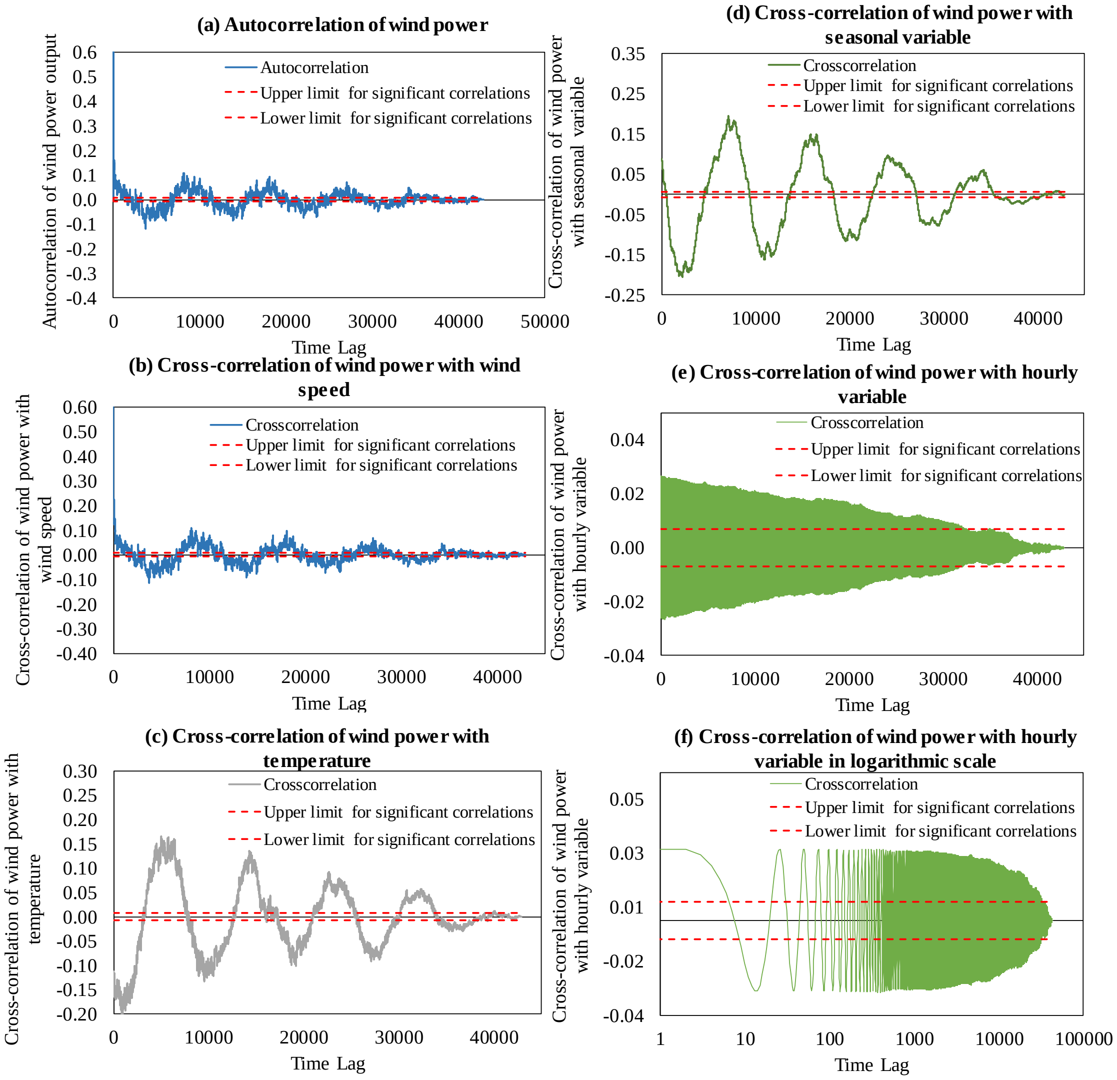

Figure 2. Cross-correlations for input data applied for the wind power prediction

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 one-hour ahead prediction was taken into consideration, which is depicted in the vertical axis of **Figures 3a-c.** Secondly, the error's autocorrelation and cross-correlation with each input were calculated as graphically presented in **Figures 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.

Figures 3a-c show 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.

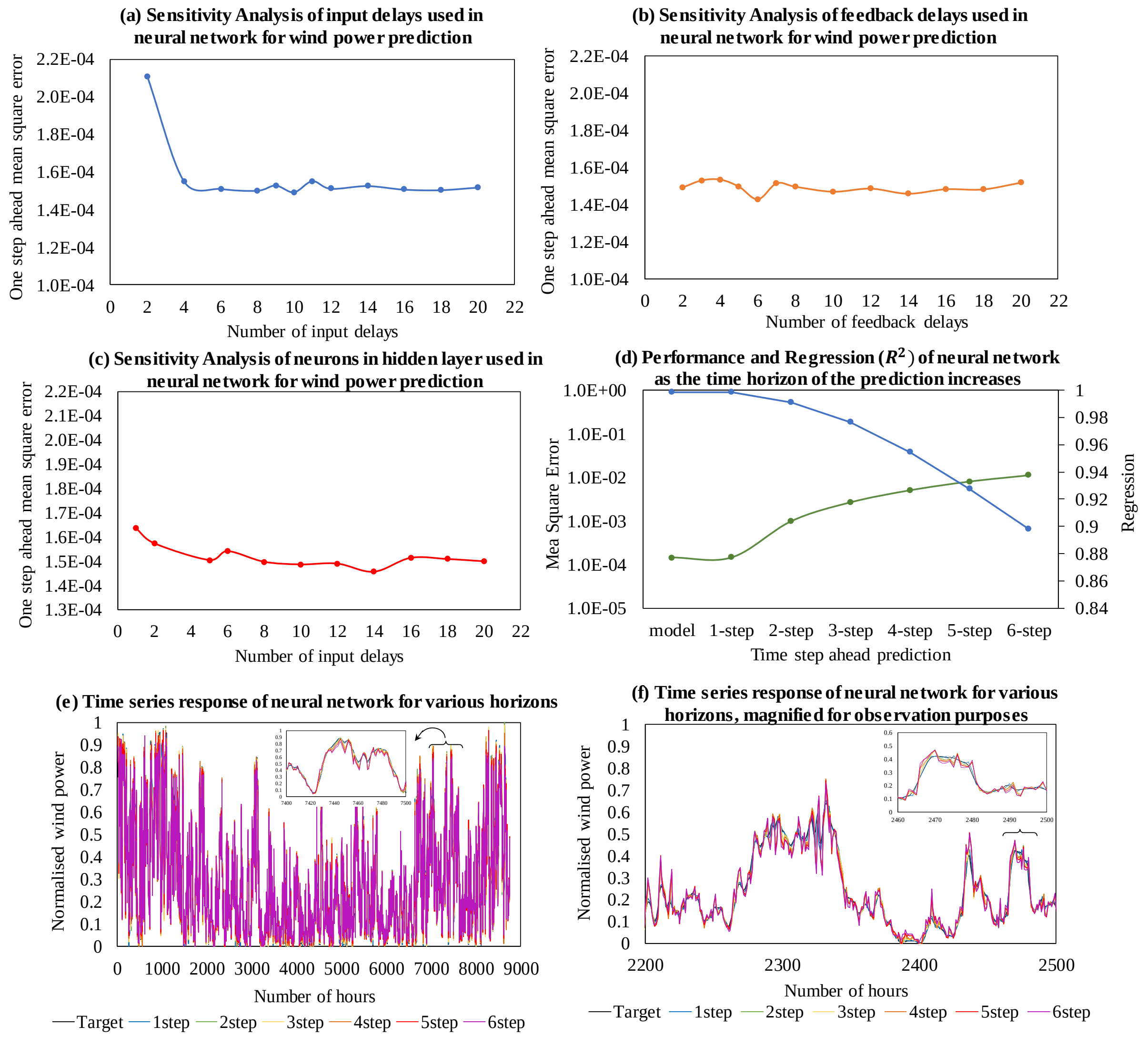

Figure 3. The sensitivity analysis and performance of ANN for wind power prediction

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 **Figure 3.d**.

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

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 **Figure 3.e 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 error of the ANN model for predicting the wind power generation is reported in the second column of **Table 9**.

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

3.1.4. 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.

Table 9. 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

In **Table 9**, 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 **Figure 4.a**, the Model (ε-SVR) has a much greater error than when the LS-SVR predicts one hour 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 **Figure 4.b,** and magnified in **Figure 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.

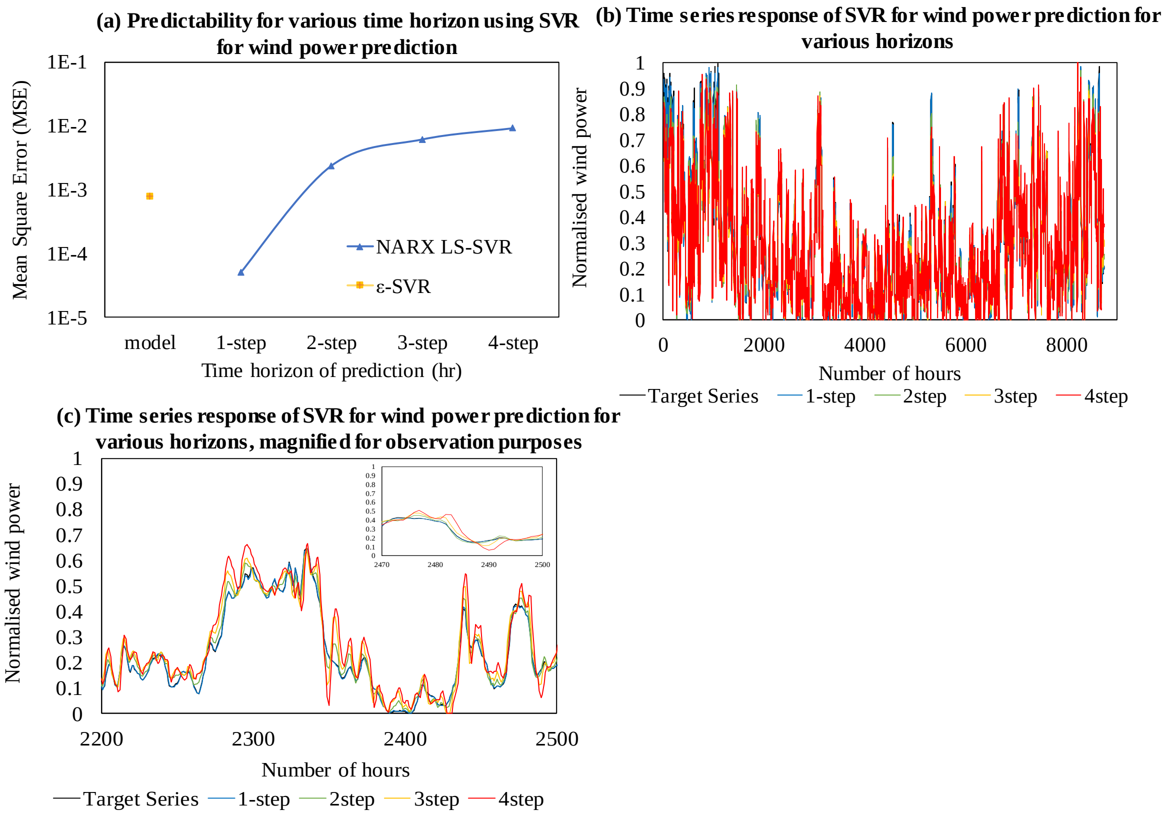

Figure 4. The sensitivity analysis and performance of the SVR for wind power prediction

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 10**. 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 **Figure 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 10. 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

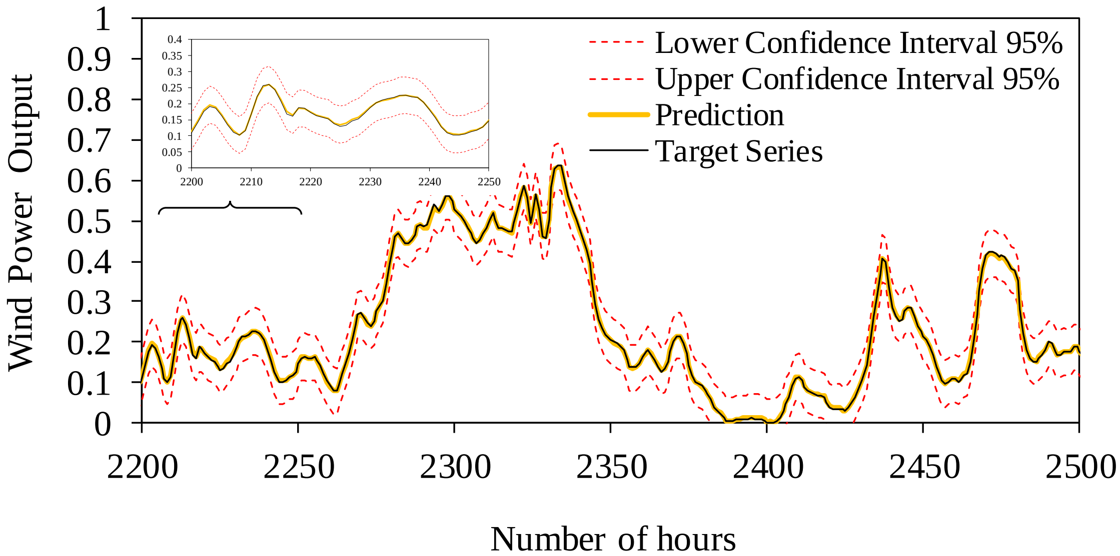

Figure 5. Time series response of GPR for wind power prediction (present time) magnified for observation purposes

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.

In **Table 11** 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 (**Figure 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 (**Figure 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 (**Figures 6.c-f**).

Table 11. 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

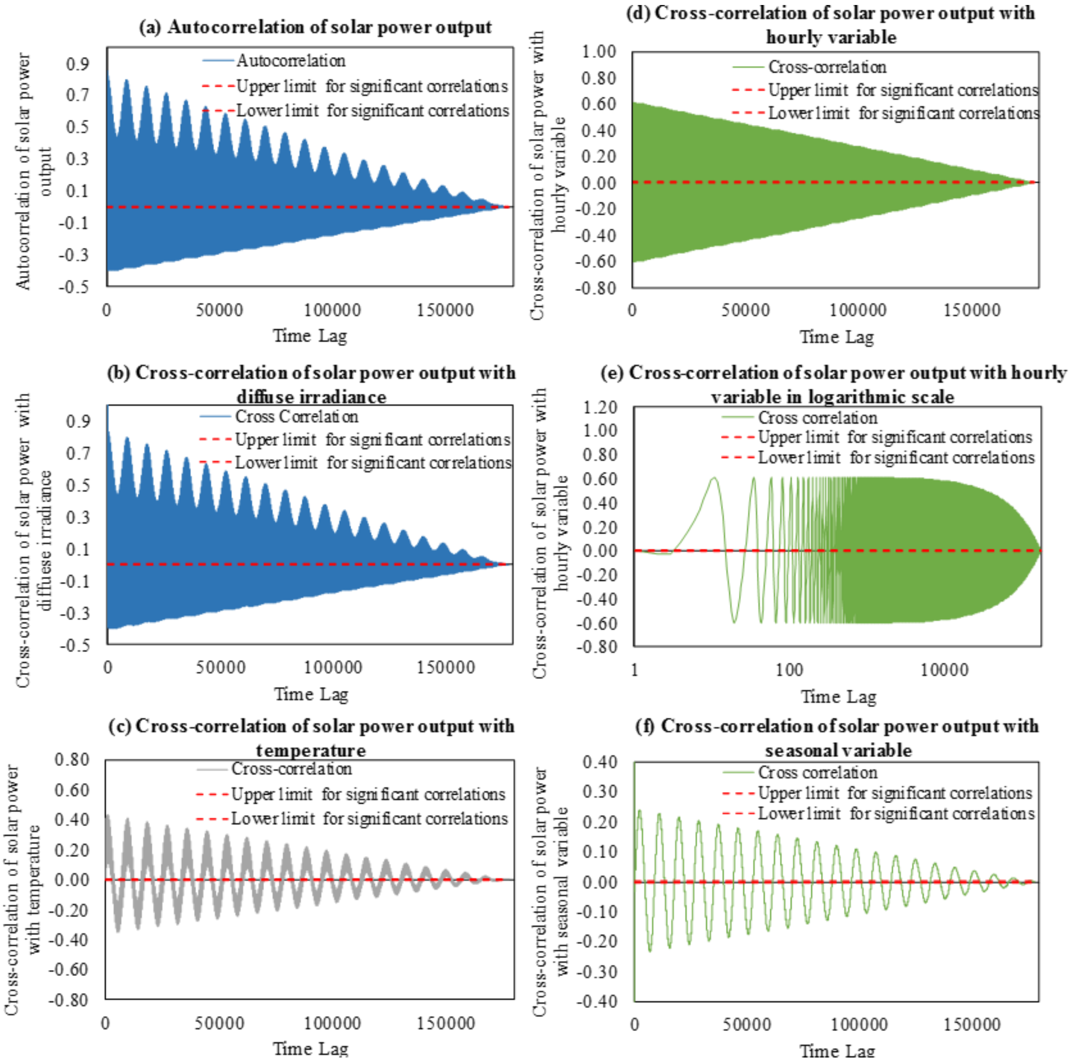

Figure 6. Cross-correlations for input data applied for the solar power prediction

3.2.2. Forecasting solar power with Artificial Neural Networks

The framework in **Figure 1** was followed to establish the ANN's architecture. More specifically, the feedback delays (**Figure 7.a**) were first studied, followed by the input delays (**Figure 7.b**), and the number of neurons within the hidden layer (**Figure 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 **Figure 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.

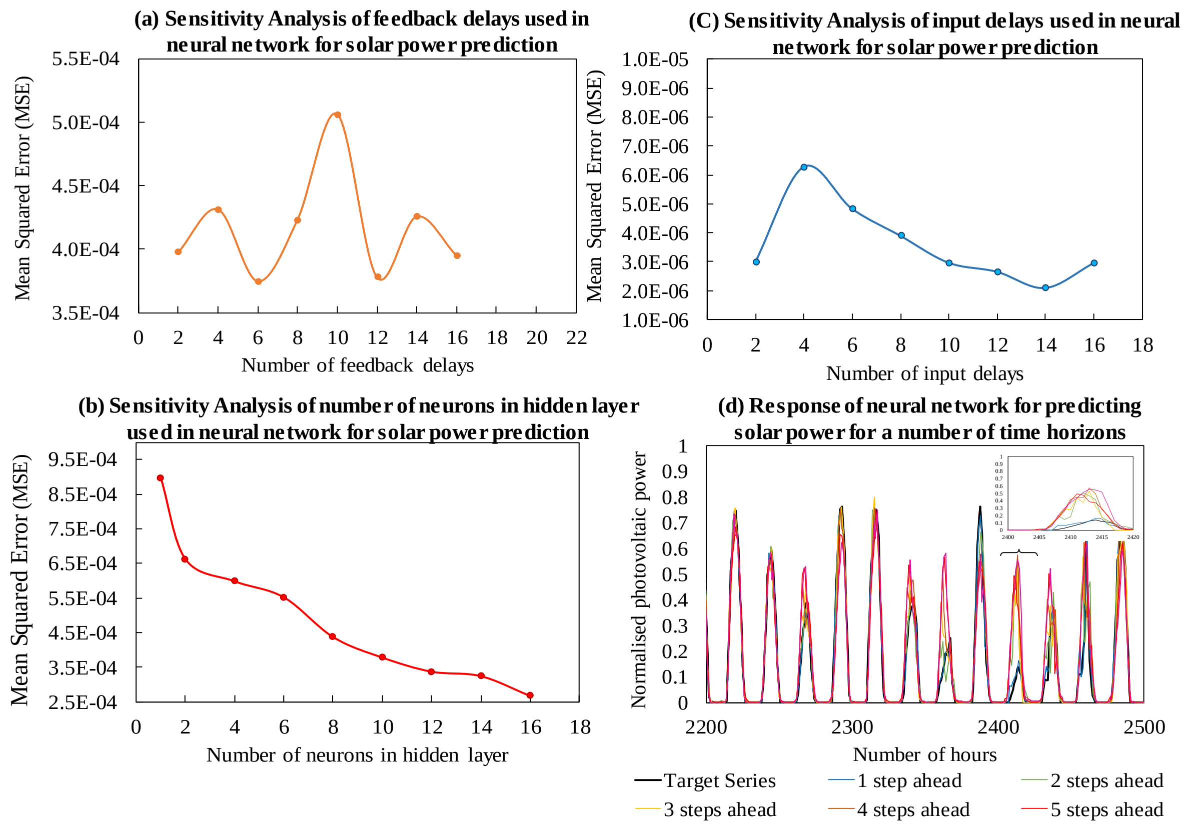

Figure 7. The sensitivity analysis and performance of ANN for solar power prediction

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 12**. 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 **Figure 7.d**. The one-hour ahead closely follows the target series and shows a very good performance, followed by the two-hour 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 hours and further, although for some days a satisfactory accuracy is achieved, there are numerous instances for which the predictions show a 200% error of solar power production which can be problematic if these models are used in an actual practice. The forecasting error of the ANN model for predicting the solar power generation is reported in the third column of **Table 9**.

Table 12. 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

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.

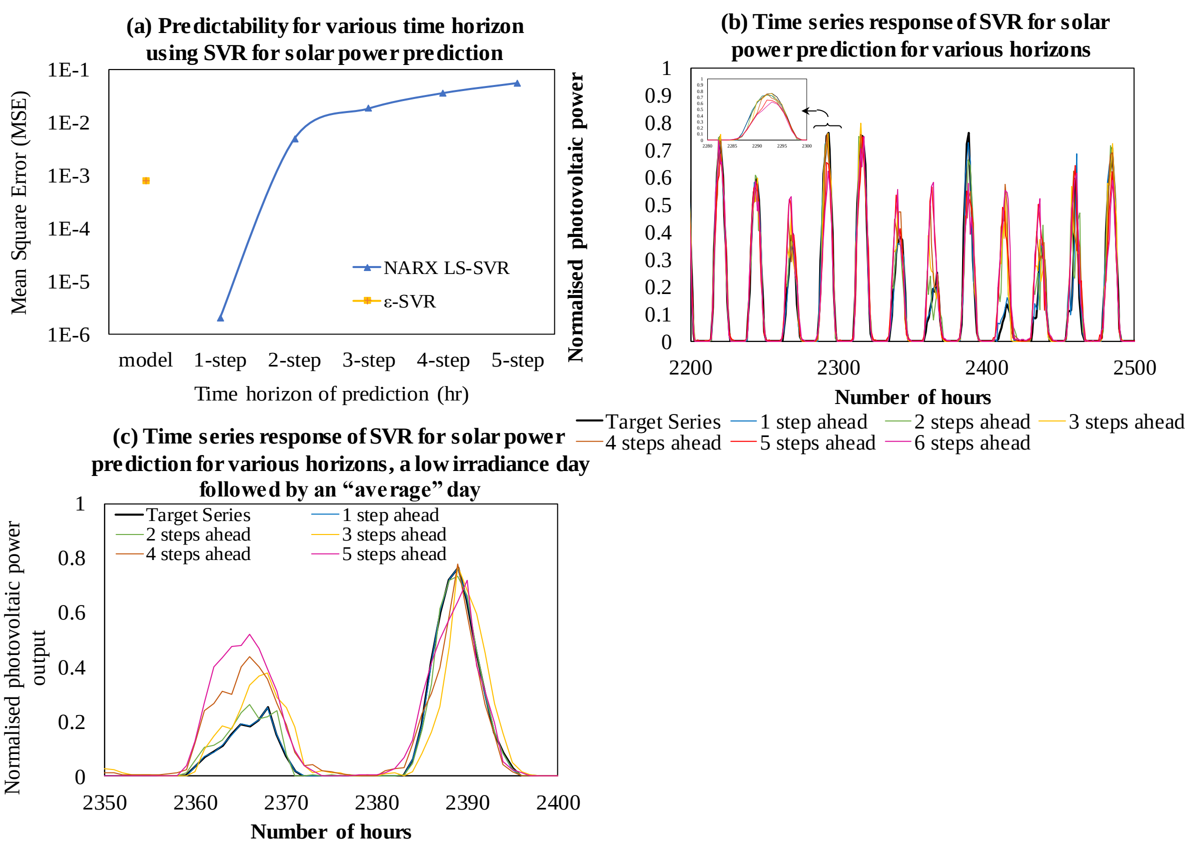

Figure 8. The sensitivity analysis and performance of SVR for solar power prediction

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 13**, and depicted in **Figure 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 **Figure 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 (**Figure 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 hours 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 one-hour ahead predictions the model can adjust its response if the day is cloudy, as it receives all the respective information with only one hour 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.

Table 13. 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

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 14** 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 **Figure 9.a** for all the testing data (the year 2014), and in **Figure 9.b** a total of 500 hours, with a view to providing a higher resolution. Even though 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.

Table 14. 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

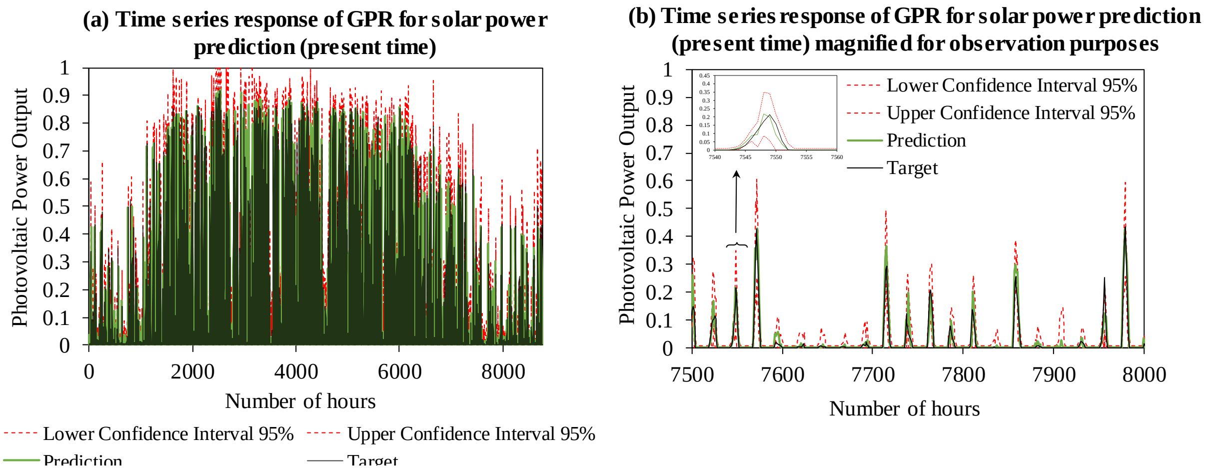

Figure 9. (a) Time series response of GPR for solar power prediction (present time) and (b) Time series response of GPR for solar power prediction (present time) magnified for observation

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 prior to excuting 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 15** 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 **Figures 10.a-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.

Table 15. 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

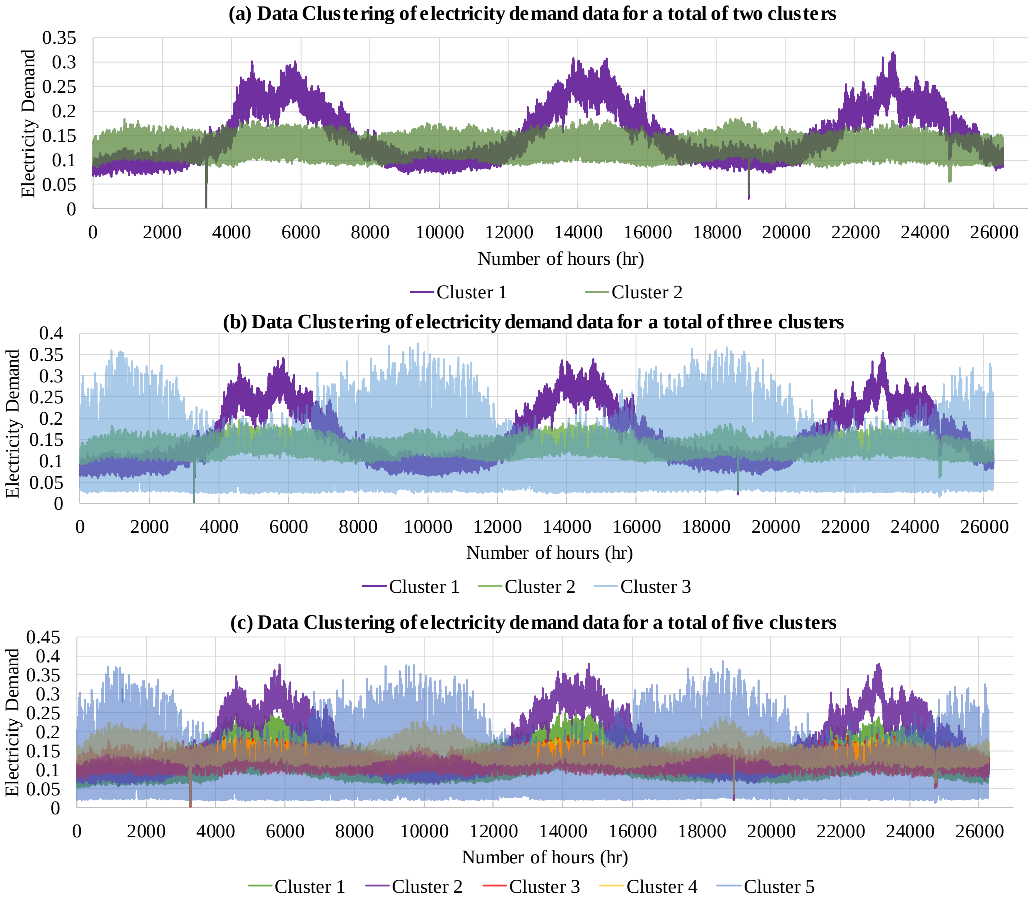

Figure 10. Data Clustering of electricity demand data for the total of (a) two (b) three, and (c) five clusters.

The number of clusters that was selected was five which is graphically represented in **Figure 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 **Figure 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.

3.3.1.2. 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 16** 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.

Table 16. Maximum absolute cross-correlations for input data used for electricity demand prediction

Input	Maximum absolute correlation
Hourly variable	0.622855
Seasonal variable	0.29743

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 (**Figure 11.a**). The dependence of the demand on the time of the day and year is represented in the cross-correlation graphs depicted in **Figure 11.a-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.

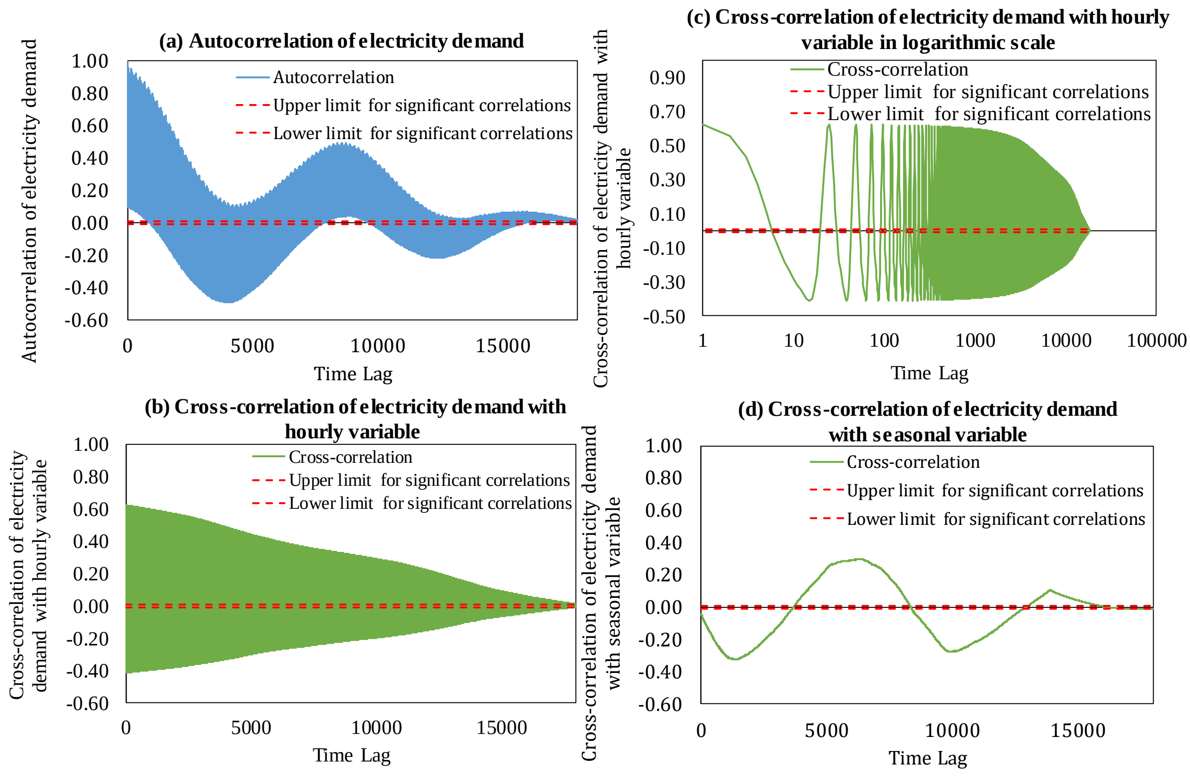

Figure 11. Cross-correlations for input data applied for the solar power prediction

3.3.2. 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 **Figure 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 **Figure 12.a-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.

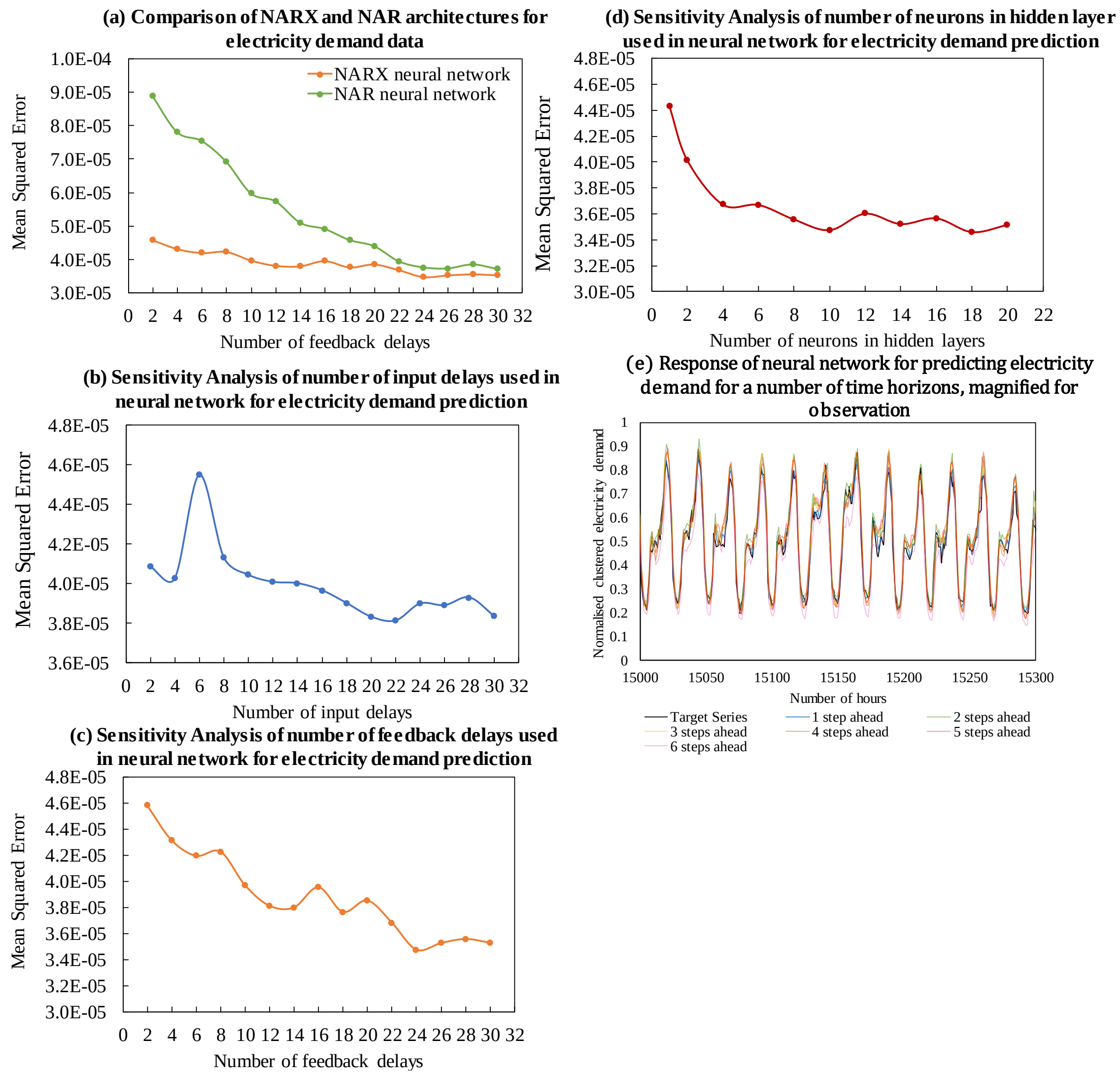

Figure 12. The sensitivity analysis and performance of ANN for electricity demand prediction

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 **Figure 12.d**. The performance of the neural networks for each time horizon respectively is enlisted in **Table 17**. As expected the accuracy of the model drops as the time horizon of the prediction increases. The forecasting error of the ANN model for predicting the electricity demand is reported in the fourth column of **Table 9**.

Table 17. 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

3.3.3. 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 18** and are graphically represented in **Figure 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 **Figure 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 **Figure 13.a-b** show 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.

Table 18. 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

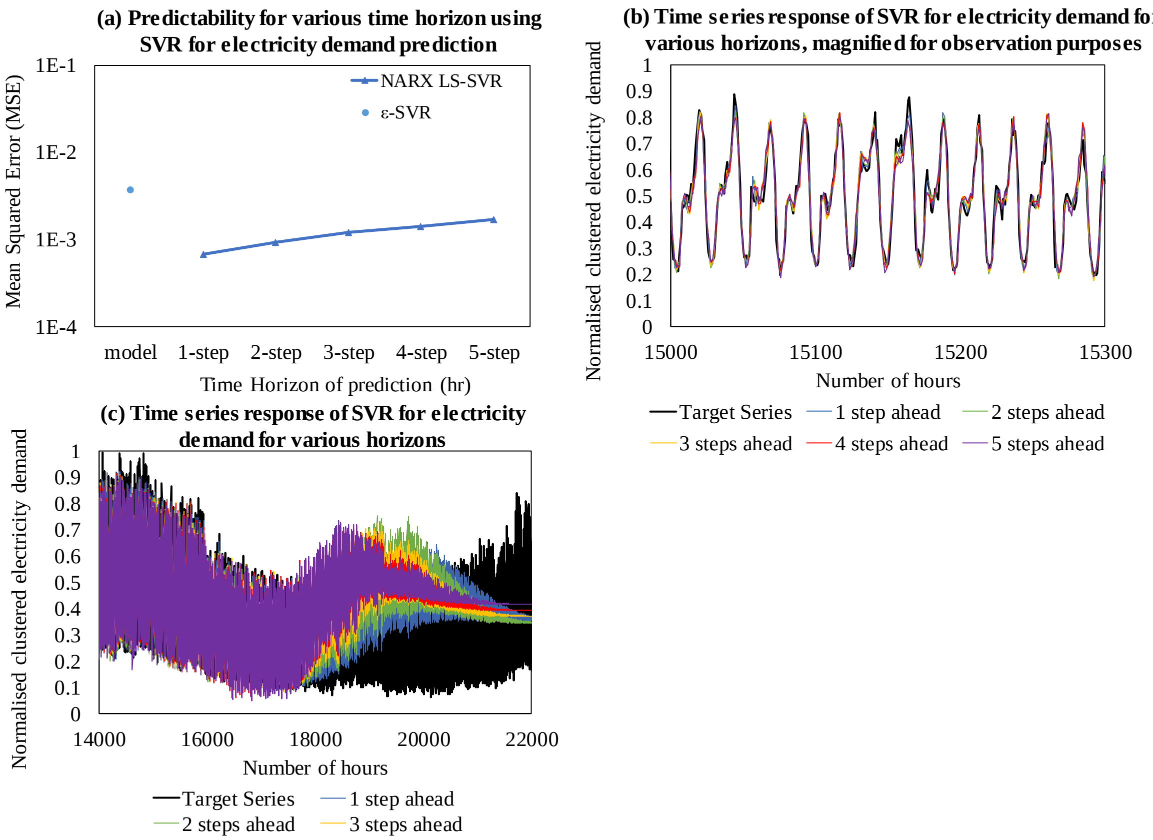

Figure 13. The sensitivity analysis and performance of SVR for solar power prediction

3.3.4. 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 19**, 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 **Figure 14.a** where it can be observed the model for a large part of the dataset does not follow the target series. In **Figure**

14.b, an area in which a good fitting was achieved is depicted and as for the method SVR, it is noted that this method has the potential of reaching a good accuracy.

Table 19. 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

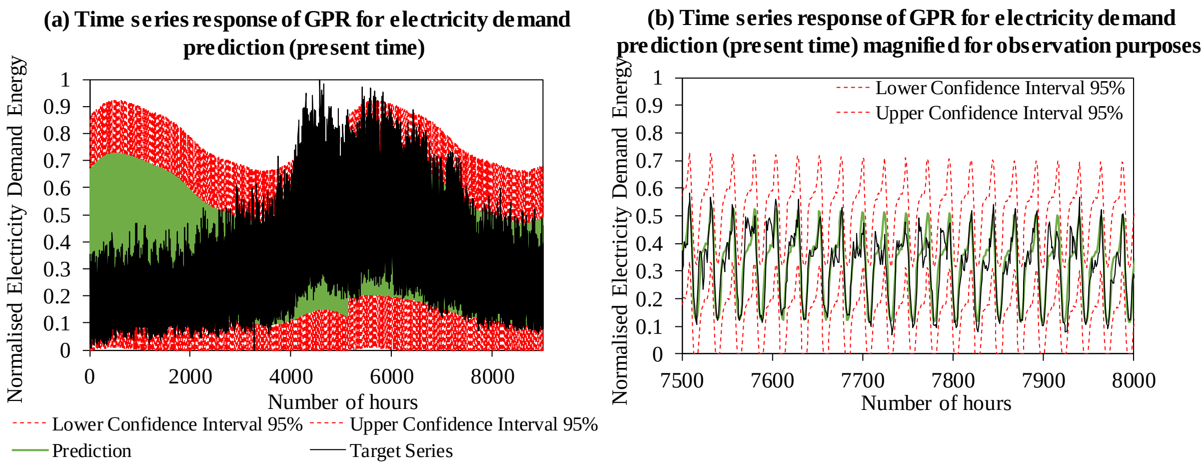

Figure 14. (a) Time series response of GPR for electricity demand prediction (present time), (b) Time series response of GPR for electricity demand prediction (present time) magnified for observation purposes

3.4. 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. **Figures 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 **Figures 15e-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 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.
- **Figures 15d-e** are similar which means that the wind and solar dataset behave in a similar manner with regard to the various predictive models.

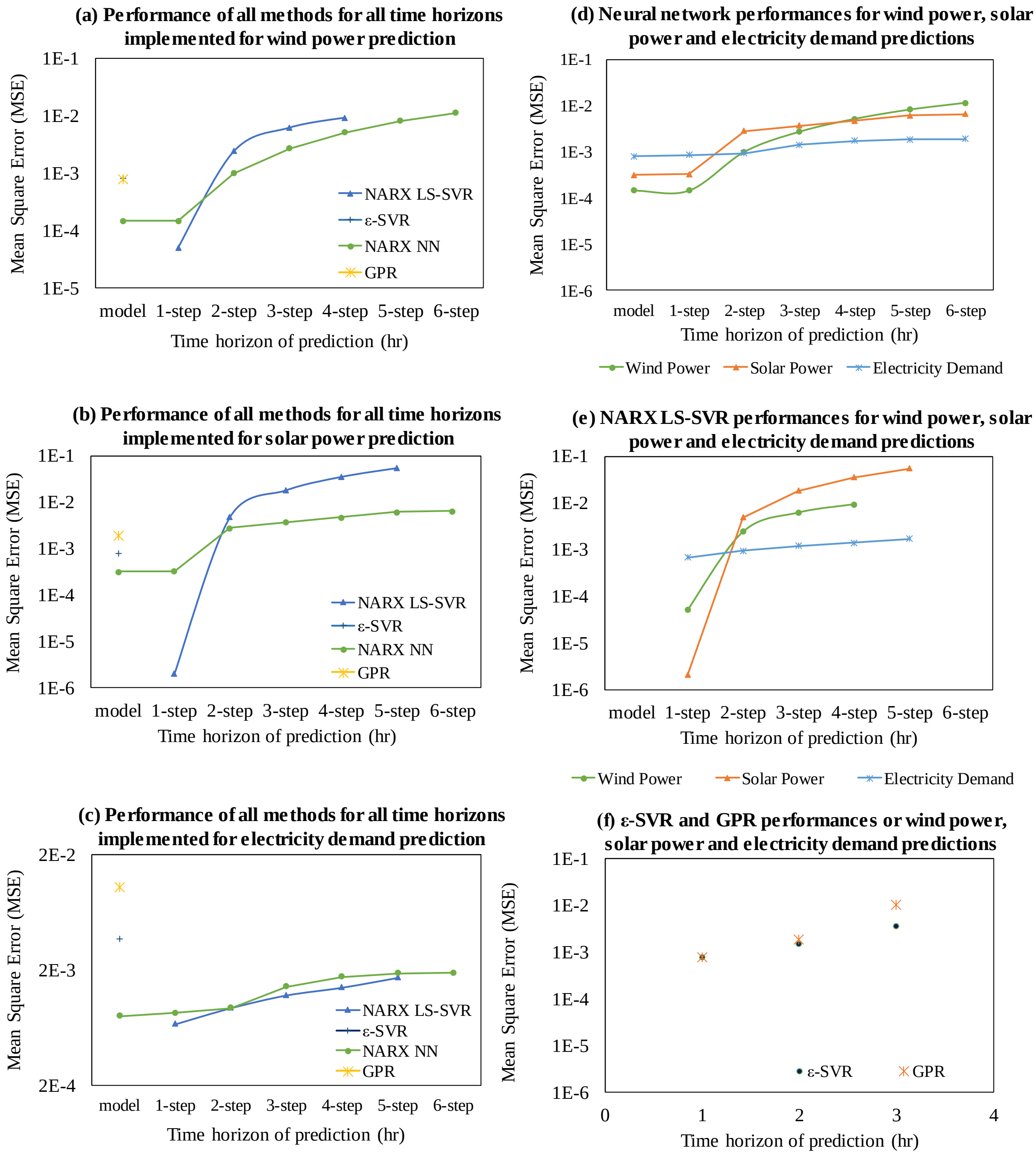

Figure 15. Comparison of the prediction methods for wind and solar power as well as demand

The best performing method built in this research was the NARX LS-SVR for one-hour 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:

- 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 20** and **Table 21** 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 20. Performance of all dynamic models

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

Table 21. 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

3.5. 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 wind and solar availability, as well as electrcity demand was formulated according to a recent publications [173]. In that contribution, the availability of wind and solar energy was clustered according into various geographical zones, and demand was considered according to its demographical distribution.

The results of error percentage are shown in **Figure 16(a-c)** respectively, and denormalized 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 **Figure 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.

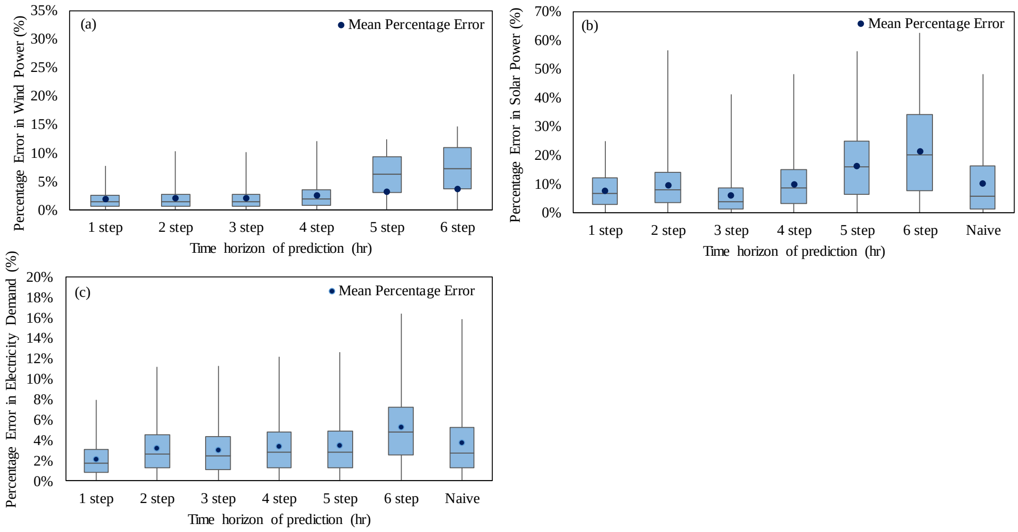

Figure 16. Box plot of percentage error distributions of (a) the wind power forecasting, (b) the solar power forecasting, (c) the electricity demand forecasting.

3.5.1. Error calculation of predictive models

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

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

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

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

3.5.3. Wind Power

3.5.3.1. 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 1kW capacity. By denormalising the predictors' output and by looking at the error distributions of each of the predicted time horizons, **Figure 16(a)** 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 20**). In **Table 22** 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.

Table 22. 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%

3.5.3.2. 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:

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

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.

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

Table 23. 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

Using the values in **Table 23** [174] the mean capacity factor is estimated to be 30.52%. In **Table 24**, 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.

Table 24. 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

3.5.4. Solar Power

3.5.4.1. 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 25** and **Figure 16(b)**). 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 hours. 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.

Table 25. 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%

3.5.4.2. Quantification of errors in dimensional units.

In this section, the 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 26.** The mean percentage error of naive and predictive model are reported in **Table 27**.

Table 26. 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

Table 27. 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

3.5.5. Electricity Demand

3.5.5.1. 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 **Figure 16(c),** and the mean values of the error are given in **Table 28**. 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 hours 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.

Table 28. 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%

3.5.5.2. 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 [175] looking at the average hourly load curves of households without electricity heating the peak load typically reaches 600W (**Table 29**).

Table 29. 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

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 an electricity grid.

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.

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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 Critetion
BP	Back Propagation Neural Network
BR	Bayesian Regularisation
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

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