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THE JOINT SCHEDULING OF EV CHARGING LOAD WITH BUILDING MOUNTED WIND POWER USING SIMULATION-BASED POLICY IMPROVEMENT

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ABSTRACT

Nowadays, with the popularity of e-commerce or internet sales, freight transport logistics has gained a rapid development in city, especially small package delivery business. The electric vehicles (EVs) are considered as one of the most promising means to tackle the large portion of carbon emission from urban freight transport logistics. Nowadays, the huge number of high-rise buildings and technology advances have created conditions to mount on-site wind power generators on the buildings. Considering that modern buildings are usually equipped with large parking lots for EVs, we focus on the problem to schedule the charging load of EVs for package delivery with building mounted wind power in this paper, which shows vital practical significance to promote a future of sustainable transport. The total charging cost of EVs is selected as the objective function with the aim to best utilize building mounted wind power at multiple buildings to charge the EVs. Three major contributions are made in this paper. First, multiple parking locations and multiple parking events for the EVs are considered and we formulate the problem as a constrained MDP problem. Second, a Simulation-Based Policy Improvement (SBPI) method is proposed to solve the problem. Third, several numeric experiments are conducted to validate the performance of the SBPI method and we show that the total charging cost of EVs can be apparently reduced and more building mounted wind power can be utilized to charge the EVs using the SBPI method.

Keywords—Building-mounted wind power; electric vehicles (EVs), package delivery, sustainable trasport

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I. INTRODUCTION

Nowadays, e-commerce or internet sales has facilitated the rapid growth of freight transport logistics in cities, especially small package delivery business. Over the years, the industry of city logistics has greatly developed around countries. Take China as an example, there are over tens of delivery companies today compared with the only Express Mail Service (EMS) at the beginning of 2000. Currently, the vehicles for package delivery are mostly gasoline-powered, which account for about 20% CO_2 emissions in cities [1]. In recent years, electric vehicles (EVs) gain extensive attention for city goods transport with no emission [2]. Some package delivery companies even have begun to promote the adoption of EVs, such as FedEx, UPS and TNT [3]. In the past, the trucks or cars used for package delivery are usually below capacity or running almost empty on the road because of the just-in-time deliveries and asymmetrical patterns of trades. Nowadays, sustainable transport seeks to reduce empty traffic movement of city logistics in neighborhoods or congested urban centers. The neighborhood drop-off points or customizing loading areas of vehicles for package delivery begin to be introduced in cities [4]. In other words, an EV for package delivery is often parked in a public location or a building centralized in a neighborhood for several hours. The customers are allowed to pick up their packages at the arrangement location during the parking time or the couriers will delivery packages door to door in the neighborhood. After a period of time, the courier will drive to another location.

Nowadays, high-rise buildings become pervading in order to accommodate the world's increase of population, especially in big cities. It is reported that the total number of buildings higher than 200 meters has exceeded 1, 000 by the end of 2015, making a 392% increase from the year 2000 [5]. The huge number of high-rise buildings and technology advances have created conditions to mount on-site wind generators on the buildings [6], [7]. An investigation concludes that wind power utilization on high-rise buildings in Hong Kong is already feasible theoretically [8]. Considering that modern buildings are usually equipped with large parking lots for EVs, we focus on the problem to schedule the charging load of EVs for package delivery with on-site wind power generation at multiple buildings in this paper. The issue to use building mounted wind power to charge the EVs for package delivery parked in the buildings shows vital practical significance in the following aspects. First, the wind resources are closely related to the height. The height of high-rise buildings in modern cities creates conditions to harness the wind resource to generate electricity with a high efficiency, which is both economic and environmental. Second, the on-site wind power at the buildings can be directly utilized without a need to build a transmission system or be integrated in the power system. The variability of on-site wind power generation at the buildings can be alleviated by dispatching the EV charging load. Third, by using the on-site wind power at the buildings to charge the EVs for package delivery, the compact resulting from of EV charging load on the existed building energy system may be greatly decreased.

There exist a lot of research works related to the scheduling of EV charging load. In [9], an hourly coordination of aggregated plug-in electric vehicle (PEV) fleets with volatile wind power is studied. The random driving behaviors of PEV fleets are considered. The problem is to dispatch the generation units and charge/discharge of PEV fleets to minimize the grid operation cost. In [10] and [11], a stochastic matching problem between the charging load of EV aggregators and uncertain wind power is explored. The problem is to decide the amount of energy charged to each EV aggregators over the optimization horizons. In [12], the problem to schedule deferrable loads such as EVs and thermostatically controlled loads, with a mix of wind power and solar energy is studied. Different from the review works mentioned above, we focus on the joint scheduling of the charging load of EVs for package delivery with building-mounted wind power in urban area in this paper. Multiple parking events and multiple parking locations (buildings) for the EVs are considered. The problem is to decide the charging process of each EV instead of an EV aggregator during their parking time in different buildings. In our problem, we assume that the EVs may be owned by multiple delivery companies and have contracted with a charging service provider (e.g. a monthly flat fee is charged from each delivery company based). The problem is studied from the perspective of charging service provider, who aims to minimize the total charging cost for all the EVs in order to gain profits.

The challenges related to the problem lie in the following aspects. First, there exist multiple randomness. Both building mounted wind power at multiple buildings and the driving behavior of EVs for package delivery in the system are random. Hence, the problem is a stochastic optimization problem. Second, the problem is a multi-stage decision problem. The charging decisions for each EV are time-correlated. Third, there are multiple constraints. In order to guarantee the quality of delivery service, the travel demand of EVs should be satisfied. Moreover the charging behaviors of the EVs are constrained by their parking locations. In other words, the building mounted wind power just can be used to charge the EVs parked in the corresponding building. Forth, there are multiple curses of dimensionality. Both the system spaces and decision spaces increase exponentially with the problem size.

Three major contributions are made in this paper. First, multiple parking locations (buildings) and multiple parking events for the EVs are concerned in our problem and we formulate the problem as a constrained Markov decision process (MDP) problem. Second, a Simulation-Based Policy Improvement (SBPI) method is proposed to deal with the constrained MDP problem. Third, a series of numeric experiments with different populations of EVs are conducted to demonstrate the performance of the SBPI method.

The reminders of this paper are arranged as follows. In Section II, the problem to schedule the charging load of EVs for package delivery with building mounted wind power at multiple buildings is modeled as a constrained MDP problem. In Section III, a SBPI method is developed to solve the constrained MDP problem. In Section IV, a series of numeric experiments are conducted to demonstrate the performance of the SBPI method. In section V, we briefly conclude the paper.

II. PROBLEM FORMULATION

A. System Architecture

In this paper, we consider a EV population of N owned by multiple delivery companies. That means more than one EV may be parked in a building at the same time. The EVs are arranged for package delivery in a region of a city and may be parked in M designated high-rise buildings to delivery packages every day. There are wind turbines installed on each high-rise buildings in the system. The on-site wind power at the buildings can be directly utilized to charge the EVs parked in the corresponding building, when the building mounted wind power is not enough to supply the EV charging demand, power from the power grid can supplement but with charge. The system architecture is depicted as Fig. 1. In the system, the EVs are required to report their charging demands and parking time durations to the local coordinator when they arrive at a building. And the local coordinators are required to inform the central system operator of the EV charging demands as well as the on-site wind power generation at the buildings. The system operator is authorized to decide the charging decisions of the EVs in the system.

In this paper, the problem to schedule the EV charging load with building mounted wind power at multiple building is studied in a discretized framework on a daily basis. Each day is equally divided into *T=48* time slots, corresponding to a $\Delta t = 30$ minutes' interval. The problem is formulated as a constrained MDP problem and the details are present below.

B. Modeling

1) **System States:** we define he system state at time slot t as $S_t = \left[W_t^j, L_t^i, E_t^i, D_t^i\right], (i \in \{1,2,...,N\}, j \in \{1,2,...,M\})$,where W_t^j is on-site wind power at building j, E_t^i and L_t^i denote the remaining required charging energy and remaining parking time (or trip time) of EV i, D_t^i represents the location of EV i. We

define $D_t^i \in \{1,2,...,M,M+1\}$ and if $D_t^i = M+1$, EV i is on travel from one building to another and L_t^i represents the remaining trip time, otherwise EV i is parked in a building denoted by D_t^i and L_t^i denotes the remaining parking time.

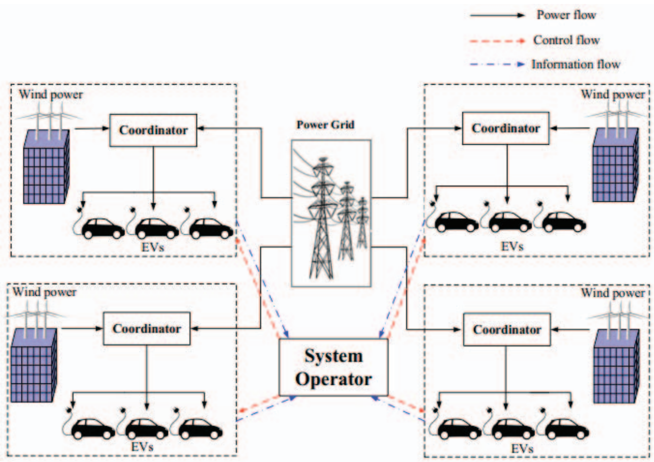

Fig 1. System architecture

2) **Action Space:** in order to simply the discussions, the charging power of the EVs is set constant in our problem. Hence, the charging decisions at time slot t can be denoted by a binary vector as $A_t = \left[z_t^1, z_t^2, ..., z_t^N\right]$, where $z_t^i \in \{0,1\}$. If $z_t^i = 1$, EV i is selected to be charged at times slot t, otherwise $z_t^i = 0$.

3) System Dynamics: with the system state S_t and the charging decision A_t at time slot t given, the dynamics of each state component can be depicted as follows.

The dynamics of the remaining parking time ($D_t^i \le M$) or remaining trip time ($D_t^i = M+1$) for EV i can be described as

$$L_{t+1}^i = \begin{cases} L_t^i - \Delta t & \text{if } L_t^i > 0 \\ \tau_{t+1}^i & \text{if } L_t^i = 0, D_t^i = M+1 \\ \eta_{t+1}^i & \text{if } L_t^i = 0, D_t^i \le M \end{cases} \tag{2.1}$$

where τ_{t+1}^i and η_{t+1}^i are random variables, τ_{t+1}^i denotes the parking time when EV i arrives at a building at time slot $t+1$. η_{t+1}^i represents trip time when EV i departures from a building at time slot $t+1$.

Similarly, the location transition of EV i at time slot t is as

$$D_{t+1}^i = \begin{cases} D_t^i & \text{if } L_t^i > 0 \\ R_{t+1}^i & \text{if } L_t^i = 0, D_t^i = M+1 \\ M+1 & \text{if } L_t^i = 0, D_t^i \le M \end{cases} \tag{2.2}$$

where $R_{t+1}^i \in \{1,2,...,M\}$ is a random variable and represents the building that EV i arrives at time slot $t+1$.

The dynamics of the remaining required charging energy of EV i can be depicted as

$$E_{t+1}^i = \begin{cases} E_t^i - z_t^i \cdot P \cdot \Delta t & \text{if } L_t^i > 0, D_t^i \le M \\ B_t^{i+1} & \text{if } L_t^i = 0, D_t^i = M+1 \\ 0 & \text{otherwise} \end{cases}$$

where B_t^{i+1} is the energy state of EV i when it arrives at a building at time slot $t+1$.

4) System Constraints: The action A_t at time slot t with respect to system state S_t is implicitly constrained as follows.

$$0 \le E_t^i \le E_{\text{cap}} \tag{2.3}$$

$$0 \le E_t^i \le L_t^i \cdot P \cdot \Delta t \tag{2.4}$$

where E_{cap} is the battery capacity of the EVs. In this paper, we assume the EVs are homogenous. In other words, the parameters for the EVs are the same. The constraint (2.3) imposes that the required charging energy for EV i can't exceed the battery capacity of the EV. The constraint (2.4) implies that the required charging energy of EV i can't exceed the maximum possible charging energy during the parking time. The constraint (2.4) is used to guarantee the travel demands of EVs

5) Objective Function: as mentioned previously, the problem to schedule the EV charging load with building mounted wind power is studied from the perspective of charging service provider, who aims to gain profits by offer charging service for the EVs owned by several delivery companies. Considering that the wind power is much more cost-efficient compared with thermal power generation, without loss of generality, building mounted wind power is assumed free in our problem. Therefore, the main charging cost of the EVs is to purchase electricity from the power grid when the building mounted wind power is not enough to supply the EV charging demand. In order to best utilize the on-site wind power, the total charging cost of the EVs is selected as the objective function. Hence, the one-step cost function and the objective function can be defined as follows.

The one-step cost function at time slot t is defined as

$$C_t(S_t, A_t) = \beta_t \cdot \sum_{j=1}^{M} \max\left(P_t^{(j,EV)} - W_t^j, 0\right) \cdot \Delta t \tag{2.5}$$

Where $P_t^{(j,EV)} = \sum_{i \in \{i|D_t^i = j\}} z_t^i \cdot P$ is the total charging power of the EVs in building j at time slot t. β_t is the electricity price of power grid at time slot t.

Since the problem is a stochastic optimization problem, the expected total charging cost of the EVs is selected as the objective function, which can be described as

$$J(\pi, S_1) = E_{S_1}^{\pi}\left[\sum_{t=1}^{T} \beta_t \cdot \sum_{j=1}^{M} \max\left(P_t^{(j,EV)} - W_t^j, 0\right) \cdot \Delta t\right] \tag{2.6}$$

where S_1 denotes the initial state of EVs in the system and $\pi = [d_1, d_2, ..., d_T]$ is the charging decisions for the EVs over the optimization horizons. .

As described above, the problem to schedule the EV charging load is formulated as a MDP problem with system states and decision variables of high-dimensional vectors. Therefore, both the state spaces and decision spaces increase exponentially with the problem size. It will be an intractable task if traditional dynamic programming methods, such as backward induction method [13], are employed. In order to tackle the situation, a SBPI method is proposed in the paper to approximate the solution of the stochastic optimization problem. The details with respect to the method is described in Section III.

C. on-site wind power

The amount of electricity generated by a wind turbine depends two factors including available wind resource (wind speed) and the power curves. A Weibull distribution is often used to describe the stochastic characteristic of wind speed [14]. Considering that the actual power curves of wind turbines are often unavailable, the following equations can be used to estimate the power output of wind power generators [15].

$$W_t = \begin{cases} W_{\text{cap}} & v_{\text{Rated}} \le v_t \le v_{\text{cutout}} \\ W_{\text{cap}} \left(\dfrac{v_t}{v_{\text{Rated}}} \right)^3 & v_{\text{cutin}} \le v_t \le v_{\text{Rated}} \\ 0 & otherwise \end{cases} \tag{2.7}$$

where v_t denotes the instantaneous wind speed at time slot t, v_{cutin} and v_{cutout} represent the cutin and cutout speed for building mounted wind turbines, v_{Rated} and W_{cap} are the rated wind speed and wind power capacity for the wind turbines.

III. SOLUTION METHODOLOGY

As mentioned above, it will be time-consuming or even an intractable task to solve the MDP problem proposed in Section II using traditional dynamic programming methods. In this section, a SBPI method is proposed to approximate the optimal charging policy for the EVs in the system. The SBPI method is a rollout algorithm and firstly designed to approximate the solutions of sequential decision problems [16]. This method is extended to solve MDP problems in [17] and [18]. The main idea of SBPI method is to improve from an existed basic policy (e.g. a heuristic policy) to obtain an improved policy. Before we describe the details of the method, we first assume there is an existed basic charging policy denoted by $\pi^b = \left[d_1^b, d_2^b, ..., d_T^b \right]$.

The main idea of the SBPI method is to improve decisions stage by stage. For instance, the charging decision A_t at time slot t can be evaluated using the Q-factor defined as

$$Q_t(S_t, A_t) = C_t(S_t, A_t) + E[V(S_{t+1}) \mid S_t, A_t] \tag{3.1}$$

where $V(S_{t+1})$ is the optimal value function from time $t+1$. Intuitively, the optimal value function $V(S_{t+1})$ depends on the optimal charging policy, i.e.

$$V(S_{t+1}) = E\left[\sum_{k=t+1}^{T} C_k\left(S_k, d_k^*(S_k)\right) \mid S_t \right] \tag{3.2}$$

where $\pi^* = \left[d_1^*, d_2^*, ..., d_T^* \right]$ is the optimal charging policy for EVs over the optimization horizons. For instance, d_k^* denotes the optimal charging decision for the EVs at time slot k.

Hence, the optimal charging decision for the EVs at time slot t can be chosen by comparing the Q-factors, i.e.

$$d_t^*(S_t) = \arg\min_{A_t \in \boldsymbol{A}_t} Q_t(S_t, A_t)$$

Where $\boldsymbol{A}_t$ represents the charging decision space at time slot t.

Considering that the optimal charging policy is unknown before the problem is totally solved, the basic idea of policy improvement method is to use a basic policy $\pi^b = \left[d_1^b, d_2^b, ..., d_T^b \right]$ to estimate the Q-factor, that is

$$\hat{Q}_t(S_t, A_t) = C_t(S_t, A_t) + E\left(\hat{V}(S_{t+1}) \mid S_t, A_t\right) \tag{3.3}$$

where we have $\hat{V}(S_{t+1}) = E\left[\sum_{j=t+1}^{T} C_j\left(S_j, d_j^b(S_j)\right) \mid S_t \right]$.

Based on the estimated Q-factor, an improved charging decision for the EVs at time slot t can be obtained as

$$\hat{d}_t(S_t) = \arg\min_{A_t \in \boldsymbol{A}_t} \hat{Q}_t(S_t, A_t) \tag{3.4}$$

The performance of the improved policy has been proved in [18], that is $J(\hat{\pi}, S_1) \le J(\pi^b, S_1), \forall \pi^b$ and S_1, provided that the Q-factors are estimated accurately enough. In this paper, the performance of the SBPI method applied to our problem is demonstrate through a series of numeric experiments. This will be present later.

Additionally, there exist multiple randomness in our problem making it computationally impossible to compute the expectations of the optimal value function, the common random number technique is used in this paper to approximate the expectations. The details about the common random number technique can be find in [17]. The main idea of common random number technique is to compare actions at each stage using a common set of sample paths. For instance, the estimated Q-factor can be approximated by

$$\hat{Q}_t(S_t, A_t) = C_t(S_t, A_t) + \frac{1}{N_s} \sum_{\omega=1}^{N_s} \sum_{k=t+1}^{T} \left[C_k\left(S_k, d_k^b(S_k)\right) \mid \varsigma_\omega \right] \tag{3.5}$$

Where N_s represents the total number of sample paths in a common set, ς_ω denotes the randomness of the sample path ω.

IV. NUMERIC RESULTS

In this section, a series of numeric experiments are conducted to validate the performance of SBPI method in solving the constrained MDP problem in this paper.

A. Parameters

In the numeric experiments, we consider there are $M=5$ high-rise buildings in the system. The number of EVs are set as N=8, 10, 12, 15 and 18, respectively. A Weibull distribution with shape and scale parameters of 1.309 and 7.0576, is used to describe the stochastic characteristics of wind speed [17]. The parameters for the EVs and building mounted wind power at each building are listed in TABLE I. Q represents the energy consumption rate for the EVs. A research [19] reveals that the energy consumption rates of EVs are related to the vehicle's velocity, acceleration and roadway grade. In order to simplify the discussions, in this paper, the energy consumption rates for the EVs are set constant as Q=5kW.

In the simulations, the distances between M=5 buildings are listed as TABLE II. For instance, it will take a delivery courier 1.5 hours to drive from building 2 to building 3. The probability for an EV departure from one building to travel to the other four obeys a uniform distribution, corresponding to the same probability of $p = 0.25$. Without loss of generality, we set the electricity price of power grid as $\beta_t = 1RMB / kWh$ over the optimization horizons. A common set of Ns=50 sample paths is used to estimate the Q-factors at each time slot. And Ma=50 sample paths are replicated to validate the performance in each numeric experiment.

TABLE I. Parameters for the EVs and wind power

EVs	Wind power
$E_{\text{cap}} = 40kWh$	$W_{\text{cap}} = 15kW$
P=4kW	$v_{\text{cutin}} = 3.5m/s$
Q=5kW	$v_{\text{cutout}} = 25m/s$
	$v_{\text{rated}} = 10m/s$

TABLE II. The distance between M=5 buildings (Unit: hour)

M	**1**	**2**	**3**	**4**	**5**
1	0	0.5	1	2	1.5
2	0.5	0	1.5	1.5	1
3	1	1.5	0	1	1.5
4	2	1.5	1	0	0.5
5	1.5	1	1.5	0.5	0

In the numeric experiments, a greedy policy π_1 is selected as the basic policy, in which the EVs begin to be charged when they arrive at a building until the charging demand is satisfied. The greedy policy π_1 can be described as follows.

$$\pi_b : z_t^i = \begin{cases} 1 & if\ D_t^i \le M, L_t^i > 0, E_t^i > 0 \\ 0 & otherwise \end{cases} \tag{4.1}$$

And we use $I_D(\pi_1)$ to denote the improved policy from π_1 using the SBPI method in the numeric results as follows.

B. Simulation Results

The results of the numeric experiments with N=8, 10, 12, 15 and 18 in the system are shown in TABLE III. We can conclude that both the average and deviation of the total EV charging cost are apparently reduced using $I_D(\pi_1)$ than that of π_1. Moreover, the proportion of the reduced average charging cost is around 40%. In other words, the proportion of the average total charging cost of the EVs doesn't increase with the total number of EVs in the system. The reason is that the optimal charging behaviors of the EVs are constrained by the parking locations in our problem. That means, the on-site wind power at the buildings just can be used to charge the EVs parked in the corresponding building.

Furthermore, the amount of on-site wind power at the buildings used to charge the EVs using π_1 and $I_D(\pi_1)$ is analyzed and shown in Fig. 2. From Fig. 2, we can conclude that more than 80% of the total charging power of the EVs comes from on-site wind power generation at the buildings in our numeric experiments. Therefore, it is promising to develop a sustainable transport for package delivery if the building mounted wind power is properly utilized. In addition, we can observe that the total charging power of the EVs are the same using π_1 and $I_D(\pi_1)$ in our simulations, but more on-site wind power at the buildings are used to charge the EVs using $I_D(\pi_1)$. And with the increase of the total number of EVs in the system, the proportion of wind power used to charge the EVs using π_1 decreases faster than that using $I_D(\pi_1)$. This demonstrates that the improved policy $I_D(\pi_1)$ shows better performance than the basic policy π_1 with the increase of the total number of EVs in the system. .

V. CONCLUSION

In this paper, we consider the problem to schedule the charging load of EVs for package delivery with building mounted wind power at multiple buildings to help develop a sustainable transport. Multiple parking locations and multiple parking events for the EVs are concerned in the stochastic optimization problem. The total charging cost of the EVs is selected as the objective function in order to best utilize the on-site wind power to charge the EVs. We formulate the problem as a constrained MDP problem and a Simulation-Based Policy improvement (SBPI) method is proposed to approximate a suboptimal charging policy for the EVs. A series of numeric experiments with varied number of EVs in the system are conducted to demonstrate the performance. Through the numeric experiments, we conclude that the average total charging cost of the EVs are apparently decreased using the improved policy than that of the basic policy using the SBPI method. Accordingly, more on-site wind power at the buildings are used to charge the EVs using the improved policy obtained from the SBPI method than that of the basic policy.

TABLE III. The performance of π_1 and $I_D(\pi_1)$

(Mean: the average EV charging cost, Std: the deviation of the EV charging cost)

No.	π_1 (RMB)		$I_D(\pi_1)$ (RMB)		Decreased
	Mean	**Std**	**Mean**	**Std**	
N=8	28.77	8.18	17.87	6.50	37.9%
N=10	44.27	10.99	26.45	8.63	40.25%
N=12	62.98	13.55	36.92	12.05	41.38%
N=15	100.46	15.35	60.17	13.32	40.11%
N=18	141.73	18.72	85.89	15.59	39.40%

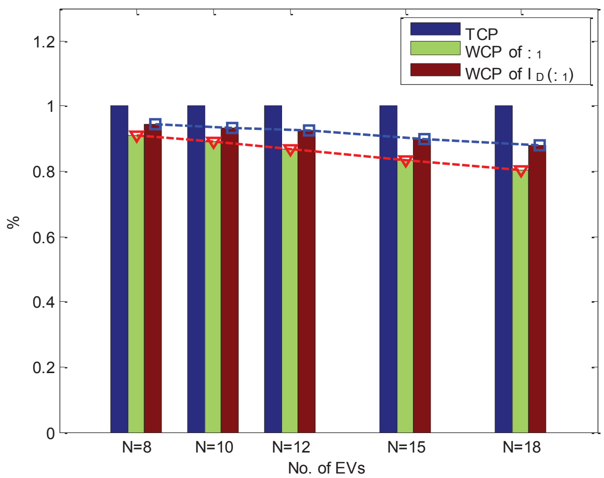

Fig. 1 Thea mount of wind power used to charge the EVs (TCP: total charging power using π_1 and $I_D(\pi_1)$, TCP: wind charging power

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