Modelling and Uncertainty Analysis of On-site Renewable Sources for Optimal EV Charging

Handong Li[1], Xuewu Dai[1], Richard Kotter[1], Nauman Aslam[1], Adrian McLoughlin[2], James Yu[3]
[1] Dept. of Mathematics, Physics and Electrical Engineering, and RENU, Northumbria University, Newcastle Upon Tyne, UK
[2] City Futures, Newcastle City Council, Newcastle upon Tyne, UK
[3] Scottish Power Energy Networks, Scottish Power Headquarters, Glasgow, UK
handong.li@northumbria.ac.uk, xuewu.dai@northumbria.ac.uk, richard.kotter@northumbria.ac.uk,
nauman.aslam@northumbria.ac.uk, adrian.mcloughlin@newcastle.gov.uk, james.yu@spenergynetworks.co.uk

***Abstract*—Road transport is the second largest dimension of carbon emission, both nationally in the UK and locally in Newcastle upon Tyne, contributing about 33% of total emission in 2020. In line with the UK's target to reach net zero by 2050 (and the city of Newcastle upon Tyne's ambition to do so by 2030), electric vehicles (EVs) play a critical role in meeting net zero road transportation though it does not automatically imply a reduction of overall emission nationally or globally if the electricity to charge EVs is sourced from the fossil fuels. To achieve optimal EV charging, a better understanding of the uncertainties of ORES power generation is necessary. ANN (Artificial Neural Network) and time series forecasting methods are used in this paper to model wind and solar power generation and the power generation of ORES. Such a model is able to represent the relationship between the power generation and the wind speed as well as solar irradiation, which is of significant uncertainties due to weather changes in both short-time (hourly) and long-term (seasonally). The proposed method uses historical solar irradiance and wind speed data, together with numerical weather prediction (NWP) data. The proposed neural network is verified with the historic data at Newcastle upon Tyne for the years 2020 to 2022. The proposed methods have a root mean square error (RSME) of 2.26 (m/s) in wind speed modelling, and the RSME of solar irradiance is 50.79 (W/m^2). The uncertainties analysis shows that the uncertainties in wind speed at Newcastle upon Tyne can be modelled as a Weibull distribution with parameters A = 19.98 and B = 1.91.**

***Index Terms*—ORES, ANN, Wind power, Renewable energy, Forecast**

I. Introduction

In line with the UK's target to reach Net Zero by 2050, one of the major goals of the EPSRC Energy theme is to increase the efficient use of renewable energy assisted by digital technologies. Electrical vehicles (EVs) charged by renewable energy are one of the solutions towards carbon-neutral road transport, which is the seconnd largest carbon emission both nationally in the UK and locally in Newcastle upon Tyne or Gateshead (contributing about 33% of total emission in 2020)[1]. The key issue is to use more renewable energy source (RES) for EV electricity usage, but the public strategy/guidance does not clearly outline considering charging management through renewable energy sources. Despite large-scale major RES projects, a recent trend in RES is that there will be increasing amount of small-scale RES installed on-site [2], here referred to as ORES.

Research related to this paper as [3] used a unique combination of meteorological time series and stochastic simulations to provide consistent variable renewable energy (VRE) generation and forecast error time series with temporal resolution in the minute scale. The contribution of [4] is to model urban energy requirements, namely local electricity consumption and on-site renewable power generation, using solely open source data and models.[5] assessed errors in projections pertaining to the capacity and production of renewable energy in the United States as well as those countries of the European Union that have strong commitments to green energy supply. [6] used a deep learning network to forecast the wind turbine power based on a long short-term memory network (LSTM) algorithm and applied a Gaussian mixture model (GMM) to analyze the error distribution characteristics of short-term wind turbine power forecasting. [7] proposed an aggregator for the optimal scheduling of a Electric Vehicle (EV) charging station. [8] proposed a deep learning method based on a discrete wavelet transformation and long short-term memory method (DWT-LSTM) as well as a scheduling framework for the integrated modelling and management of energy demand and supply for buildings. [9] presented an evaluation framework for Techno-Economic-Environmental (TEE) impact of different networks integration levels and storage devices on performance of Integrated Gas and Electricity Networks (IGENs). [10] showed analytically that there are two potential sources of uncertainty in forecast reconciliation.

Based on the above research and methodology, this paper's first provides the simulation environment for renewable energy input for future research. A neural network is trained offline using historical data to forecast solar radiance and wind speed in this paper. The distribution of errors, which represents uncertainty, is formed by the errors generated during training. The actual wind speed and solar energy data in the intended simulation environment can be considered the expected wind speed and solar irradiance plus the random error distribution. Second, this work proposed wind and solar energy models that can convert wind speed and solar irradiance into energy. Third, neural networks and time series algorithms are used to forecast solar irradiance and wind speed. Finally, this research investigates the distribution of the Newcastle upon Tyne, which follows the Weibull distribution.

II. Problem Description

The EV charging system and the on-site renewable energy sources to be investigated in this paper is illustrated in Fig. 1. which consists of various on-site Renewable Energy Sources (ORES), such as PV, wind generators, etc, a stationary battery energy storage system (BESS), a set of EV chargers (either AC or DC) and a "Energy Hub". They are connected to a local distribution network that is connected to the main grid via a transformer. The Energy Hub unit is a bank of uni-directional or bi-directional inverters that connect the ORES, BESS and EV charging stations and controls the energy exchange between the supply side and the demand side. The BESS and PV are connected through a DC bus.

In the sense of net zero road transport, the idea of such a EV charging system with on-site renewable energy sources is to utilise as much as possible the renewable electricity from the ORES to charge the EV, at minimum capacity requirement on the BESS, thus saving the investment and operation cost of the BESS. In other word, the aim is to improve the self-consumption utilisation of ORES with less energy imported from/exported to the grid and the BESS. iaiton of The challenge is how to integrate the various parts to maximize their efficiency and economy.

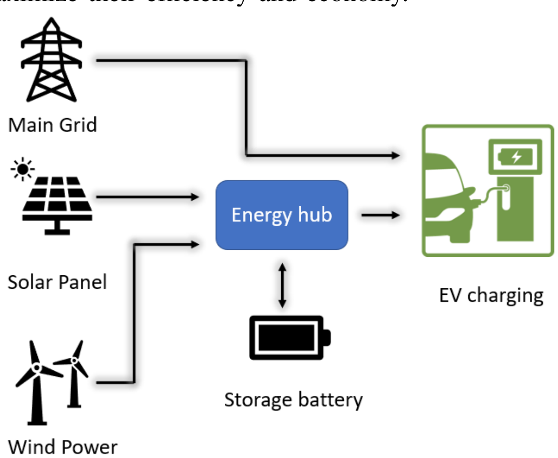

Fig. 1. A grid-connected solar-wind hybrid electric vehicle charging system for electric fleet depot with self-generated on-site renewable energy

However, the uncertainties at both the supply side and the demand side make it is difficult to find the optimal charging schedule to maximize the utilisation of ORES for EV charging. The intermittent renewable energy (wind and solar power) generation is time varying and it is challenge to have an very accurate forecast of how much renewable energy will be generated. At the EV energy demand side, the uncertainty of EV charging demands are varying due to the varying travelling demands, user behaviours, weather and traffics, etc. In this paper, the focus is the supply side to model the on-site renewable energy system and analyse it uncertainties. The purpose is to develop a realistic model to mimic the varying features of the PV and wind power generation, so that this model can be used as an "environment" for training and evaluating a reinforcement learning agent to optimize the EV charging schedule.

The volatility of renewable energy generation [11] and the forecast error of renewable energy output are the key sources of uncertainty on the source side. Environmental conditions can significantly affect the output of renewable energy, and the randomness of weather can affect the power of wind turbines. The Weibull distribution is often assumed to govern wind speed. The total horizontal sun irradiation, temperature, humidity, cloud cover, air pressure, and other factors, such wind speed, have a significant impact on photovoltaic output power [12]. According to present research, forecasting models of renewable energy output can be split into physical models and statistical models in renewable energy forecasting. The time series approach, artificial neural network method, and support vector machine method are all commonly used statistical forecasting methods. The data from the previous day's renewable energy generation is utilised as input data for the next day. In most cases, there is a difference between the actual and the expected value of renewable energy generation. Renewable energy generation has a day-ahead forecast error of 25%–40% [11]. On the other hand, in this paper's use of renewable energy, the real charging load of EVs shows significant uncertainty due to random changes caused by vehicle operation, traffic, the environment, people behavior and other factors [13]. To simulate EV load demand and charging time, study [14] employed fuzzy approaches to split the essential parameters in EV load modelling into categories. Both the spatial and temporal uncertainty of EVs can be considered using the hybrid fuzzy-MCS technique.

In summary, this paper employs a neural network and time series technique to forecast the amount of energy produced depending on the parameters of a solar and wind turbine. The inaccuracies that arise in the projections are the source of uncertainty in energy generation. As shown in Fig. 2, this method can establish an environment where energy production combined with the uncertainty of EV charging can serve as a foundation for subsequent energy supply and generation matching.

III. Modelling with Power Generation Uncertainties

In this section, neural networks are adopted to develop the model to simulate the uncertain wind power and solar power generation. Fig. 2 illustrates the overall modelling, where $P_E(k)$, $P_G(k)$, $P_B(k)$, $P_S(k)$ and $P_W(k)$ are the Ev demand power, the power from the grid, the battery power, the solar power and wind power at the time interval k, respectively. All these power constitute the system environment and output the state S_K. In this paper, the neural network is trained offline with historical wind speed and solar radiation data, utilising neural network (NN) and time series approaches. The error distribution generated throughout the training procedure is the uncertainty. As a result, the wind speed and solar radiation data are the neural network's predictions plus the randomly generated errors. This figure is taken as the actual wind speed and solar radiation statistics in this scenario. Renewable energy is created for charging the EVs using the wind and solar models presented in this section.

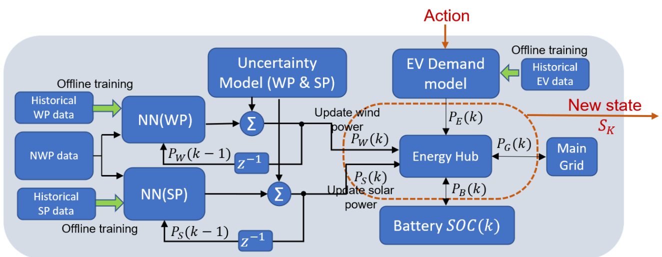

Fig. 2. Diagram of the electric fleet depot use case with self-generated renewable energy

A. Neural Networks for wind speed forecasting

Neural networks are a type of machine learning model that processes data by forming structures that resemble synaptic connections in the brain. The units that process information in neural networks are often classified into three categories: input unit, output unit, and hidden unit as Fig. 3 shows. The input unit receives signals and data from the outside, while the output unit produces the system's output. The hidden unit is located between the input and output units, and its construction is not visible from outside the network system. The strength of the connections between neurons is influenced by their characteristics such as weights, in addition to the three units that process information.

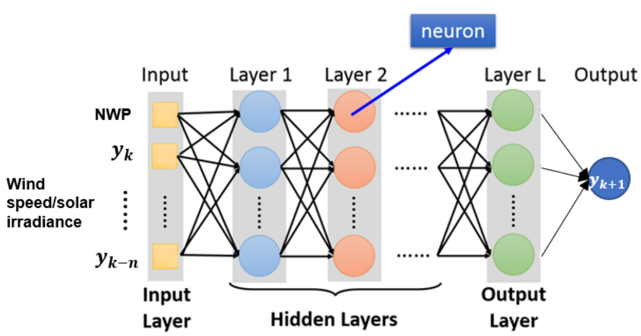

Fig. 3. Neural network structure diagram

The creation of a recurrent or feedback neural network as a nonlinear autoregressive network with exogenous inputs (NARX) model is the focus of this research. The network's learning process is aided by the Levenberg–Marquardt algorithm. A recurrent neural network is a network model that includes at least one path that returns back to the starting point, or to a neuron with feedback. As in feedforward neural networks, each connection in this network is given a delay in addition to a parameter[15]. NARX is one example of a recurrent neural network that predicts future output values based on past values of and their related input values, as demonstrated in:

$$y(t) = f(x(t-1), \ldots, x(t-m), y(t-1), \ldots, y(t-n)) \quad (1)$$

where m is the delay of the input $x(t)$, n is the delay of the output $y(t)$. The Levenberg-Marquardt algorithm is favoured for small networks since it requires more memory but takes less time to compute. When the maximum number of epochs is reached, the maximum time is reached, performance is minimised to the target, or the performance gradient falls below the minimum gradient, training is terminated. The Root Mean Square Error (RMSE) is used to express the training's performance, which is:

$$RMSE = \sqrt{\frac{1}{a}\sum_{i=1}^{a}(y_i - \widehat{y}_i)^2} \quad (2)$$

where the number of samples is indicated by a, the actual value of the ith sample is indicated by y_i, and the predicted value of the ith sample is shown by $\widehat{y}_i$.

B. Wind power model

The mechanical power taken from the available wind energy by the wind turbine blades provides the electrical output power in the Wind turbine systems. From [16], the mechanical power extracted by a wind turbine is calculated using aerodynamic theory as follows:

$$P_m = \frac{1}{2}\rho A u^3(t) C_p(\theta, \lambda) \quad (3)$$

where p_m represents the mechanical power extracted by a wind turbine, A represents the blade swept area, and u represents the wind speed. $C_p(\theta, \lambda)$ is the fraction of available wind energy that a wind turbine harvests. θ is the blade pitch angle, and λ is the tip speed ratio. It assumes a fixed rotational speed and ignore the fraction, the electrical power output of the wind turbine can be simplified as:

$$P_m = \frac{1}{2}\rho A u^3(t) \quad (4)$$

Thus, the corresponding output curves for wind speed - power generation are as fig.4. Where u_r stands for rated wind speed, u_c for cut-in speed (when the electrical power output increases above zero and power production begins), and u_f for furling wind speed (when the turbine is shut down to prevent structural damage).P_{er} is the rated power with the value of 1.5Mw. It supposes that output power grows between u_c and u_r and then remains constant between u_r and u_f as shown in the diagram. All other conditions result in zero power output. As a result, the aforementioned conditions can be condensed into the following piece-wise function:

$$P_m(t) = \begin{cases} 0 & \text{, if } u(t) \leq u_c \\ \frac{P_{er}(u_c^3 - u^3(t))}{u_c^3 - u_r^3} & \text{, if } u_c < u(t) \leq u_r \\ Per & \text{, if } u_r < u(t) \leq u_f \\ 0 & \text{, if } u_f \leq u(t) \end{cases} \quad (5)$$

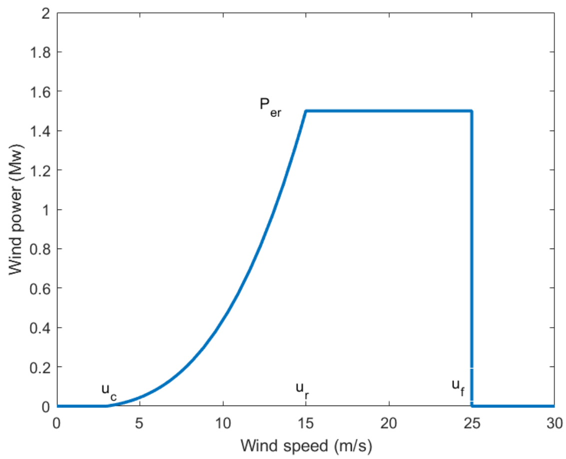

Fig. 4. Neural network structure diagram

According to equation (3), the problem of wind energy generation can be evaluated using the parameters of the projected wind speed and the actual wind turbine used. Combined with equation (1), the prediction of the wind speed can be expressed as:

$$u(t) = W_{NN}(NWP(t-1), \dots, NWP(t-m), \\ u(t-1), \dots, u(t-n)) \tag{6}$$

where $W_{NN}(NWP, u)$ is the neural network function for wind speed. NWP is the NWP data of the last m hours. n is the last n hours of the wind speed.

C. PV model

Akhbari et al [17] expressed the DC power provided by a solar PV source as:

$$P_{dc}(t) = I_{eff}(t)\eta_g A_s \tag{7}$$

where $I_{eff}(t)$ represents the incident efficient radiance (Wm^{-2}), η_g represents the solar PV source efficiency and A_s represents the solar PV source effective surface area (m^2). The efficiency of solar PV sources is affected by ambient temperature, temperature loss coefficient, and nominal operating cell temperature, according to [18]. The solar energy generation is modelled in this paper, using solar panels installed on the top floor of the Pandon building at Northumbria University's city centre campus. It has a 20% PV efficiency ($\eta_g = 20\%$) and an effective area of 188 m^2 ($A_s = 188$). Because the power of solar energy and solar incident efficient radiance are linearly related in the equation above, the key to forecasting solar energy output is to estimate $I_{eff}(t)$. Combined with equation (1), the prediction of the solar irradiance can be expressed as:

$$I_{eff}(t) = W_{NN}(NWP(t-1), \dots, NWP(t-m'), \\ I_{eff}(t-1), \dots, I_{eff}(t-n')) \tag{8}$$

this paper utilise the same technique for forecasting solar irradiance as it do for predicting wind speed. However, the values of m' and n' in this case differ from those in the neural network time series approach of wind speed.

D. Uncertainty model

The uncertainty in this study is mostly expressed in the difference between the predicted and true values. The key to taking into account system uncertainty is to create an accurate renewable energy probability distribution model. This research forecasts historical wind speed and solar irradiation data using the neural network prediction model described above. The final result can be used to construct an error probability distribution. This error distribution represents the forecast's uncertainty. So in the model designed in this paper, the true value of the renewable energy source (wind speed and solar irradiance) can be expressed as:

$$S_{Act}(t) = S_{Pred}(t) + e(t) \tag{9}$$

where $S_{Act}(t)$ is the actual renewable energy source can be used as an input energy in the design system of this paper (see Fig.2). $S_{Pred}(t)$ is the output data from the neural networks. $e(t)$ is the error generated from the historical data.

IV. Results

This section of the paper analyses weather data for the Newcastle upon Tyne, using historical data. This data was used to train and test a neural network model. The errors in the neural network were used to create uncertainty models for wind speed and solar radiation. Finally, Newcastle upon Tyne's actual solar and wind speed statistics are compared to the predictions.

A. Historical data analysis

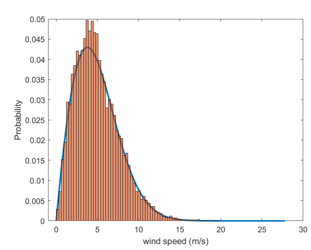

Fig. 5. Newcastle upon Tyne wind speed distribution

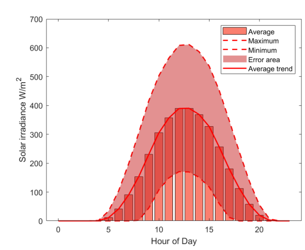

Fig. 6. Newcastle upon Tyne solar irradiance full day distribution

In the paper, wind speed, solar radiation and NWP data for Newcastle-upon-Tyne with latitude 54.9792°N, longitude 1.59446°W, from April 1st, 2020 to April 1st, 2022 is utilized. [19]. Fig. 5 and Fig. 6, respectively, show wind speed and sun radiation distribution statistics. The wind speed distribution follows the Weibull distribution parameter A = 19.98 and B = 1.91. The Weibull distribution is commonly used in industrial manufacturing, weather prediction, reliability and failure analysis, as well as life insurance models for the quantification of recurring claims. Its probability density is:

$$f(x; A, B) = \begin{cases} \frac{B}{A}(\frac{x}{A})^{B-1}e^{-(x/A)^B} & \text{if} x \leq 0 \\ 0 & \text{if} x > 0 \end{cases} \tag{10}$$

where, A is the scale parameter and B is the shape parameter. The historical solar radiation data are distributed by being averaged to 24 hours per day, as shown in Fig. 6. The fluctuation range is shown in the area within the dashed line in this figure.

B. Neural network prediction renewable source

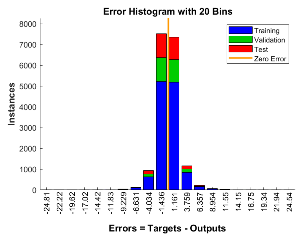

Fig. 7. Neural network performance for wind speed

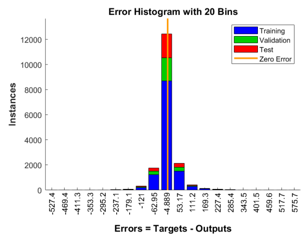

Fig. 8. Neural network performance for solar irradiance

For wind speed forecasts, the neural network utilised in this paper uses NWP data and the first 15 hours of wind speed data. The solar irradiance neural network is fed with NWP data and the first 12 hours of solar irradiance. The first n hours were chosen depending on the degree of correlation with the lowest trend. For wind speed and solar radiation, the neural network has four hidden layers with ten neurons each and one output layer. In the algorithm, the collected data were randomly divided for training, validation, and testing, with 70% of the data being used for training and the model being adjusted based on its error, 15% of data being used to measure model generalisation and signalling the end of training when generalisation stops improving, and the remaining 15% of the data being used for testing in order to provide an independent measure of the model's performance.

The frequency of errors in training, validation, and testing data sets is presented in the error histograms in Fig. 7 and Fig. 8, respectively. The difference between the network's outputs and the expected outputs is used to calculate the error. The majority of wind speed errors fall between -4.034 and 3.759 (m/s), and the majority of solar irrdance errors fall between -62.95 and 53.17 (W/m^2). The RMSE values were calculated to evaluate the training's outcomes. The root average squared difference between the network's outputs and the expected outputs is the RMSE. The lower the RMSE value, the better the performance. The RMSEs values for wind speed and solar irrdance, respectively, are 2.26 and 50.79.

C. Uncertainty in renewable energy generation

Fig. 9 and Fig. 10, respectively, demonstrate the error statistics provided by the trained neural network for the predictions of wind speed and solar radiance, respectively. The difference between the predicted and actual values is the error. The distribution of errors does not follow the Gaussian distribution after statistical tests. Accordingly, the predicted values plus the errors randomly created in Fig. 9 and Fig. 10 can be utilised to build up the simulation to generate real wind speed and solar radiance.

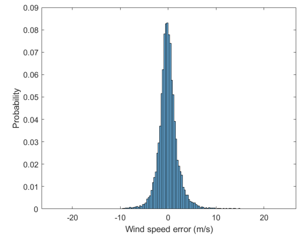

Fig. 9. Wind speed error distribution

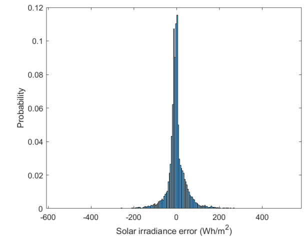

Fig. 10. Solar irradiance error distribution

D. Practical verification

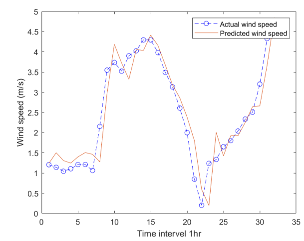

Fig. 11. Wind speed practical verification

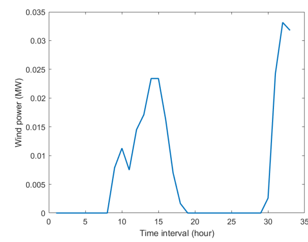

Fig. 12. Predicted wind power

The wind speed for 31 hours following April 2nd, 2022 00:00 is utilised as the validation set in this paper in order to validate the neural network's accuracy, as shown in Fig. 11. It displays a $0.3419 m/s$ average error. According to equation (3), the projected wind speed is converted into wind energy in Fig. 12.

The solar radiation for 36 hours after April 1, 2022 is utilised as the validation set in this paper to validate the neural network's accuracy, as shown in fig.13. It has a $30.5652 W/m^2$ average error. According to equation (4), the projected solar irradiance is converted to solar energy in Fig.14. The energy generated by solar panels on the roof of Northumbria University's Pandon Building is used as the validation method in this paper. The projected solar irradiance generated energy, the actual solar irradiance generated energy, and the solar energy created by the actual device are all represented in fig.14.

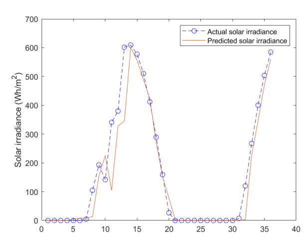

Fig. 13. Solar irradiance practical verification

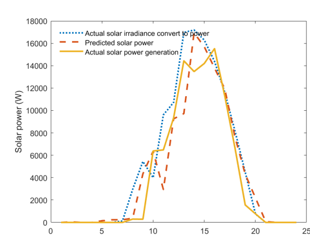

Fig. 14. Predicted solar power

V. Conclusion

Using NWP data as well as historical data, this paper successfully created and evaluated an artificial neural network model in the form of a recurrent NARX model to reliably estimate hourly solar radiation and wind speed in Newcastle upon Tyne, UK. This paper uses realistic renewable energy sources combined with uncertainty in wind speed and solar irradiance to build up a relevant simulation scenario. In future research, this simulation can be applied in order to optimise EVs' dispatching and charging schedule under the uncertainties of both EVs' demands as well as ORES supplies. The wind distribution in Newcastle upon Tyne follows the Weibull distribution with parameters A = 19.98, B = 1.91. The RMSE values of 2.26 and 50.79 for wind speed and irradiance, respectively, demonstrate the model's accuracy. The error histogram also indicates that each dataset displays low error values, with the majority of errors falling between -4.034 and 3.759 (m/s) for wind speed, and -62.95 to 53.17 (W/m^2) for solar irradiance, respectively. Finally, actual meteorological circumstances were used to verify the forecasts in this study, with an average error for wind speed of 0.3419m/s, and for solar power of 30.5652 W/m^2. Larger data sets and additional features for the neural network's training, validation, and testing phases could improve the results even more. This can make the model more robust to cope with bigger changes in weather patterns.

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