A Simulation Environment of Solar-Wind Powered Electric Vehicle Car Park for Reinforcement Learning and Optimization

Handong Li[a], Xuewu Dai[a*], Richard Kotter[a], Nauman Aslam[a], Yue Cao[b]
[a] Dept. of Mathematics, Physics and Electrical Engineering, and ReNU, Northumbria University, Newcastle upon Tyne, UK
[b] School of Cyber Science and Engineering, Wuhan University, China
Email: {handong.li, xuewu.dai,richard.kotter,nauman.aslam}@northumbria.ac.uk,yue.cao@whu.edu.cn

***Abstract*—The transportation sector is the second greatest contributor to carbon emissions in the UK and Newcastle upon Tyne, accounting for around 33 % of total emissions in 2020. In accordance with the United Kingdom's goal 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 crucial role in achieving net zero road transportation. However, if the electricity used to charge EVs is derived from fossil fuels, this does not necessarily imply a reduction of overall emissions nationally or globally. To achieve optimal EV charging, a deeper comprehension of the unpredictability of (on-site renewable energy sources) ORES energy output is required. In this paper, the predicted renewable energy generated is used as the actual value for the reinforcement learning algorithm simulation environment. Such a model is able to represent the relationship between the power generation and the wind speed as well as solar irradiation, which are characterized by significant uncertainties due to weather changes in both the short-time (hourly) and long-term (seasonally). The uncertainty 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. As for energy demand, this paper integrates information from an Oslo (Norway) car parking garage based set of EV charging stations with EVs' demand statistics. The charging habits of EV users range from 800 minutes to 1,000 minutes of parking time, and from 5 kWh to 20 kWh in terms of charging energy. The maximum connection frequency for EV charging is 20 minutes. In addition, this paper develops methods for stochastic EV charging and parking space occupancy employing actual data. On the basis of the aforesaid renewable energy generation and the EV charging status, it is possible to develop a decision algorithm to optimal renewable energy efficiency.**

***Index Terms*—ORES, reinforcement learning, Wind power, Renewable energy, EV**

I. Introduction

In accordance with the United Kingdom's aim of reaching Net Zero by 2050, one of the primary objectives of the EPSRC's energy topic is to promote the effective use of renewable energy through digital technology. Electric vehicles (EVs) powered by renewable energy are one of the possibilities for achieving carbon-neutral road travel, the second largest source of carbon emissions in the United Kingdom and in Newcastle upon Tyne or Gateshead (contributing about 33% of total emission in 2020)[1]. The primary challenge is to increase the use of renewable energy sources (RES) for EV electricity, yet the public strategy/guidance does not clearly describe charging management through RES. Recent trends in RES indicate that there will be a growing number of small-scale RES deployed on-site [2], also known as on-site renewable energy sources (ORES).

Photovoltaic (PV) systems, which can reduce the parking demand stress, also show variation due to weather conditions. A hybrid optimization algorithm for energy storage management is proposed, which shifts its mode of operation between the deterministic and rule-based approaches depending on the electricity price band allocation [3]. [4] presents a new multistage distribution expansion planning model where investments in distribution network assets, RES, Energy storage systems (ESS) and EV charging stations (EVCS) are jointly considered. An online optimal control strategy for power flow management in microgrids with on-site battery, renewable energy sources, and integrated EVs is presented in [5]. A reinforcement-learning-based energy management algorithm is proposed to reduce the operation energy costs of the target smart energy building under unknown future information in [6]. One such group objective considered in the paper includes marketing flexibility (charging or discharging) to the Day-ahead (DA) spot market, which can provide both a) financial incentives to the owners of such systems, and b) an increase in the overall absorption rates of renewable energy. The responsible agent for marketing and offering such flexibility, herein aggregator, is directly controlling the participating batteries, in exchange to some financial compensation of the owners of these batteries. A novel approach to reduce renewable generation curtailments and increasing system flexibility by means of electric vehicles' charging coordination is represented in [7]. For uncertainty analysis on the energy demand side, [8] suggests a stochastic method for simulating the uncertain time and amount of plug-in electric vehicles (PEVs) charging demand.

Based on the above research and methodological approaches, this paper provides the simulation environment for renewable energy input match the EVs charging demand for future reinforcement learning algorithm. The contributions of this paper are three-fold:

- Design a simulation environment for reinforcement learning that combines the energy requirements of renewable energy and EV charging.

- Development of models for wind and solar energy are suggested in this study which have the ability to transform wind speed and solar irradiance into generation predictions.
- A data-driven simulation. Realistic data of a EV car park collected from our previous project SEEV4City [9] are used to simulate the EV charging events.

II. Problem Description

The solar-wind powered EV car park and the charging system to be studied in this paper is illustrated in Fig. 1. This system comprises of various On-site Renewable Energy Sources (ORES) including solar panels and wind generators, a stationary battery energy storage system (BESS), a collection of EV chargers (either AC or DC), and an Energy Hub to monitor and control the energy flow in the system. The system is also connected to the main grid. The Energy Hub maintains a bank of unidirectional or bidirectional inverters that connects the ORES, BESS, EV charging stations, grid connection and controls the energy exchange between the supply and demand sides.

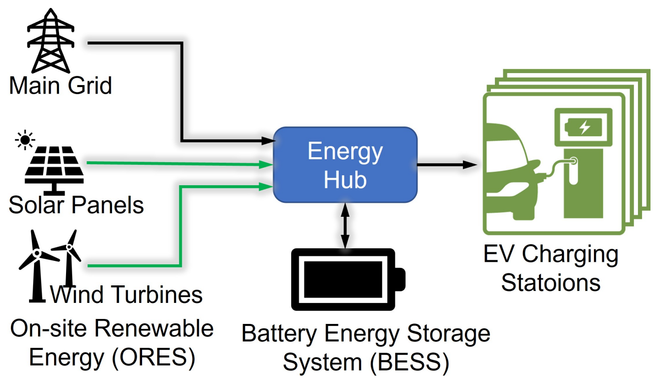

Fig. 1. A grid-connected solar-wind hybrid electric vehicle charging system for EV car parks

The purpose of an EV charging system with on-site renewable energy sources is to use as much renewable electricity from the ORES as feasible to charge the corresponding EVs while only using the minimum amount of capacity from the BESS, minimising the BESS's capital and operational costs. In other words, the objective is to enhance the use of ORES with less energy imported from/exported to the grid and the BESS. The problem is to combine the numerous components in order to enhance their efficiency and economy.

To maximise the use of ORES for EV charging, it is difficult to determine the ideal charging schedule due to the uncertainty on both the supply and demand sides. The creation of intermittent renewable energy (wind and solar power) fluctuates with time, making it difficult to accurately predict how much renewable energy will be produced. On the energy demand side for EVs, the unpredictability of EV charging demand is variable owing to shifting travel demands, user behaviours, weather and traffic conditions, etc. This research focuses on modelling the supply side of the on-site renewable energy system and the random allocation of energy on the demand side using actual data. The purpose is to develop a realistic model to mimic the varying features of the PV and wind power generation for the uncertainty EV charging, so that this model can be used as an environment for training and evaluating a reinforcement learning agent or any other algorithms to optimize the EV charging schedule.

The major sources of uncertainty on the source side are the volatility of renewable energy generation and the prediction inaccuracy of renewable energy output. The generation of renewable energy may be strongly impacted by environmental circumstances, and the unpredictability of weather can impact the output of wind turbines. It is commonly considered that the Weibull distribution governs 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 [9]. On the other hand, 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 [10]. Since renewable energy resources (RES) play a critical role in future distribution systems [11] considers the presence of RES and their stochastic nature has been modeled. [12] provides a new idea and technological approach for the sectional dispatch of the power grid and optimizing EV load in the future. In order to solve the problem of the electric vehicle (EV) charging amount fluctuation caused by the variation of driving speed during dynamic wireless charging [13] proposes an EV dynamic wireless charging control method adapting to speed change.

In summary, this paper employs solar irradiance and wind speed as uncertain sources of energy generation. Reinforcement learning can be used as an algorithm to integrate energy generation and consumption by analysing the uncertain demand for EV charging as a source of energy from the carpark charging stations. Using this method, as seen in Fig. 2, an environment in which energy production is coupled with the uncertainty of EV charging may be constructed as the platform for subsequent matching of energy supply and generation.

III. Modelling with Power Generation and Demand

In this section, the predicted power is 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 demanded power, the power from the grid, the stationary battery capacity, the solar power and wind power at the time interval k, respectively. All of these power elements constitute the system environment and output the state S_K. In this section, meteorological data such as historical data on wind speed and sun radiation are utilised to forecast the next time step in the production of renewable energy. In this setting, both the generation of the renewable energy and the demand for the charging energy from EVs are random and uncertain. This design aims to maximise the usage of renewable energy and decrease the amount of energy that may be came from the main grid and stationary batteries.

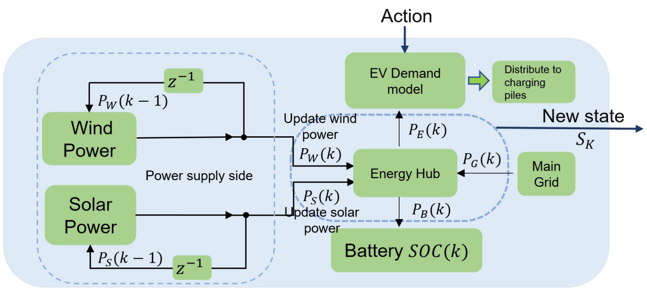

Fig. 2. Diagram of the electric fleet depot use case with self-generated renewable energy

A. Wind power model

The electrical output power of wind turbine systems is generated by the mechanical power extracted from the available wind energy by the wind turbine blades. Using aerodynamic theory, the mechanical power extracted by a wind turbine from [14] is determined as follows:

$$P_m = \frac{1}{2} \quad Au^3(t)C_p(\ ; \ ) \tag{1}$$

where P_m is the mechanical power taken by a wind turbine, is the density of air, A is the swept area of the blades, and u is the wind speed. $C_p(\ ; \ )$ represents the proportion of available wind energy produced by a wind turbine. is the pitch angle of the blade, whereas is the tip speed ratio. Assuming a constant rotational speed and disregarding the percentage, the electrical power output of a wind turbine may be calculated as follows:

$$P_m = \frac{1}{2} \quad Au^3(t) \tag{2}$$

The 10kW horizontal axis wind turbine (HAWT) used in this paper as [15] is modelled in Table 1 along with its technical characteristics, where u_r represents the rated wind speed, u_c represents the cut-in speed (when the electrical power output rises above zero and power generation begins), and u_f represents the furling wind speed (when the turbine is shut down to prevent structural damage). P_{er} is the rated power with a 10kW value. As illustrated in the picture, it is assumed that the output power increases between u_c and u_r and then remains constant between u_r and u_f. All other conditions result in the emission of 0 power. Consequently, the aforementioned criteria may be condensed into the piece-wise function shown below:

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

TABLE I
SPECIFICATIONS OF THE 10KW WIND TURBINE GENERATOR [15]

Parameter	Values
Type	Three blade upwind
Rated power (kW): P_{er}	10
Start up wind speed (m/s): u_s	3.4
Cut in wind speed (m/s): u_c	3.1
Rated wind speed (m/s): u_r	13
Furling wind speed (m/s): u_f	15.6
Max. design wind speed (m/s): u_m	54
Rotor shaft speed (rpm): R	60-350

According to equation (3), the problem of wind energy generation may be analysed using the parameters of the anticipated wind speed and the actual wind turbine employed. In combination with equation (1), the following expression may be used to forecast wind speed:

$$\begin{aligned} u(t) = W(&NWP(t-1); \ldots; NWP(t-m); \\ &u(t-1); \ldots; u(t-n)) \end{aligned} \tag{4}$$

where $W(NWP; u)$ is the predicted function for wind speed. NWP is the NWP data of the last m hours. n is the last n hours of the wind speed.

B. PV model

Akhbari et al [16] expressed the DC power provided by a solar PV source as:

$$P_{dc}(t) = I_{eff}(t) \ {}_g A_s \tag{5}$$

where $I_{eff}(t)$ represents the incident efficient radiance (Wm^{-2}), $_g$ 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 [17]. 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 $I_{eff}(t)$. The PV model parameters of the simulation in this work learn from the actual solar panel system at the Pandon Building at Northumbria University. The entire array will provide 23,000 kWh annually for the Northumbria University pandon building solar power system, saving 10 tonnes of CO2. The parameters for the 30 kW solar PV system are shown in Table 2.

Combined with equation (5), the prediction of the solar irradiance can be expressed as:

$$\begin{aligned} I_{eff}(t) = W(&NWP(t-1); \ldots; NWP(t-m'); \\ &I_{eff}(t-1); \ldots; I_{eff}(t-n')) \end{aligned} \tag{6}$$

This research proposes a technique for forecasting renewable energy from NWP data and time series. Nonetheless, the primary contribution of this article is the creation of an environment that combines the production of renewable energy with the charging of EVs. Therefore, the approach of renewable energy prediction is not restricted to time series. The values of m' and n' in this case differ from those in the predicted approach of wind speed.

TABLE II
PARAMETER FOR THE 30KW SOLAR POWER SYSTEM [18]

Parameter	Values
Peak power (kW)	29.84
Production (estimate) (kWh/year)	23,024.00
Panels	Seraphim SPR-6PB-265
Area (m^2):A_S	188.00
Inverter	Solar Edge SE17000 & SE4000
Orientation	180° (SOUTH)
Slope	11°

C. EV Charging Demand

This paper proposes ten fixed charging piles (stations) for EVs' charging. It is also possible to adjust the number of the charging piles based on the real circumstances. During each k interval, the charging piles are free to either charge or not charge the EVs. As seen in Fig. 3, the light blue rectangles indicate the charging states at each time step k. There are 96 time steps of 15 minutes length each if the design is based on one day as an episode.

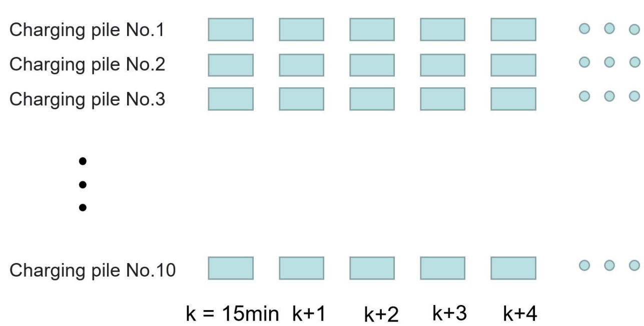

Fig. 3. Charging piles model

Noting that the connect time is less than or equal to the charging time is important. This suggests that the majority of EV owners attach the charging plug and then leave the vehicle. The expectation is that when they return to the EV, it will be completely charged or meet driving requirements. So in Fig. 4, the dark blue block represent the connect time and the red block is the charging time within the connect time. Therefore, the design should optimise the utilisation of renewable energy. This should determine the optimal charging time for the generation of the renewable energy. In addition, since the user's return time is unpredictable, early charging is also a requirement.

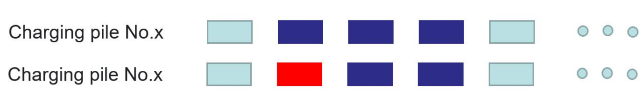

Fig. 4. charging piles occupancy

Based on the above conditions this paper can summarise the equation as

$$P_E(k) = \sum_{k=m}^{n} \sum_{i=1}^{10} EC_i(k) \tag{7}$$

where $P_E(k)$ is the total required power from the EVs as shown in Fig. 2. $EC_i(k)$ is the energy to be charged from every EVs. m and n is the time period required for the EV to be charged. And the iterative equation for charging the EV i is:

$$EC_i(k+1) = EC_i(k) - a_i(k)P_v \cdot \frac{1}{4} \tag{8}$$

where $a_i(k)$ is the action from the agent and $a_i(k) \in [0; 1]$. It displays if the EV is currently being charged or discharged (0 for discharge and 1 for charge). P_v represents the charging power. Since the k time period is set to 15 minutes in this article, it is multiplied by 1/4 when converted to energy. The following is the iterative formula for EVs allocation of charging piles as

$$\begin{aligned} &Leave : PO(k+1) = PO(k) - PO_L(k) \\ &Park : PO(k+1) = PO(k) \\ &Arrive : PO(k+1) = PO(k) + PO_A(k) \end{aligned} \tag{9}$$

where $PO(k)$ denotes the occupancy status of the 10 charging piles set in this paper $PO(k) = [po_1(k)::::po_i(k)::::po_10(k)]$, $po_i(k) \in [0; 1]$ and 0 means no occupancy, 1 means a car is parked in this space. $PO_L(k)$ is the EVs leave status vector, where 1 indicates the EV has left and 0 indicates it has not. $PO_A(k)$ is the arrival status vector for the electric vehicle, where 1 signifies that the EV has arrived and 0 indicates that it has not.

IV. NUMERICAL RESULTS

This section presents the generation of renewable energy and the EVs charging demand energy of the environment for the subsequent reinforcement learning algorithm.

A. Renewable Source Generation

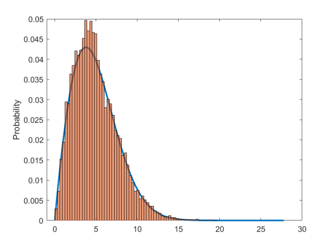

Fig. 5. Newcastle upon Tyne wind speed distribution

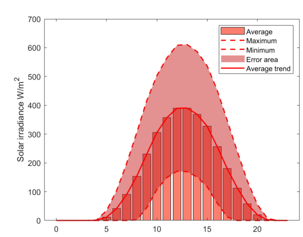

Fig. 6. Newcastle upon Tyne solar irradiance full day distribution

The historical weather data from Newcastle upon Tyne was used to obtain the predicted renewable energy. The 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:

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

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. Therefore, in the design of the environment, the uncertainty of the energy generated by wind and solar energy is generated randomly, and the generated energy is used to meet the EV's energy requirements.

B. EV Charging demand analysis

In terms of energy usage, this paper combines statistics on EV demand with data from an Oslo (Norway) car parking garage-based set of EV charging stations. The connection time data in Fig. 7 represents how long an EV is connected to a charging station. That may or may not be equal to how long the EV parks at the parking space, but obviously the parking time would be at least the length of the connection time. However, depending on the EV battery status (or the charging policy), the connection time is not always the same as the charging time. However, the connection time is a good index for the charging time, in particular, when the connection duration is relatively short and the EV leaves without being fully charged. Comparing the connection duration of year 2017 (Fig. 7, on the left) and that of year 2019 (Fig. 8, on the right), it can be found that the pattern are similar, but the number of sessions in year 2019 is much higher than that in year 2017. An in-depth analysis suggests that the highest frequency of charging sessions is in the range about 20 minutes. Figure 7, only depicts the charging session shorter than 1441 minutes (24 hours) and the fully data sets also shows that some charging session are longer than 24 hours. A few ones are longer than 4 days. These extremely long charging sessions only take a small portion and represents rare scenarios, and is regarded the outlier data. This outlier data is not considered in this analysis section. Fig. 8 depicts the daily energy use for charging the EVs over a period of 600 days. In order to allow reinforcement learning agent to experience every scenario, the configuration of the reinforcement learning simulation environment necessitates that this study calculates the average daily energy consumed to charge the EV.This energy is also distributed uniformly across each time interval. To determine EVs charging action, the algorithm can select a time period that best matches with the renewable energy generation. From the paper used data, the mean charging demand for electric vehicles is 12.83kWh, with a standard deviation of 16.24. The smallest demand energy is 0.0kWh, while the maximum demand energy is 91.15kWh. Therefore, the above data will be incorporated into the simulation environment for future reinforcement learning designs.

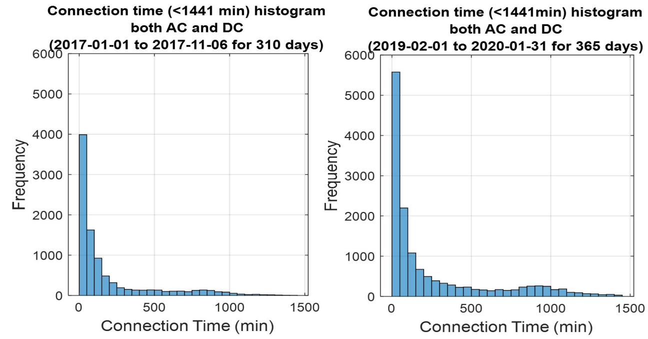

Fig. 7. Connection time distribution

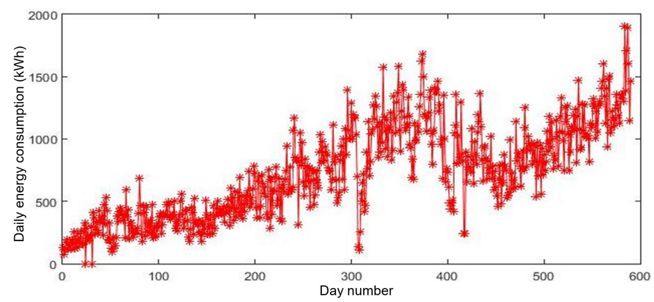

Fig. 8. Average daily energy consumption

In this study, the following results can be achieved after processing the aforementioned data. The average parking time of EVs is 194 minutes, with a standard deviation of 346. The shortest parking time is 1 minute, and the longest is 1439 minutes. In the simulation, 10 parking spaces were selected from the aforementioned data to serve as the reinforcement learning environment (Fig. 3). In 15 minutes (k), the likelihood of having no parked EVs is 0.91, for one parked car it is 0.074, for two parked cars it is 0.013 and for three parked cars it is 0.003 at the same k period. These data are inputted into the algorithm's environment to generate the parking time period shown in Fig. 9. White shading indicates a vacant parking space, whereas black shading indicates one that is occupied. Based on the aforementioned car arrival distribution, Fig. 10 displays parking occupancy data for three days (k=288) that have been generated at random.

V. Conclusion

This paper creates an useful simulated environment by combining real renewable energy sources with the unpredictability of wind speed and solar irradiation. This simulation can be used in future study to optimise the dispatching and charging schedule for electric vehicles (EVs) in the presence of uncertain EV demand and ORES supply using the reinforcement learning technique. The distribution of wind in Newcastle upon Tyne follows the Weibull distribution with parameters A =