Electric Fleets with On-site Renewable Energy Sources (EFORES): Data-driven Dynamic Dispatching and Charging under Uncertainties

Dr. Handong Li, Dr. Xuewu Dai, Dr.Richard Kotter and Prof. Nauman Aslam

Mathematics, Physics and Electrical Engineering, Northumbria University Newcastle

Introduction

This project is to investigate the possibility to intelligently integrate the dynamic charging demand of fleets of electric vehicles with the highly variable On-site Renewable Energy Sources (ORES) by developing a data-driven reinforcement learning (RL) decision support tool.

The Novelty, Originality and Significance:

Empirical data driven intelligent optimal dispatching and charging schedule of business electric fleets to maximize the efficient use of high variable on-site renewable energy at lowest cost of facility investment, and thus more green energy is used in road transport with less impacts on power grid.

Problem Description

The main charging facility at the depot has various ORES (PV, wind generators, etc), a static battery energy storage system (BESS) and a set of EV chargers (either AC or DC). They are connected to a 400 V local distribution network that is connected to the main grid via a transformer. The Energy Hub unit is a bank of unidirectional or bi-directional inverters that connect the ORES 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. The challenge is how to integrate the parts to maximize their efficiency and economy.

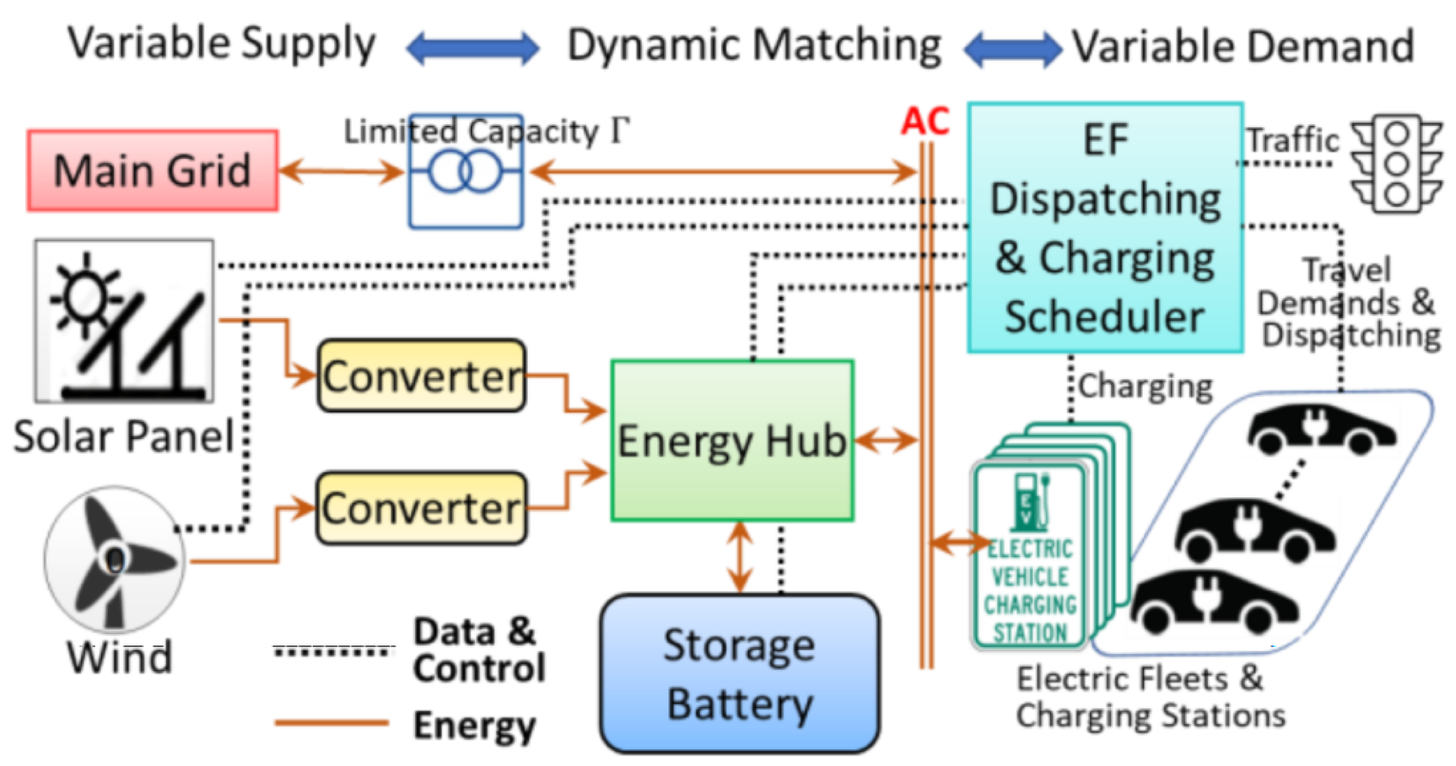

Figure 1:Diagram of the electric fleet depot use case with self-generated renewable energy

Aims and Objectives:

- A systematic investigation of the spatial-temporal pattern and uncertainties of both EV demand and ORE supply.
- An optimised EV dispatching and charging schedule by developing a Reinforcement Learning based decision making.
- Development of a techno-economic analysis tool to evaluate emission reduction in urban environment.

Methodology

Reinforcement Learning for optical decision on charging and dispatching

The system block diagram of reinforcement learning is as follows. The environment is constituted by the uncertainty of renewable energies. The reward is the capacity status of the battery. The state function is the actual power and the estimated power. The action consists of charging and non-charging actions of each EV in the fleet.

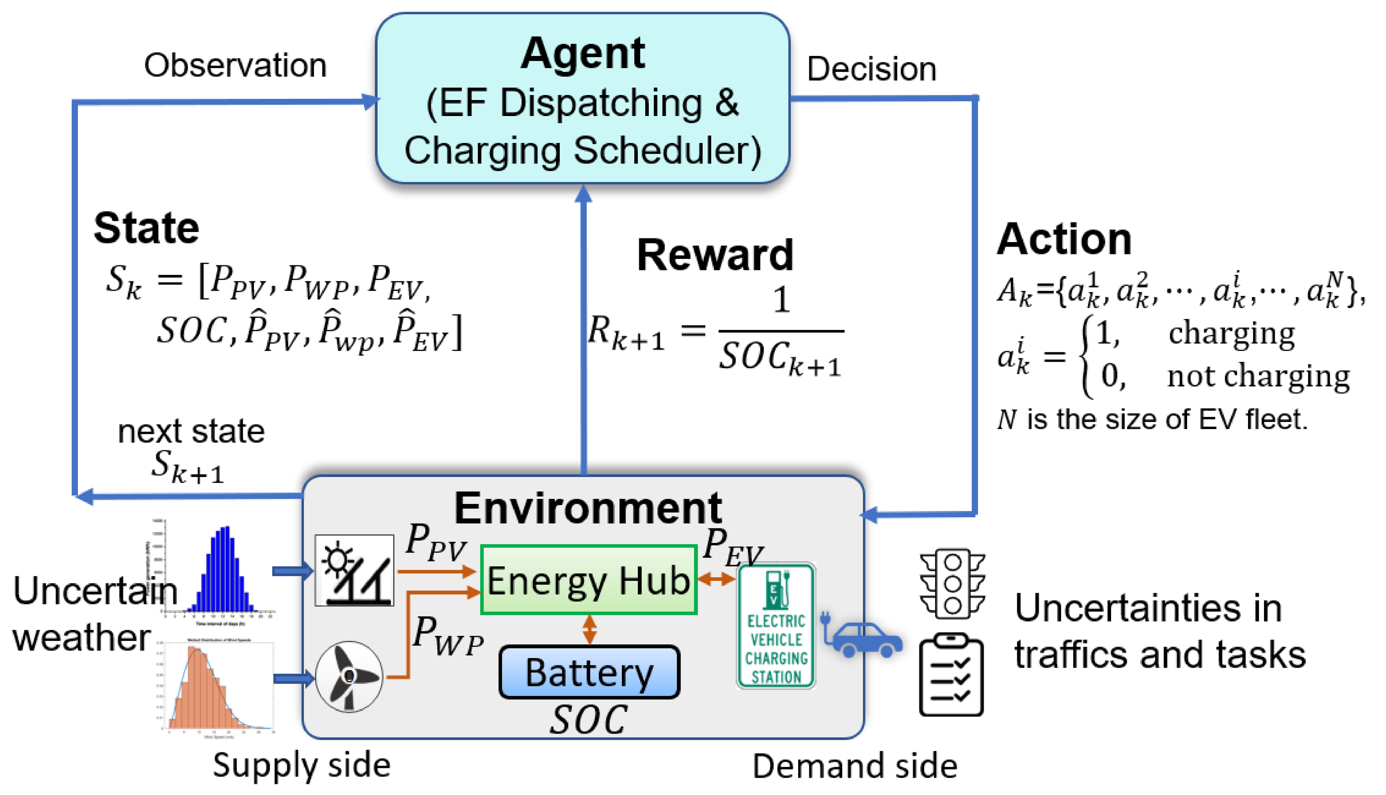

Figure 2:Diagram of the reinforcement learning

Project information: One year project with Scottish Power (Future Networks) and Newcastle City Council

On-site Renewable Energy Source (ORES) Modelling

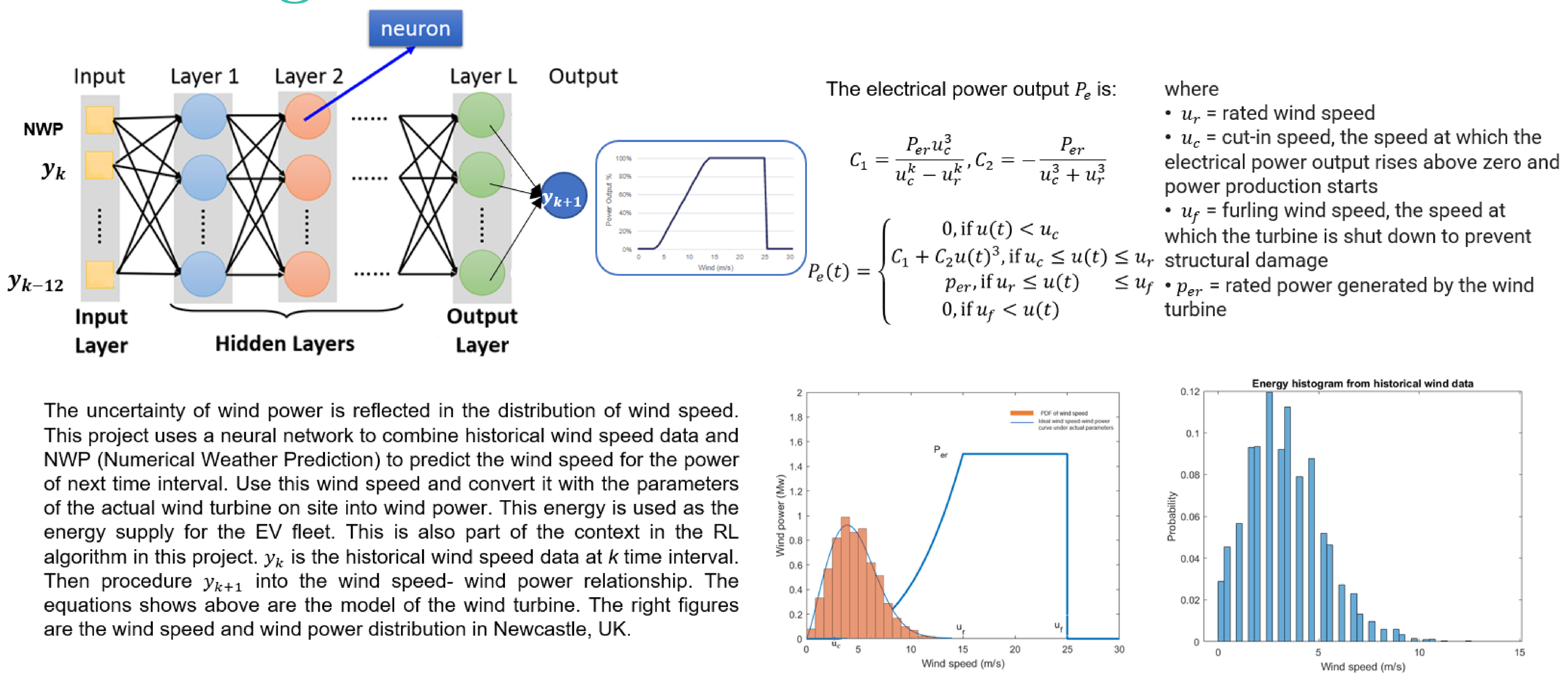

Figure 3:Wind forecasting and energy conversion[1]

Solar energy analysis

The power generated from the plant modeled in [2] during discrete time interval of the day is shown in Figure. 4. The monthly average solar irradiance and ambient temperature from [2] are presented in Figure. 4. The relationship between the power generation and solar irradiance can be expressed as:

$$p_s(t) = GHI(t) \cdot \eta_g A_s$$

where $GHI(t)$ (Global Horizontal Irradiance) is the solar irradiance (Wm^{-2}); η_g is the solar PV source efficiency; A_s is the solar PV source effective surface area (m^2); $P_s(t)$ is the Pv output power. It can be seen from the formula that there is a linear relationship between the generation of GHI and PV energy. The two graphs on the right side of Figure 4 count the distribution of the GHI index and the corresponding standard deviation in the Newcastle area within a day. According to this data, the uncertainty of solar energy can be reflected to provide the environment for the RL algorithm.

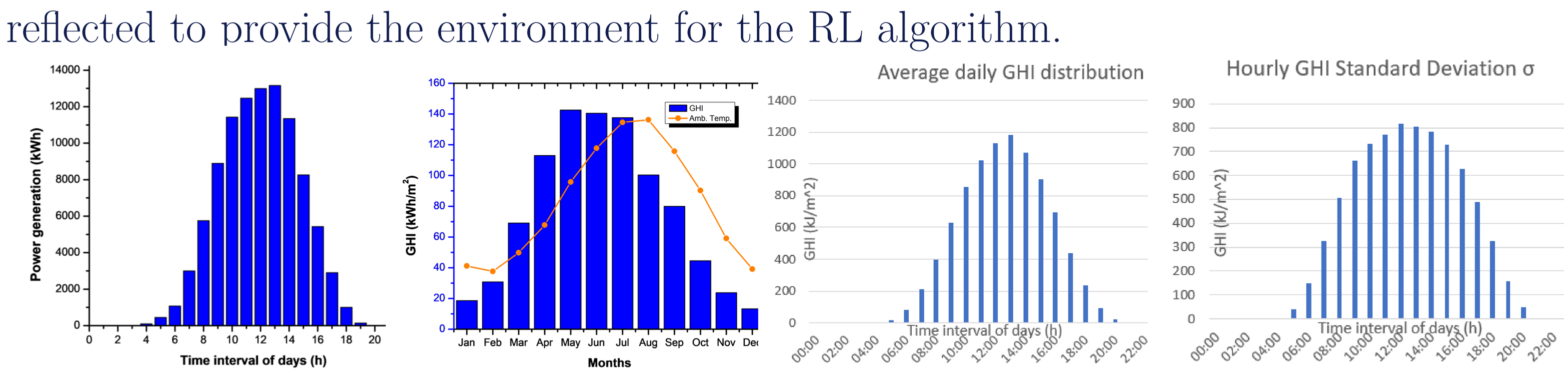

Figure 4:Daily and monthly distribution of solar energy

Electric Vehicle Fleet Demand Modelling

Dividing the day into 24 time periods by 1 h, and the charging load pf EVs' demand occurs in each time period as shown in Figure.5 and Figure.6.

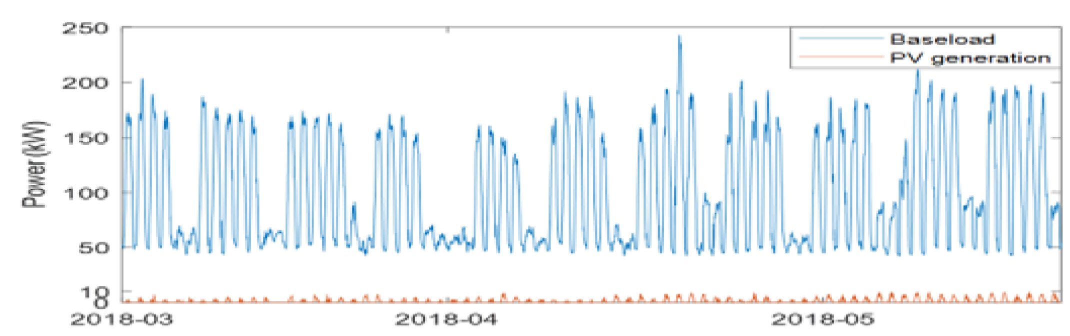

Figure 5:Hourly power consumption of Leicester [3]

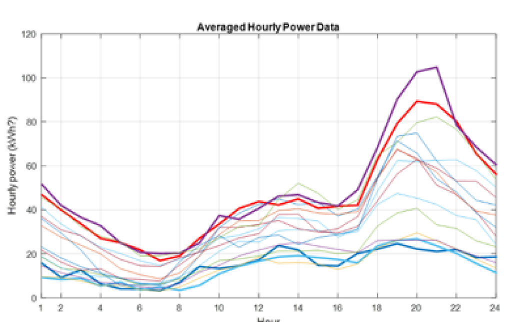

Figure 6:Averaged hourly power load at different month [3]

Future work and Conclusion

The following is a summary of the contents of this poster.

- To maximise economy and efficiency, the RL algorithm is designed to match the uncertain renewable energy supply with the uncertain energy demand of the EFs.
- Based on historical data from Newcastle, create a neural network and a time series algorithm to predict wind speed, then use the expected wind speed to build a model to convert it into uncertain wind power.
- Create an energy demand model for the EV fleet based on the charging and discharging rules.

Future work

- A techno-economic-environmental optimisation approach to analysing of emission reduction with collaborative EFs
- Prototyping and case study of a local council.

Reference

[1] W. Cranstone. Uk onshore wind (investment fundamentals). Technical report, Gresham House Asset Management Limited, 5 New Street Square, London EC4A 3TW, June 2019.

[2] R. R. Urs, Z. Ali, M. Marzband, K. Saleem, B. Mohammadi-Ivatloo, and A. Anvari-Moghaddam. A technical assessment on photovoltaic power generation under varying weather profile–northumbria university pilot. In *2020 IEEE 29th International Symposium on Industrial Electronics (ISIE)*, pages 811–815. IEEE, 2020.

[3] D. Xuewu, K. Richard, P. Ghanim, W. Yue, D. Ridoy, B. Edward, M. Mousa, and d. H. Jorden, van. Final report - oslo operational pilot. Technical report, Interreg North Sea Region SEEV4-City, Oslo City Council: Sture Portvik, July 2020.