Optimal Valley-Filling Algorithm for Electric Two-wheeler Charging Stations

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ABSTRACT

In Vietnam, comprehensive measures are required to accommodate and encourage the potential development of electric two-wheelers in urban traffic and the rooftop solar power potential. In the case of PV-integrated electric two-wheeler charging stations, numerous vehicles charging simultaneously may trigger very high peak loads which adversely impacts other loads and the distribution grid. In this study, an optimal valley-filling algorithm for electric two-wheeler charging stations is proposed. The proposed algorithm can update the variation of available vehicles as well as the dynamic changes in the energy level of individual E2Ws at each time slot. The simulation results proved that the proposed method can effectively perform valley filling, significantly improving the total load profile compared to uncontrolled charging and average charging schemes.

Keywords-electric two-wheelers; charging station; valley-filling; solar power; charging algorithms

I. INTRODUCTION

It has been shown that the utilization of renewable energy, especially rooftop photovoltaic (PV) power, for Electric Vehicle (EV) charging contributes to achieving multiple objectives such as: (1) meeting the charging demand while reducing adverse impacts of charging loads on the distribution grid, (2) encouraging self-generation-self-consumption and mitigating negative impacts of high PV penetration rate into the distribution grid, (3) reducing the need for grid upgradation, and (4) reducing greenhouse gas emissions [1]. Furthermore, in developing countries like Vietnam, electric two-wheelers (E2Ws) are considered suitable for the existing transport infrastructure and socio-economic conditions [2, 3]. However, the transition from fossil fuel motorcycles to E2Ws requires appropriate and comprehensive measures regarding infrastructure planning and charging solutions for this type of vehicle. Uncontrolled EV charging may increase peak load and energy losses and trigger inefficient system operation [4]. If charging stations are located in offices, apartment buildings, factories etc., uncontrolled charging could result in very high peak loads, because the arrival and departure of vehicles usually concentrate on certain times and vehicles tend to be charged at their maximum permitted rate as soon as they are connected.

Regarding load shifting and valley filling solutions, numerous approaches have been proposed such as broadcasting charging tariffs with different rates depending on total load level [5], leveraging quadratic programming [6], leveraging linear programming and receding horizon control [7]. However, these studies only focus on electric car charging infrastructure instead of E2W charging stations. The research on improving load profile for E2W charging stations is still limited. Although charging power and battery capacity of E2Ws is negligible compared to electric cars, hundreds of E2Ws charging simultaneously can result in a very high peak load. In addition, scheduling numerous vehicles requires appropriate approaches regarding architecture and scheduling algorithms.

Several works have conducted research on the E2W charging station feasibility [1, 3], E2W charging station architecture [8], and scheduling algorithms for E2W charging stations in Vietnam [9, 10]. However, these works have not addressed the uncertainties regarding the arrival and departure of vehicles. Thus, this study proposes an algorithm that dynamically updates both the availability of vehicles at each timeslot and the change in energy level of vehicle batteries.

The main contributions of this work are: (1) a valley-filling algorithm for PV-integrated E2W charging stations is proposed, (2) the algorithm is able to update the variation of available E2Ws and energy levels of vehicles, (3) by adopting the algorithm, PV utilization for charging is proved to be more efficient, (4) the algorithm contributes to adverse impact mitigation of EV charging and PV on other loads and on the distribution grid.

II. PROBLEM FORMUALTION AND THE PROPOSED ALGORITHM

A. Objective Function

Most studies consider charging problems being scheduled in a day or a scheduling horizon which is usually discretized into 96 timeslots of 15 minutes [11]. For the load profile improving problem, the optimization objective aims to minimize the load fluctuation. This can be interpreted as total load variance minimization. Thus, the objective function would be as in (1):

$$\min F_{obj} = \frac{1}{M}\sum_{t=1}^{M}\left(D_S^t + \sum_{i=1}^{N} P_i^t - \mu_{ave}^S\right)^2 \quad (1)$$

Subject to:

$$\sum_{i=1}^{N} P_i^t \leq min\left\{\sum_{i=1}^{N} P_{cmax_i}, \sum_{i=1}^{N} P_{bmax_i}\right\} \quad (2)$$

$$\sum_{i=1}^{N} P_i^t \leq P_{feedermax} - D_S(t) \quad (3)$$

$$\sum_{i=1}^{N} A_i(FSOC_{EVi} - ISOC_{EVi}) = \sum_{i=1}^{N}\left(\int_{t_0}^{t_m} \eta_i P_i(t)\right) \quad (4)$$

where M is the total timeslot number of the scheduling horizon, D_S^t (also known as netload) is the total power of non-EV loads subtracting the power generated by the PV system at time t, N is the total number of E2Ws been serviced during the scheduling horizon, P_i^t represents the charging power of $E2W_i$ at timeslot t, η_i is the charging efficiency of $E2W_i$, P_{cmax_i} is the maximum allowable charging power for the i^{th} charger, P_{bmax_i} is the maximum allowable charging power for the battery of the $E2W_i$, $P_{feedermax}$ represents the maximum allowable exchange power between the microgrid and the distribution grid, A_i is the battery capacity of $E2W_i$, $FSOC_{EVi}$ is the State of Charge (SoC) of $E2W_i$ at the departure time, $ISOC_{EVi}$ is the initial SoC of $E2W_i$, and μ_{ave}^S represents the average power of total load during the scheduling horizon which is expressed as in (5):

$$\mu_{ave}^S = \frac{1}{M}\sum_{t=1}^{M}\left(D_S^t + \sum_{i=1}^{N} P_i^t\right) = \frac{1}{M}\sum_{t=1}^{M} D_S^t + \sum_{i=1}^{N}\frac{A_i(FSOC_{EVi} - ISOC_{EVi})}{\eta_i.M.\Delta_T} \quad (5)$$

Constraint (2) shows that at any timeslot, total charging power of all E2Ws in the charging station cannot exceed the maximum allowable of all chargers and batteries. Besides, it also must not exceed the supply capacity of the grid as in constraint (3). Constraint (4) is the energy requirement constraint. This constraint assures that at the departure time, E2Ws reach their required SoC level. Considering the E2Ws individually, the following constraints should be met:

$$A_i\left(FSOC_{EV_i} - ISOC_{EV_i}\right) = \int_{t_0}^{t_m} \eta_i . P_i(t) \quad (6)$$

$$P_t^i \leq min\left\{P_{cmax_i}, P_{bmax_i}\right\} \quad (7)$$

$$A_i . ISOC_{EV_i} + \int_{t_0}^{t_m} \eta_i . P_i(t) \leq A_i \quad (8)$$

$$A_i . ISOC_{EV_i} + \int_{t_0}^{t_m} \eta_i . P_i(t) \geq A_i . \left(1 - DOD_{max}^{EV_i}\right) \quad (9)$$

where $DOD_{max}^{EV_i}$ is the maximum depth of discharge of an $E2W_i$. Constraint (6) is the required energy constraint. Charging power at timeslots must satisfy (7). Constraint (8) is the maximum battery capacity constraint while depth of discharge constraint is as in (9).

B. Real-Time Update and Algorithm Proposition

To address the issue of arrival/departure uncertainty, the charging station must update the available E2Ws, including the existing E2Ws and any new E2W arrival/departure. It is assumed that the charging station is able to recognize the nominal capacity of the onboard battery, the battery SoC [12], and the maximum permitted charging power via a Vehicle Information System (VIS) which is responsible for providing E2W information to the station controller [13]. After communicating with the VIS and E2W owners, scheduling data are updated depending on the new arrivals and departures. The proposed algorithm can be summarized in the following steps:

- Step 1: Considering the current timeslot, the charging station dynamically updates the E2Ws connected to the station, including newly arriving E2Ws and departing E2Ws. Current SoC measurement data must also be acquired.
- Step 2: Finding the charging pattern of E2Ws by solving the objective function.
- Step 3: Applying the charging pattern to the E2Ws at the current timeslot.

After the three steps, in the next timeslot, the process of updating, finding charging patterns, and applying charging patterns repeats until the end of the scheduling horizon.

III. CASE STUDY AND SIMULATION RESULTS

This study assumes that the forecast data of solar generation and conventional load are available and sufficiently accurate. The charging station is assumed to be in Vietnam, servicing up to 250 vehicles in each working shift. A working day consists of two shifts: the morning shift is from 7:30 to 15:00 and the afternoon shift is from 14:30 to 21:00. The E2W batteries have a capacity of 1,200 Wh. Maximum charging/discharging powers are 400/-400 W, respectively. Batteries are not allowed to discharge if the SoC is less than 20%. At the end of the working shift, the E2W batteries are full. For the purpose of investigating the performance of the proposed algorithm, this case study does not investigate the variation in the non-EV load profile as well as PV generation in different days or different seasons. Sets of these data are generated and used as the input data for the algorithm.

A. Data of Initial SoC

With 250 E2Ws per working shift, the data of the initial SoC of the E2Ws in this case study are generated based on the research results of [14]. The vehicles have the initial SoCs shown in Table I.

B. Arrival/Departure Behavior

Numerous studies have shown that the probability distribution of arrival and departure time could be statistically modeled with proper probability density functions like the normal distribution function [1, 15].

TABLE I. INITIAL SOC OF E2WS

Initial SoC	E2W Number	Initial SoC	E2W Number
90 – 100%	29	40 – 50%	28
80 – 90%	37	30 – 40%	21
70 – 80%	37	20 – 30%	15
60 – 70%	37	10 – 20%	8
50 – 60%	35	0 – 10%	3

Thus, in this study, patterns of arrival/departure which follow a normal distribution function, are generated. The probability distribution parameters are:

- Morning arrival time: mean: 7.25, deviation: 0.12.
- Morning departure time: mean: 14.75, deviation: 0.12.
- Afternoon arrival time: mean: 14.25, deviation: 0.12.
- Afternoon departure time: mean: 20.75, deviation: 0.12.

Arrival/departure patterns are used as input for algorithm verification.

C. PV Power Output

In this case study, a 225 kWp solar system is simulated based on weather data in Hanoi, Vietnam. The system consists of 542 PV panels. Each panel has a power rating of 415 Wp. The PV power outputs of a typical day in January (month with the lowest solar irradiance) and in June (the highest solar irradiance month) are simulated as in Figure 1.

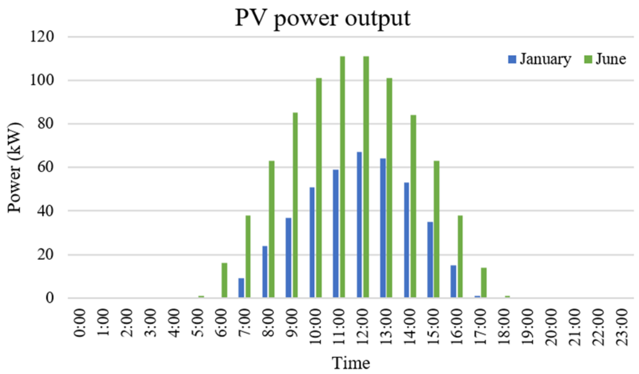

Fig. 1. PV power output in January and in June.

Because sufficiently accurate solar power data are assumed to be available, this study only utilizes simulation results of the PV system as input data for the proposed algorithm. Thus, the variation in solar power output in different days and different seasons is not considered in this work.

D. Non-EV Load

For the purpose of algorithm verification, conventional load data are retrieved from the dataset in [16]. The non-EV load profile is shown in Figure 2. It should be noted that for a two-shift commercial center, a relatively flat profile occurs during working hours. Conventional load reaches its valley in the early morning and rapidly increases when the morning shift starts. However, in the case of solar power participation, solar power can partially supply load, triggering a more fluctuating netload curve.

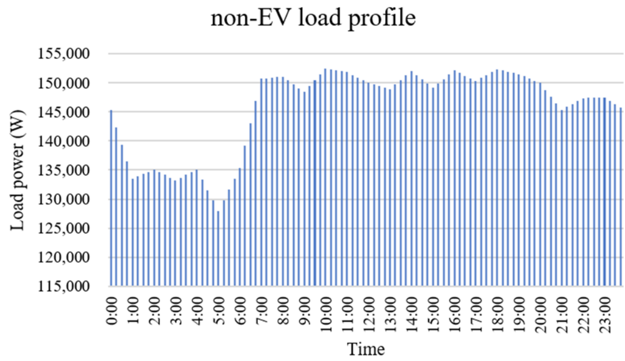

Fig. 2. Non-EV load profile.

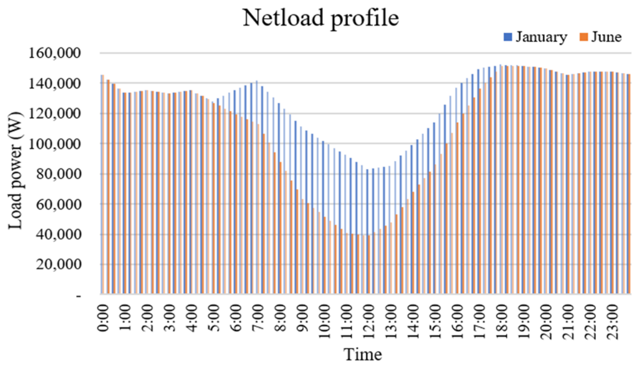

Fig. 3. Netload profile.

Figure 3 shows the netload profile in January and in June, respectively. In January, the minimum netload value is 82,967 W at 12:00 and the maximum is 1.84 times higher at 18:00. In June, due to the high PV power output, the netload profile is more fluctuating. The maximum netload value is 151,647 W (at 19:00) which is 3.89 times higher than the minimum netload of 38,967 W at noon.

E. Simulation Results

In this work, several operation scenarios are proposed and analyzed to investigate the algorithm's effectiveness. Because battery wear and tear cost may be a crucial barrier, this work does not consider the Vehicle-to-Grid (V2G) feature. Hence, the case study includes the following operation scenarios:

- Scenario 1: Charging load does not participate in the microgrid. This scenario is analyzed to evaluate netload variation in the case of solar power participation.
- Scenario 2: Average charging: The E2Ws are charged at constant rate to reach their required SoC at their departure time.
- Scenario 3: Uncontrolled charging: The E2Ws are charged at the maximum allowable power as soon as they are connected to the station.
- Scenario 4: Smart charging: The E2Ws follow the proposed algorithm.

Figure 4 depicts the total load profile of the four scenarios in a typical day in January.

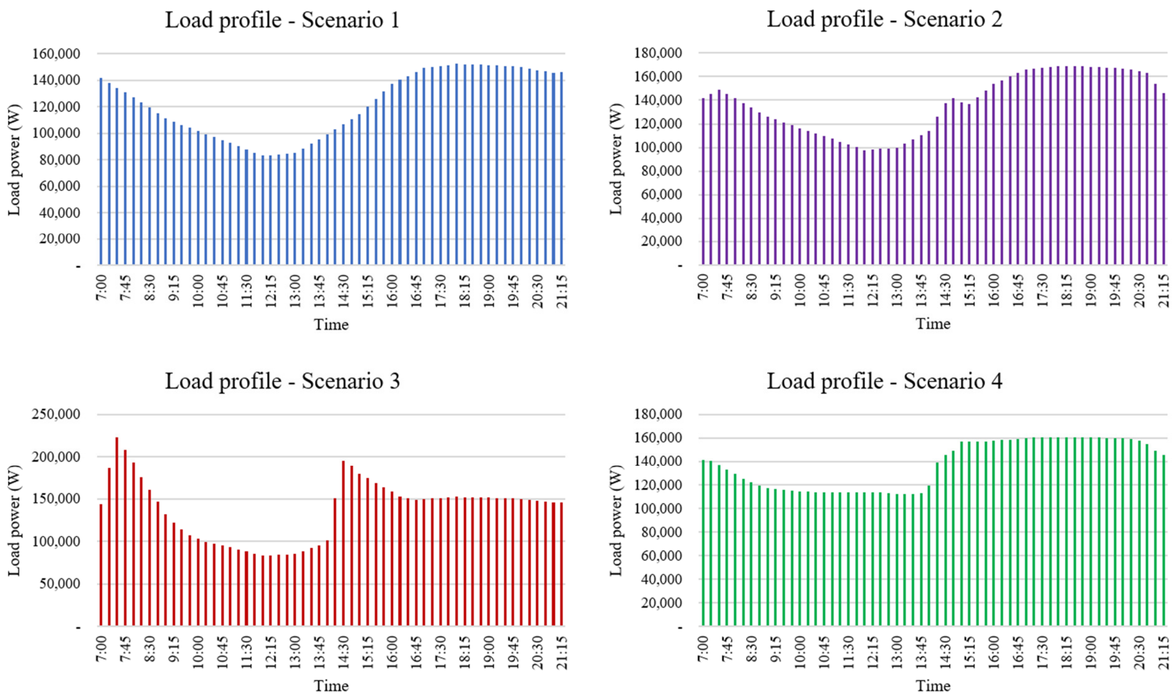

Fig. 4. Total load profile in the considered scenarios.

Considering time, when the E2Ws are available at the charging station, in January, the peak conventional load is 152,467 W at 10:00 AM. This value is 1.05 times higher than the lowest value of 145,333 W at 21:00. However, when solar power participates in the system, the peak netload of 152,300 W (at 18:00) is 1.84 times higher than the lowest netload of 82,967 W (at 12:00). Thus, solar power participation deteriorates the total load profile, triggering a more fluctuating curve. In scenario 2, because E2Ws are charged at constant rates, the total load profile remains almost the same as in scenario 1. However, in arrival/departure periods, because E2Ws connect/disconnect to the station at different time, total charing power will gradually increase/decrease (Figure 5). Thus, the shape of aggregated load would be different compared to scenario 1. In addition, 250 E2Ws servicing per shift results in around 14,690 W higher total power consumption than that of scenario 1.

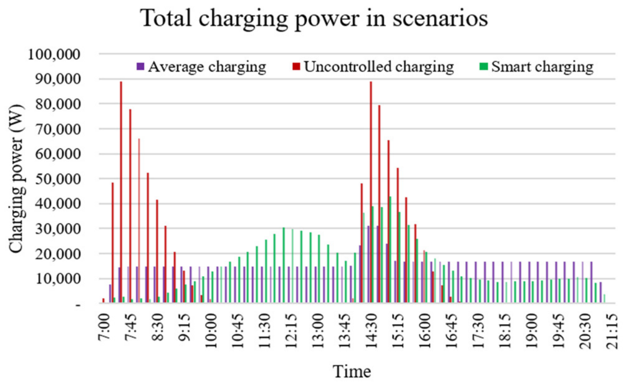

Fig. 5. Total charging power profiles.

Generally, the average charging scheme manages to evenly distribute the charging power during parking time (Figure 5). Thus, it does not significantly impact the total load profile. However, during the shift transition time (from 14:30 to 15:00), the average charging scenario produces a high total charging power (Figure 5), because the vehicles from the previous shift have not left the charging station yet, while the vehicles of the next shift have arrived, resulting in a large number of E2W charging simultaneously at the shift transition period.

Under scenario 3, because E2Ws are charged at their maximum permitted rate as soon as they are connected to the station, total load reaches very high peaks at arrival times. To be specific, the first peak of 223,308 W occurs at 7:30 and the second peak of 195,435 W is at 14:30. After reaching the peaks, total charging power declines swiftly because E2Ws stop charging when their energy requirements are met (Figure 5). Thus, after several timeslots, the total load gets back to the netload. Uncoordinated charging triggers the worst load profile. The peak load is 223,308 W, being 2.69 times higher than the base load of 82,967 W. The total load profile shows a dramatical improvement under the proposed smart charging strategy. E2Ws are charged at low load periods and avoid increasing peak load. Compared to the other scenarios, this scheme produces the flattest aggregated load profile. Valley filling effect is clearly demonstrated. Furthermore, because valley load time coincides with high PV generation time, the E2W charging power profile is quite consistent with the PV power output, implying that the smart charging scheme can utilize solar power for charging more effectively. Charging profiles and battery capacity profiles of several E2Ws in January and in June are illustrated as in Figures 6-11. These E2W are representatives of high, medium, and low initial SoC as show in Table II.

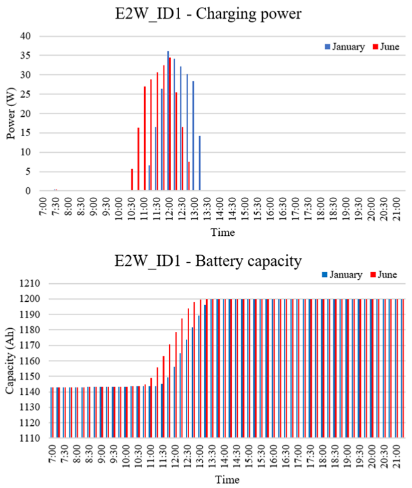

Fig. 6. Profiles of E2W1.

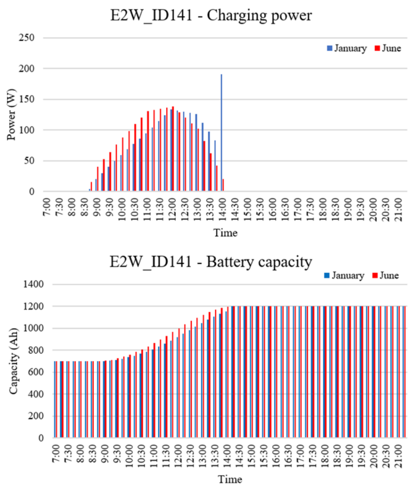

Fig. 7. Profile of E2W141.

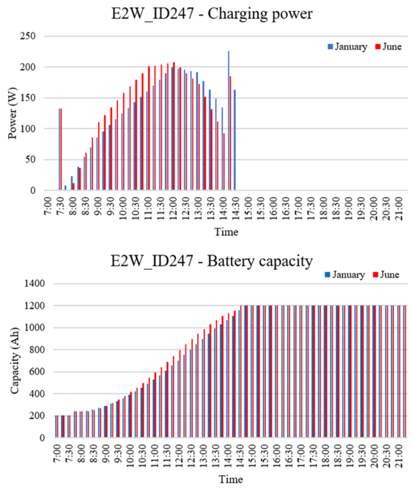

Fig. 8. Profile of E2W247.

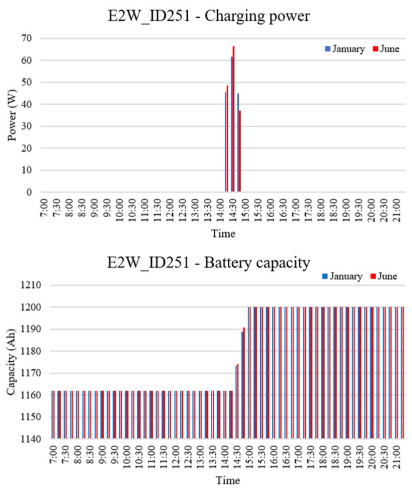

Fig. 9. Profiles of E2W251.

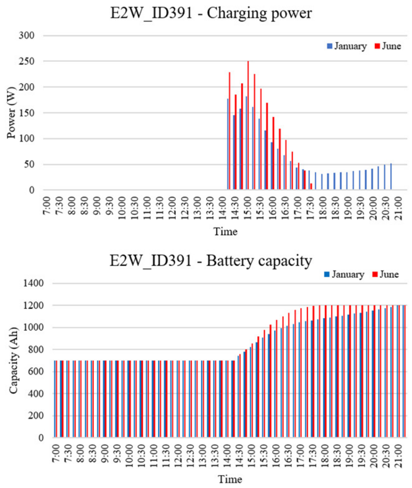

Fig. 10. Profiles of E2W391.

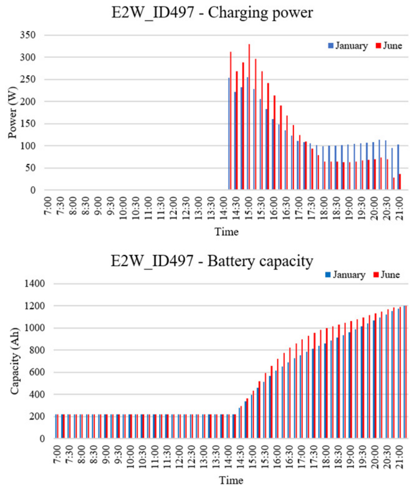

Fig. 11. Profiles of E2W497.

TABLE II. HIGH, MEDIUM, AND LOW SoC E2W REPRESENTATIVES

Shift	Initial SoC	E2W ID
Morning	90 – 100%	1
	50 – 60%	141
	10 – 20%	247
Afternoon	90 – 100%	251
	50 – 60%	391
	10 – 20%	497

Simulation results reveal that E2Ws of the morning shift tend to charge from 10:00 to 13:30 while E2Ws of the afternoon shift perform charging from 14:15 to 16:30. This time also corresponds to the periods of highest solar power. In June, the abundance of solar power results in a lower netload valley than in January. Thus, the valley filling algorithm will schedule vehicles to be charged at higher rates. As a consequence, charging processes in June end earlier than in months with lower solar generation.

Considering E2Ws with different initial SoCs, the lower ones (E2W_ID247; E2W_ID497) are charged at higher speed than the higher ones (E2W_ID141; E2W_ID1; E2W_ID391; E2W_ID251). Simulation results also show that all charging processes end before departure time and all E2Ws reach their energy requirements.

IV. CONCLUSION

The participation of solar power into energy systems may deteriorate the total load profile if PV power output is not consistent with conventional load profile. Smart charging scheduling may offer an effective solution for improving aggregated load profile. Thus, it can contribute to mitigating adverse impacts of high PV penetration rate and emerging charging load on the energy systems.

In the context of Vietnam, E2Ws emerge as a promising alternative for gasoline-powered motorcycles. In the case of numerous E2Ws implement charging simultaneously such as charging in parking of factories, office buildings, commercial centers, apartments etc., solutions addressing high aggregated charging load, effectively scheduling, load shifting, and valley filling would become imperative.

This study proposes a valley filling algorithm for PV-integrated E2W charging stations. When current timeslot changes, the station controller would update arrival/departure events, update new energy level of available vehicles then implement scheduling. The process of updating, finding charging patterns and applying charging patterns repeats until the end of the scheduling horizon.

Simulation results show that, compared to uncontrolled charging and average charging schemes, the proposed algorithm proves its effectiveness in valley filling. E2Ws are scheduled to be charged at valley load time, effectively leveraging the flexibility of charging load and at the same time, can indirectly lesser adverse impacts of PV sources and E2W on the distribution grid.

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