Optimal Electric Vehicle Charging for Solar-Wind Powered Car Park

Yuhao Ma, Xuewu Dai*, Jing Jiang, Richard Kotter, Nauman Aslam
Faculty of Engineering and Environment, Northumbria University, Newcastle upon Tyne, NE1 8ST, UK
Email: xuewu.dai@northumbria.ac.uk

***bstract*—The rapid growth of electric vehicles (EVs) has presented unique challenges and opportunities in the field of sustainable transportation by integrating renewable energy sources (RES), such as on-site solar and wind power, with EV charging infrastructure. This paper proposes a novel concept of a solar-wind-powered EV car park equipped with smart charging technology, aimed at maximizing the utilization of solar and wind energy for charging EVs. The proposed solar-wind-powered EV car park combines on-site local photovoltaic (PV) panels, wind turbines, battery energy storage system (BESS), with EV charging stations to create a self-sustaining ecosystem. The proposed optimization strategy and smart charging system is to optimizes the allocation of solar power based on demand, vehicle charging requirements, and available solar and wind energy. Simulation results show that the optimized power allocation may reach 100% utilization rate of renewable on-site solar and wind energies, with significant improvement compared with the conventional non-optimized charging strategy. The efficient use of local renewable nergy resources while minimizing the size of the BESS contribute to the investment and operation cost saving on BESS and ower grid.**

Keywords—Electric Vehicles, Smart Charging, Solar Power, Wind Power, Battery Energy Storage Systems, Optimization

I. INTRODUCTION (*HEADING 1*)

It is estimated that the number of electric vehicles (EVs) is about 27 million all over the world and, by 2050, the it ay reach 700 million, and 416 million charging piles will be constructed, And the total capacity of EV charging demand is expected to more than 2900 TW by 2050 [1]. While EVs are widely used around the world, it is inevitable that such a great number of EV demand brings a huge challenge to the power grid. With the increasing demand of EV charging, The connection of EVs with grid system will cause different issues such as harmonics, degradation of power quality, voltage instability, stress on transformer, threatening the stability of grid and impact on the supply and demand balance [2]. In addition, one of the main purposes of replacing the traditional internal combustion engine vehicles with EVs is to reduce the usage of fossil fuels and emission of greenhouse gas like carbon dioxide. However, charging EVs with the electricity generated from fossil fuels (oil, coal and gas), it does not help reducing the emission. Increasing the electrification of vehicles may not actually reduce the road transport emission globally. Instead, we need to increase the percentage of electricity generated from renewable sources, thus charging the EVs with renewable energy sources (RES).

Charging strategies have major impacts on the energy system and the utilization of the renewable energies. Generally speaking, charging strategies can be characterised by how the time and frequency of EVs charge are managed and can be categorised into un-controlled (un-coordinated) charging and controlled(coordinated) charging [3]. The most common and easiest deployed charging method s uncoordinated charging, which refers to the charging behaviour of EVs without any centralized control or coordination. An EV either starts charging battery immediately once arriving at EV car park and being connected to the charging station, or after a simple user-defined adjustable start delay, or charging in a fixed period (e.g. only charging in the off peak period in the night). Uncoordinated EV charging, although simple and straightforward, may cause overload, higher peak demands and more voltage/frequency deviation, which can strain the power grid during peak hours, necessitating grid upgrades and negatively impacting grid stability and overall system efficiency. In addtion, uncoordinated charging may lead to an uneven distribution of load, limiting the benefits of renewable energy integration and grid optimization, thus more investment on the grid infrastructure and more operation costs.

On the other hand, coordinated EV charging, also known as smart charging, involves the intelligent management of EV charging to optimize system efficiency and minimize grid stress and/or costs [4]. This approach utilizes advanced algorithms and communication technologies to schedule and control charging based on grid conditions, renewable energy availability, and user preferences. A study conducted by Amjad etc. [5] investigated the benefits of coordinated EV charging in a residential setting. The research demonstrated that by coordinating charging schedules, it is possible to reduce peak demand, enhance load balancing, and increase the utilization of renewable energy resources. Coordinated charging also has the potential to provide grid services, such as demand response and frequency regulation, contributing to grid stability.

To charge EVs with more renewable energies, this paper investigate how to charge EVs with local on-site renewable energy sources (ORES), like PVS and WTS, to mitigate the stress on the power grid and realize the goal of reducing environmental pollution. However, the power generation of ORES is highly variable, resulting in an undesired fluctuation at the supply side. On the demand side, EVs' charging demand also comes with uncertainties, to meet various tasks with dynamic travelling and charging demands. In shifting EV energy from less variable fossil electricity (imported from the grid) to more variable on-site ORES, the main challenge is the charging strategy of maximizing self-consumption of own ORES under those uncertainties, whilst meeting the variable EV demands, at minimized cost in energy storage and less impact on grid's peak load.

This paper develops an optimal dispatching and charging model of the solar-wind-powered EV car park and proposes a mixed-integer linear programming (MILP) method to optimize the EV charging. This paper focuses on solving the problem of intermitted power generation of photovoltaic system (PVS) and wind power system (WPS) and the uncertainty of EV charging demands by integrating battery energy storage system (BESS) into these intermitted power sources, thus reducing the dependency and impact on local power grid and achieve better utilization of intermittent PVS and WPS for EV charging.

II. Related Work

In recent years, with the growing application of electric vehicles all over the world, massive work has been done to research the impact of EVs' charging demand to the local grid and reasonable solutions to satisfy those demand with local renewable energy source (RES) to reduce the carbon emission, instead of traditional fossil fuel power generation [6,7]. However, due to the intermittence and variance of both the demand side (EVs) and supply side (RES), it's hard to satisfy the charging demand and largely use the RES. So many researchers use optimization method, energy storage system and V2G (shortly for vehicle-to-grid) technology to realize the real-time power allocation (RTPA) considering both demand and supply sides. The abstract of optimization strategies and power sources of different research is listed in the Table 2.1 below.

Table 1. Optimization strategies for EV charging

Study	Optimization Methodologies	Energy Sources considered
[8]	Linear Programming (LP)	Grid
[9]	BLP (binary LP)	Grid, V2G
[10]	MILP*	Grid, V2G, PVS, ESS
[11]	RTPA**	Grid, PVS
[12]	GA (Genetic Agorithm)	Grid, PVS
[13]	Modified CSO***	Grid, V2G, PVS
[14]	Stochastic MILP (SMILP)	Grid, PVS
[15]	Kernel-based Esimator	Grid, PVS

MILP: Mixed Integer Linear Programming
RTPA: Real-Time Power Allocation for EVs
CSO: Cat swarm optimization

Linear programming (LP) is one of the useful approaches to address the problem of EVs charging scheduling. In [8], a LP mathematical model was founded to realize both the increase of the profit of using local renewable energy, decrease of the charging cost and the huge impact to the grid from massive loads of EVs. In [9], a two-layer optimization method called Binary Linear Programming (BLP) is utilized to achieve both goals of optimizing the subscribed power load profile with nonlinear convex optimization,

Mixed Integer Linear Programming (MILP) is a widely used method to optimize the utilization of RES and satisfying the EVs' charging demand. Yao etc., [10] propose an optimal charging and discharging scheduling based on MILP to maximize the utilization of local solar energy, satisfy all EV users' charging demands and minimize the total operation cost of the parking lot by selling the power back to the grid when the electricity price is high, considering V2G, ESS and the variation of electricity price and PVS's current output power.

There is still some place to be advanced like smooth the process of charging and discharging for EV and ESS [11], solving the problem of charging the EV with early leaving and optimize the total capacity of ESS, etc. While in many studies, the EV users' demand is assumed as a time-varied function, which could be depicted with distribution modelling. But it is ignorable that in some conditions, the real charging responses are influenced by many factors, like electricity price and users' demand for EV. So, in [12], an optimization strategy is proposed, for a region equipped with WTS and PVS, to reduce peak-to-valley difference with the model construction of EV users' charging response to the price proportion and demand factors.

In Ahmad's research [13], the optimal way to place solar-powered charging station in the distribution network, is investigated with forecasting EV load demand, evaluation of PV output with a Feed-forward neutral network. The improved chicken swarm optimization method is applied to get the best location of the charging station. The optimized place is proved to improve the load profile and reduce the power loss. However, assumptions of demand of EV are too ideal in some degree and will be better if considerations like more random initial values and activity-based behaviour of drivers are taken.

The research in [14] gives a more comprehensive model for the charging strategies of different vehicle fleets in a PV-powered car park, according to three kinds of drivers among commercial, long-term and short-term customers. But the model also has its limitation in the constant battery charging without thinking about the necessity for charging different EVs. Moreover, if variance of EV fleet in different places and PV output forecasting based on the real data is taken into consideration, this model will be more reliable and appliable for more cases.

Different from the previous strategy, in [15], a kernel-based estimator is introduced to compute the cost-effective solutions for an EV supply equipment with limited power supply, which is worth further research due to finite capacity of the local RES. The real-world data is also utilized for cross validation of the proposed framework, which demonstrate its reliability. But the proposed framework will be improved by introducing some energy storage methods with energy storage.

III. Problem Formulation

This paper is to optimize the EV charging of a solar-wind-powred EV car park, which has the electrical energy from thre sources: local on-site photovoltaic system (PVS), wind power system (WPS) and power grid. The uncertainties of both EV charging demands and the power supply of PVS and WPS are considered in the optimization. Integrating energy storage system (ESS) into these intermitted power sources, thus reducing the dependency and impact on local power grid and achieve better utilization of intermittent PVS and WPS for EV charging. The basic framework is shown in figure 1.

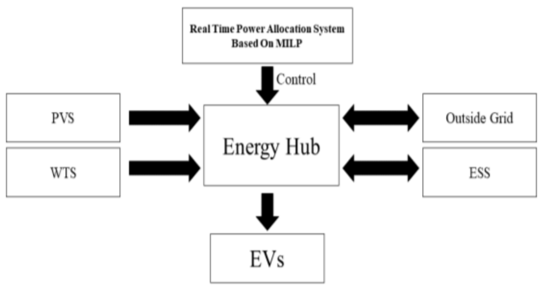

Figure 1. The block diagram of solar-wind-powred EV car park charging system.

At the power supply side, it consists of PVS and WTS, providing energy to EVs and ESS. During the shortage period of RES supply, outside grid and ESS will compensate that gap between supply and demand. The real time power allocation system will control the energy hub to realize the whole system's power allocation under optimal objections. Arrows in this figure shows directions of power flow.

A. Notations

The notations used in this paper are summarised in the table below:

TABLE 1. NOTAITONS

Symbol	Definitions
N	Number of charging stations (aka piles)
T_s	Time step size (sampling interval)
$u_{n,j}$	a binary decision variable. $u_{n,j}$=1, n-th charging station charges at time step j; =0 not charging
x_j	charging rate of n-th charging station at j, real decision variable [0, 1].
y_j	charging rate of BESS at time j, real decision variable $[-1, 1]$
z_j	Power rate of imported energy from the power grid, real decision variable [0,1]
P_{grid}^{max}	Maximum load allowance of power grid
P_{ESS}^{max}	Maximum power rate of BESS
K_n^{arr}	Arrival time of n-th EV
δ_n^j	Status of charging pile n at step j
P_n^{max}	The maximum charging power of EV
γ_n^{min}	The minimum SOC of EV
H	Total operational hour
J	Total time step
E_{ESS}^{cap}	ESS capacity
η_{ESS}	Charging/discharging efficiency of BESS
K_n^{dep}	The departure step of n-th EV
γ_n^{max}	The maximum SOC of EV
γ_n^{init}	The initial SOC of EV at arrival step

B. EV Cahrging Procedure

Let t_n^{arr} and t_n^{dep} represent the arrival and departure time for a EV parks at and connects to the n-th charging station, and j represent the time slot, T_s is the duration of a time slot. T_s is also known as *time step*. Givn a time horizon of T, then the total number of time slots is $J = T/T_s$ and $j = \{0, 1, 2, \cdots J\}$. At each time step, an EV may arrive and occupies a charging station for battery charging. It may also departure when it is fully or partially charged. For example, given a time step of $T_s = 15$ minutes, if the time horizon of charging schedule to be optimized ti 24 hours (i.e. one day), then J =96. To model the process of EV arrival and departure, and the EV chargin demand, the arrival and departure events are allocated to a timeslot as follows:

$$K_n^{arr} = ceil\left(\frac{t_n^{arr}}{T_s}\right) \tag{2}$$

$$K_n^{dep} = floor\left(\frac{t_n^{dep}}{T_s}\right) \tag{3}$$

where K_n^{arr} and K_n^{dep} are the time step of an EV arrives at and departs from n-th charging station, $K_n^{arr} \in \{1,2,3, \cdots J\}$ and $K_n^{dep} \in \{1,2,3, \cdots J\}$

The status of a charging station is modelled as a binary variable δ_n^j

$$\delta_n^j = \begin{cases} 1, & \forall j \in [K_n^{arr}, K_n^{dep}] \\ 0, & \forall j \notin [K_n^{arr}, K_n^{dep}] \end{cases} \tag{4}$$

Eq. (4) shows that, tt time step j, if one of the arrival EVs is allocated to (or parked at) the n^{th} charging station, then δ_n^j=1. Otherwise $\delta_n^j = 0$, which means the n^{th} charging station at step j is free.

Let γ_n^j be the state of charge (SOC) of the EV arrives at the n-th charging station at time step j, γ_n^j changes as follows:

$$\gamma_n^j = \begin{cases} \gamma_n^0, & if\ j = K_n^{arr} \\ min\ (\gamma_n^{j-1} + \frac{\eta_n^c P_n^{max} S_n^{c,j} T_s}{E_n^{cap}} u_n^j, 1), & if\ j \in [K_n^{arr}, K_n^{dep}] \end{cases} \tag{5}$$

where u_n^j is the decision variable to determine whether n^{th} EV should be charged at time step j as Eq. (6).

$$u_{n,j} = \begin{cases} 1, & \text{EV parked at nth station is charged at step } j \\ 0, & \text{EV parked at nth station is not charged at step } j \end{cases} \tag{6}$$

when an EV arrives, the SOC γ_n^j is initialized with a constant value γ_n^0 to represent how much energy is left for an EV. . Afterwards, γ_n^j could be deduced by the previous status and decisive variable. E_n^{cap} is the capacity of the EV battery.

Similarly, the SOC of the BESS can also me modelled by Equation 7 & 8.

$$\gamma_{ESS}^j = \begin{cases} \gamma_{ESS}^0, & when\ j = 1 \\ \gamma_{ESS}^{j-1} + \frac{\eta_{ESS} P_{ESS}^{max} x_j T_s}{E_n^{cap}}, & if\ j \geq 2 \end{cases} \tag{7}$$

where x_j is the decision variable to determine the charging/discharging rate of BESS. x_j is a real number between -1 and 1. Positive charging rate ($x_j > 0$) indicates BESS is in charging, and negative charging rate ($x_j < 0$) indicates BESS is in discharging. .

$$\begin{cases} BESS\ is\ being\ charged, & if\ 0 < x_j \leq 1 \\ BESS\ is\ discharging, & if\ -1 \leq x_j < 0 \end{cases} \tag{8}$$

C. Objective Function Design

The objective function is depicted by Eq. (9), which represents the absolute value of the electricity consumed by the whole system. The optimized solution of this function means that the system reduces the dependence on the outer grid, including getting power from it or sold power to it, as much as possible.

$$F = \frac{T_s}{60} \sum_{j=1}^{J} \left| \sum_{n=1}^{N} (P_n^{max} x_{n,j} u_{n,j}) + P_{ESS}^{max} y_j - P_{PVS}^{j} - P_{WTS}^{j} \right| \quad (9)$$

where P_{PVS}^j and P_{WTS}^j are the output power of PVS and WTS at step j.

D. Objective Function Design

It is also necessary to add some constraints as Equation 10 to 14, to ensure the system operates safely and stably.

Constraint 1 (Equation 10): At any step, the total power imported from the power grid should not be over the maximum load allowance P_{grid}^{max} of power grid

$$\left| \sum_{n=1}^{N} (P_n^{max} x_{n,j} u_{n,j}) + P_{ESS}^{max} y_j - P_{PVS}^{j} - P_{WTS}^{j} \right| \leq P_{grid}^{max} \quad (10)$$

Constraint 2 (Equation 11): At any step, the SOC of EV should not exceed the upper limits. Besides, the SOC of EV should reach the basic requirement when it departs.

$$\begin{cases} \gamma_n^j \leq \gamma_n^{max}, \forall j \in [1, J] \\ \gamma_n^{K_n^{dep}} \geq \gamma_n^{dep} = 0.8 \end{cases} \quad (11)$$

Constraint 3 (Equation 12): At any time j, the SOC of BESS should be restricted within lower and upper limits. Besides, the SOC of BESS should reach the basic requirement at the end of the working cycle.

$$\begin{cases} \gamma_{ESS}^{min} \leq \gamma_{ESS}^{j} \leq \gamma_{ESS}^{max}, \forall j \in [1, J] \\ \gamma_{ESS}^{J} \geq \gamma_{ESS}^{thres} = 0.8 \end{cases} \quad (12)$$

Constraint 4 (Equation 13): The change of the BESS charging and discharging power is limited. This is to avoid the oscillation of power and protect the battery. It also smooth the power profile of BESS.

$$|x_j - x_{j-1}| \leq k_{ESS}, \forall j \in [2, J] \quad (13)$$

where k_{ESS} is a constant between 0 to 1 to control the change of the charging /discharging rate of the BESS.

Constraint 5 (Equation 14): The change rated of the grid power is also limited to avoid the oscillation of power and protect the grid. Thus, it also realizes the goal of smoothing the power curve of grid.

$$\left| P_{grid}^{j} - P_{grid}^{j-1} \right| \leq k_{grid} P_{grid}^{max}, \forall j \in [2, J] \quad (14)$$

where k_{grid} is a constant between 0 to 1 to control the changing speed of P_{grid}^j

In a summary, the optimal charging of solar-wind-powered EV car park can be formulated as

$$\min_{u_{n,j}, x_j, y_j} F = \frac{T_s}{60} \sum_{j=1}^{J} \left| \sum_{n=1}^{N} \left(P_n^{max} x_{n,j} u_{n,j} \right) + P_{ESS}^{max} y_j - P_{PVS}^{j} - P_{WTS}^{j} \right|$$

s.t. constraints (10), (11), (12), (13), (14)

$$u_{n,j} \in \{0,1\}$$
$$0 \leq x_j \leq 1, x_j \in \mathbb{R}$$
$$-1 \leq y_j \leq 1, y_j \in \mathbb{R}$$

The smart charging is optimized by minimizing the objective function of the absolute value of the power exchange with the grid. This is solved by using a mixed integer linear programming (MILP) solver.

IV. RESULTS AND DISCUSSIONS

In this section, simulation results of a typical solar-wind powered EV car park is presented. The configuration and parameters of the case study is listed in table below. The total simulation hour is 30 hours and, as a result, the time step is J =120 with the time step size is T_s=15 minutes.

TABLE II SYSTEM CONFIGURATION AND PARAMETERS' VALUES

Parameters	Value
N	200 vehicles
T_s	15 minutes
J	Time horizon 120 steps (30 hours)
P_{grid}^{max}	400 kW
P_{ESS}^{max}	15 kW
P_n^{max}	9.6kW max charging power
γ_n^{min}	0.35 minimum SOC of EV
E_{ESS}^{cap}	2000 kWh (BESS capacity)
η_{ESS}	0.95 BESS charging/discharging efficiency
γ_n^{max}	0.99 maximum SOC of EV batteries
γ_n^{init}	0.4 initial SOC of EV bateries at arrival

The power allocation of the solar-wind-powered EV charging system are shown in Figure 2, including the power of EV charging (blue), power imported from grid, power generation of PVS (yellow), power generation of WTS (purple), and power of ESS.

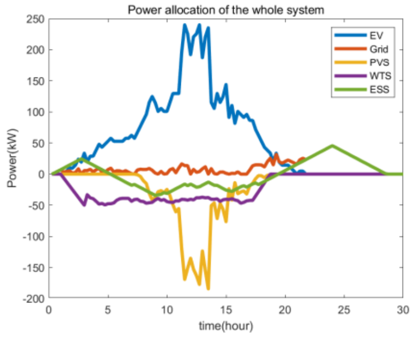

Figure 2. Power allocation of the solar-wind-powered EV car park system

The power profile under zero means providing power to the system. For example, the RES (PVS and WTS) and ESS supplies the power to the system, while EV consumes the energies generated by the RES. The peak hours of EV charging is around 11 a.m. to 14 pm., which is also the peak of PVS output. In the optimized charging, EVs tend to be charged when the PVS generate power and the ESS also discharges to reduce the power transferred to the grid. With the help of RES and ESS, the power load on the grid is reduced during the peak time of EV charging. The grid power is also smooth and stable with a small peak-valley value of 57.6 kWh. The proposed optimization and smart charging is able to reduce the peak load on the grid, thus help to improve the grid operation.

To better illustrate the performance of the proposed method, the comparation between the proposed strategy (MILP optimization with battery Energy Storage System ESS) and uncoordinated charging strategy is shown Figure 3, where uncoordinated charging strategy means that the EV start charging immediately once its arrival and finishes when its SOC reached 80% or departure time is reached.

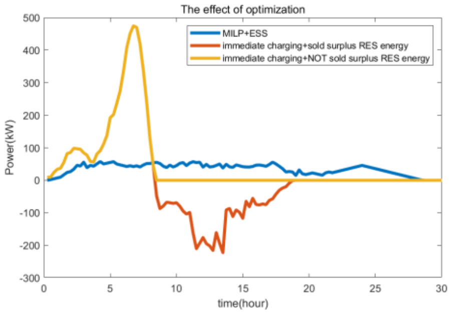

Figure 3 Comparation between the proposed MILP+EEE smart charging and the traditional uncoordinated charging

In Figure 3, the blue curve is the power imported from grid in the proposed smart charging strategy, the yellow one is the power imported from the grid in uncoordinated charging strategy without exporting excess power back to the grid, and the red one is that with exporting excess power back to the grid. One can see that the uncoordinated charging requires a huge charging demand about 475 kWh at 6:45 a.m. As one can see, the power imported from grid in the proposed strategy is less than the grid power of other two. This demonstrates that the proposed method is able to reduce the amount of energy imported from the grid, thus more renewable energies from the solar and wind power are utilized to charge the EVs. Meanwhile, the optimized power curve is far more stable than the disordered one. The peak-valley difference of disordered charging strategy is about 475 kWh, 10.39 times of this project's result, which will threaten the safety operation of the transmission and distribution system.

The comparison of the energies imported from grid are listed in results of the comparation is listed in Table 4.3.1.

TABLE III. COMPARATION WITH UNCOORDINATED CHARGING

Method	Electricity imported from Grid (kWh)	Utilization rate of RES (%)
The proposed MILP+ESS	1398	100
Uncoordinated Charging	5536	22.3

It can be seen from the table that the proposed smart acharing (MILP + ESS) method only imports 1398 kWh from the grid, which is reduced by 74.7% compared with the 5536 kWh energy imported from the grid in the uncoordinated charging method. Meanwhile, all the energy from the solar and wind power generation are used to charge the EV, resulting a 100% utilization of RES. The uncoordinated charging only use 22.3% of the RES to charge the EVs. This indicates that the utilization rate of RES could be increated by 77.7%, compared with the uncoordinated charging strategy.

V. CONCLUSIONS

In this study, a smart charging method is proposed for solar-wind powered car park.The power allocation is optimized by minimizing the objective function of the absolute value of the power exchange with the grid. This is solved by using a mixed integer linear programming (MILP) solver. Compared with the uncoordinated charging strategy, the proposed method is able to reach 100% utilization rate of the on-site solar and wind energies. It also reduce the amount of electricity imported from the power grid and smooths the power demand curve with one tenth of original peak-valley value. This will helps to reduce the carbon emission in road transport.

ACKNOWLEDGMENT

This work was supported in partial by the project Electric Fleets with On-site Renewable Energy Sources (EFORES) under grant EP/W028727/1, and the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie Grant Agreement No. 872172 TESTBED2 project.

REFERENCES

[1] [4] BNEF: Five forecasts for the global electric vehicle market in 2023," [Online]. Available: https://www.car-metaverse.com/202301/181739098.html. [Accessed 13 April 2022].

[2] N. Garwa and K. R. Niazi, "“Impact of EV on Integration with Grid System – A Review”," 2019 8th International Conference on Power Systems (ICPS), Jaipur, India, 2019, pp. 1-6, doi: 10.1109/ICPS48983.2019.9067587.

[3] [Dai01] Ahmed R. Abul'Wafa, Aboul'fotouh El'Garably, Wael A.Fatah Mohamed. Uncoordinated vs Coordinated Charging of Electric Vehicles in Distribution Systems Performance. International Journal of Engineering and Information Systems (IJEAIS), 2017, 1 (6), pp.54 - 65

[4] Li, H., Dai, X., Kotter, R., Aslam, N., Cao, Y. (2023). A Simulation Environment of Solar-Wind Powered Electric Vehicle Car Park for Reinforcement Learning and Optimization. In: Cao, W., Hu, C., Chen, X. (eds) Proceedings of the 3rd International Symposium on New Energy and Electrical Technology. ISNEET 2022. Lecture Notes in Electrical Engineering, vol 1017. Springer, Singapore.

[5] A M. Amjad, A. Ahmad, M. H. Rehmani, nd T. Umer, “A review of EVs charging: From the perspective of energy optimization, optimization approaches, and charging techniques,” Transp. Res. Part D Transp. Environ., vol. 62, no. March, pp. 386–417, 2018

[6] G. Alkawsi, Y. Baashar, D. Abbas U, A. A. Alkahtani, and S. K. Tiong, "Review of Renewable Energy-Based Charging Infrastructure for Electric Vehicles," Applied Sciences, vol. 11, no. 9, 2021, doi: 10.3390/app11093847.

[7] H. Fathabadi, "Novel wind powered electric vehicle charging station with vehicle-to-grid (V2G) connection capability," Energy Conversion and Management, vol. 136, pp. 229-239, 2017, doi: 10.1016/j.enconman.2016.12.045.

[8] [14] C. Jin, J. Tang, and P. Ghosh, "Optimizing Electric Vehicle Charging: A Customer's Perspective," IEEE Transactions on Vehicular Technology, vol. 62, no. 7, pp. 2919-2927, 2013, doi: 10.1109/tvt.2013.2251023.

[9] [15]S. Sarabi, A. Davigny, Y. Riffonneau and B. Robyns, "V2G electric vehicle charging scheduling for railway station parking lots based on binary linear programming," 2016 IEEE International Energy Conference (ENERGYCON), Leuven, Belgium, 2016, pp. 1-6.doi: 10.1109/ENERGYCON.2016.7513989

[10] L. Yao, Z. Damiran, and W. H. Lim, "Optimal Charging and Discharging Scheduling for Electric Vehicles in a Parking Station with Photovoltaic System and Energy Storage System," Energies, vol. 10, no. 4, 2017, doi: 10.3390/en10040550.

[11] N. Liu et al., "A Heuristic Operation Strategy for Commercial Building Microgrids Containing EVs and PV System," IEEE Transactions on Industrial Electronics, vol. 62, no. 4, pp. 2560-2570, 2015, doi: 10.1109/tie.2014.2364553.

[12] H. Liu, P. Zeng, J. Guo, H. Wu, and S. Ge, "An optimization strategy of controlled electric vehicle charging considering demand side response and regional wind and photovoltaic," Journal of Modern Power Systems and Clean Energy, vol. 3, no. 2, pp. 232-239, 2015, doi: 10.1007/s40565-015-0117-z.

[13] F. Ahmad, M. Khalid, and B. K. Panigrahi, "An enhanced approach to optimally place the solar powered electric vehicle charging station in distribution network," Journal of Energy Storage, vol. 42, 2021, doi: 10.1016/j.est.2021.103090.

[14] K. Seddig, P. Jochem, and W. Fichtner, "Integrating renewable energy sources by electric vehicle fleets under uncertainty," Energy, vol. 141, pp. 2145-2153, 2017, doi: 10.1016/j.energy.2017.11.140.

[15] B. Wang, Y. Wang, H. Nazaripouya, C. Qiu, C.-c. Chu, and R. Gadh, "Predictive Scheduling Framework for Electric Vehicles Considering