Decentralized Scheduling of PEV On-Street Parking and Charging for Smart Grid Reactive Power Compensation

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***Abstract*—Power quality is one of the major concerns in modern power systems, especially within smart grids where the power distribution is more dynamic and vulnerable. With drastically more plug-in electric vehicles (PEV) penetrating into the existing power distribution system, Vehicle-to-grid (V2G) technologies have attracted increasing research attention. This paper explores the potential of managing the charging pattern of PEVs for smart grid reactive power compensation. With PEVs' bidirectional AC chargers viewed as mobile reactive power resources, the scheduling of PEVs for parking and charging at distributed on-street stations is formulated into a multi-objective resource allocation problem. One objective is that stations should be allocated with adequate and timely resources (PEVs parked with an appropriate charging pattern) to compensate the time-varying reactive power of the grid. The other objective is that PEV owners should be provided with satisfying parking services with as low monetary cost as possible. We solve this multi-objective optimization problem by using the Normalized Normal Constraint (NNC) method to obtain a set of well-distributed Pareto optimal solutions. A decentralized algorithm based on Lagrangian decomposition is then used to make the optimization scalable as the number of PEVs increases. Simulation results demonstrate the satisfying quality of the obtained Pareto optimal solutions, among which one will be selected by the optimization system according to the grid requirement on the power quality.**

***Index Terms*—V2G, reactive power compensation, multi-objective optimization, Lagrangian decomposition.**

I. Introduction

With renewable energy generation surging in smart grids [1], traditional gasoline-fueled vehicles are evolving to electric vehicles (EV) or hybrid electric vehicles for both emission regulation and energy cost reduction [2], [3]. On the one hand, the renovated infrastructure of smart grids greatly facilitates the development of EVs. On the other hand, EVs also have great potential to supporting the grid with bidirectional chargers, i.e., vehicle-to-grid (V2G) technologies [4], [5]. EVs can be plugged into the grid for load shaving in peek hours, or discharging for outage recovery under emergent situations [6], [7]. However, frequent energy exchange in EV's battery will deteriorate its lifetime, which limits the application of V2G real power support.

A new perspective of V2G support leverages the bidirectional AC chargers of EVs for reactive power compensation to the grid. Reactive power compensation is important for power loss reduction, voltage regulation, and power factor correction [8], [9]. Conventional ways to get reactive power compensation are from Distributed Generation (DG) [8] and static volt-ampere reactive (VAR) compensator [10]. However, these reactive power resources are fixed in locations and have limited capacity. With the rapid development of plug-in electric vehicles (PEVs), their on-board bidirectional AC chargers can be plugged into power outlets provided by charging stations [11]. Recent research results show that while providing reactive power compensation to the grid, these on-board chargers do not affect the battery's lifetime [12], [13]. In North American, the AC charging power is usually in the range of 1.44kW to 7.68kW [14]. With their relatively smaller impact on the grid and lower cost of power outlets compared with DC charging devices, AC charging stations can be distributed more densely in the power distribution system.

To fully utilize the readily available and widely distributed AC charging stations and PEVs, this paper proposes a V2G reactive power compensation scheme based on PEV on-street parking and charging. On-street stations are constructed along roads and connected to load buses along feeders. Cars can therefore be charged while being parked on streets. PEV chargers are also treated as mobile reactive power resources, which provide flexible and efficient reactive power compensation on distributed load buses when PEVs are plugged in. Scheduling PEV on-street parking and charging properly can benefit both the grid and PEV owners. Charging stations (the grid) should be allocated with adequate reactive power resource reservoir (PEV plugged in with certain charging patterns). On the other hand, PEV owners would like to choose their convenient charging stations and parking time with minimum monetary cost. Often these two objectives are in conflict. We formulate the on-street parking and charging scheduling as a multi-objective optimization problem and apply the Normalized Normal Constraint (NNC) method. To make the optimization scalable as the number of PEVs increases, a decentralized algorithm based on Lagrangian decomposition is proposed to obtain Pareto optimal solutions.

The rest of this paper is organized as follows. Section II describes the system scheme. Section III and IV present the optimization formation and problem solving algorithms, respectively. The simulation setup and results are given in Section V. Section VI summarizes the paper.

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II. System Description

The V2G system designed in this paper consists of two aspects– system view and PEV charging/parking scheduling mechanism. The system, including both electrical and geographical information, is shown in Fig. 1. The electrical layer describes electrical grid facilities, including feeders, renewable DGs, and charging stations. Charging stations are connected to different buses along feeders. PEV plugged in charging stations are controlled for V2G reactive power compensation to meet the requirements calculated from state measurement or estimation of pilot buses. Pilot buses are some specific buses whose states, such as voltage, should be maintained by compensation. The geographical layer shows the location of on-street charging stations and PEV owners' destination points, which are information useful for PEV owners. Charging stations along one road and on the same bus form a cluster. One cluster is modeled as a charging station with its capacity defined as the number of parking/charging spaces. A PEV owner drives his or her car to a charging station from a starting point, parks / charges the car and then walks to the destination.

PEVs' parking and charging are scheduled according to the V2G system information and users' requirements. With limited on-street charging stations, PEV owners need to make day-ahead charging reservations to reduce conflicts. Sometimes people prefer free driving styles without constraints of reservations. But for those who do not make reservations, their random accesses to parking and charging cannot be well guaranteed and can only be handled on the best-effort basis, since the scheduling system does not know their intentions. Each PEV owner i submits the reservation request to the scheduling coordinator on time, indicating the preferred charging station m_i^*, required charging energy $E_{ch,i}^*$, preferred parking interval with arriving time $t_{s,i}^*$ and leaving time $t_{e,i}^*$, and maximum acceptable walking distance $d_{max,i}$. In addition to satisfy PEV owners' service request, including battery charging requirement, parking convenience, and low monetary charging cost, the power grid should also achieve the optimal reactive power compensation. Parking convenience is affected by the parking interval and walking distance. Each PEV owner has a preferred parking interval, which can be adjusted within a range with the service quality degraded. PEV owners also would not like to park their cars at stations far away from their destinations. Monetary cost consists of charging and parking costs. Charging and parking prices are time-varying and different for stations. After scheduling, a PEV with successful reservation is assigned to one of charging stations with scheduled parking interval and charging power at different time according to the design objectives.

This paper uses the model of PEV charger given in [12], [13]. P_{ch} and Q_{cp} indicate real and reactive power exchange between the charger and grid, respectively. This paper only considers the modes without battery discharging, i.e, $P_{ch} \geq 0$. The designed algorithms can be easily applied to situations with battery discharging by adjusting the designed cost functions and constraints, because the nonlinearity and decomposability of the scheduling problem do not change. When $Q_{cp} > 0$ ($Q_{cp} < 0$), the charger operates in inductive (capacitive) mode and consumes (injects) reactive power from (to) the grid. The maximum apparent power S_{max} that can be sustained by the charger depends on the grid voltage V_s and the charger's maximum allowable current I_{max} as $S_{max} = V_s I_{max}$. S_{max} sets constraints on P_{ch} and Q_{cp} by subjecting to $P_{ch}^2 + Q_{cp}^2 \leq S_{max}^2$ in operation. Therefore, the reactive compensation capability of one charging station is determined not only by the total number of connected chargers, but also the PEV charging patterns (P_{ch} and Q_{cp}).

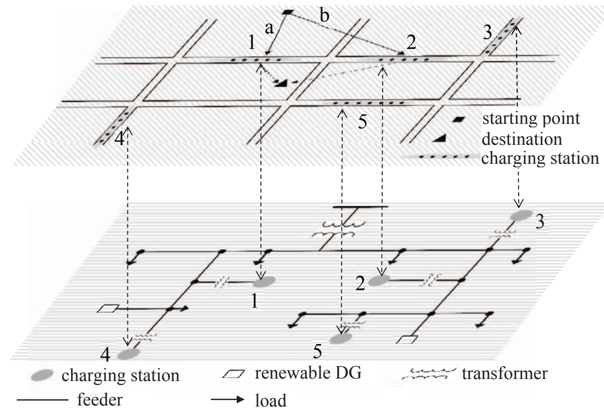


Fig. 1. Electrical and geographical information layers of V2G reactive power compensation system

III. Multi-objective Optimization Formulation

The parking and charging scheduling problem is formulated into a multi-objective optimization problem with benefits of both PEV owners and the utility grid included. For each PEV owner i, the parking cost $C_{pk,i}$ and charging cost $C_{ch,i}$ are:

$$C_{pk,i} = \sum_j x_{i,j} \sum_t u_i(t) R_{pk,j}(t) T \quad (1)$$

$$C_{ch,i} = \sum_j x_{i,j} \sum_t R_{ch,j}(t) P_{ch,i}(t) T \quad (2)$$

where $x_{i,j}$ indicates the assignment status. $x_{i,j} = 1$ means PEV i is assigned to station j. Otherwise, $x_{i,j} = 0$. $u_i(t) = 1$ if t is within the parking interval $[t_{s,i}, t_{e,i}]$. $P_{ch,i}(t)$ is the average battery charging power at time t. $R_{pk,j}(t)$ and $R_{ch,j}(t)$ are the parking and charging price of charging station j at time t, respectively. T is the length of time slot.

A satisfaction rate S_i is designed to present the parking convenience of PEV owner i. S_i consists of satisfaction in terms of walking distance and parking interval. Both long walking distance and parking interval adjustment will decrease S_i. S_i is normalized in the range $[S_{min}, 1]$ where S_{min} is the minimum acceptable satisfaction rate. PEVs are not scheduled to stations which provide parking services below S_{min}. The PEV owner's monetary cost per satisfaction is considered in optimization. For each unscheduled PEV i, a constant drop penalty PT_i is introduced, which is larger than then highest cost with feasible scheduling.

Thus, the cost function of PEV owners is the sum of all PEV owners' costs plus the drop penalty, which is to be minimized:

$$\min \quad C_{pev} = \sum_i \left[\frac{C_{ch,i} + C_{pk,i}}{S_i} + (1 - \sum_j x_{i,j}) PT_i \right] \tag{3}$$

The cost function of the utility grid is the total insufficiency of reactive power resource reservoir, which is also to be minimized:

$$\min \quad C_{utl} = \sum_j \sum_t \max \{Q_{gap,j}(t), 0\} \tag{4}$$

where:

$$Q_{gap,j}(t) = |Q_{req,j}(t)| - \sum_i x_{i,j} u_i(t) \sqrt{S_{max}^2 - P_{ch,i}^2(t)} \tag{5}$$

$Q_{gap,j}(t)$ is the gap between the reactive power requirement $Q_{req,j}(t)$ and reactive power resources reservoir for the bus connected to station j at time t. $Q_{req,j}(t)$ is calculated according to the state prediction, i.e., load, voltage, and power loss, of selected pilot buses. $Q_{req,j}(t)$ can be either consumption (positive and inductive) or injection (negative and capacitive). Because the maximum adjustable PEV charging power is only determined by the magnitude of $Q_{req,j}(t)$, for easy analysis, the magnitude $|Q_{req,j}(t)|$ is used. S_{max} is the maximum apparent power that can be sustained by the charger and assumed to be the same for all PEV chargers. Because (4) is a strong nonlinear cost function, it is reformulated into (6) with new variables $Q_{ub,j}(t)$ introduced as $Q_{gap,j}(t) \leq Q_{ub,j}(t)$ $\forall j, t$ for the decentralized algorithm.

$$\min \quad C_{utl} = \sum_j \sum_t Q_{ub,j}(t) \tag{6}$$

Thus, the multi-objective optimization problem is formulated into (7) with control variables $x_{i,j}$, $t_{s,i}$, $t_{e,i}$, $P_{ch,i}(t)$, and $Q_{ub,j}(t)$ $\forall i, j$.

$$\min \quad \{C_{pev}, C_{utl}\} \tag{7}$$

subject to the following constraints:

- Assignment: One PEV cannot be assigned to more than one charging station. At any time, the number of PEVs assigned to the charging station cannot exceed its capacity.
- Service: The total energy charged to each PEV's battery should satisfy the request. Each PEV owner also has a minimum acceptable satisfaction rate and maximum acceptable unit cost.
- Charging and compensation: PEV charging and reactive compensation is constrained by charger's maximum apparent power S_{max}. When a PEV is not assigned, its charging power has to be 0.
- Control variables: $x_{i,j}$ is a binary control variable. $t_{s,i}$ and $t_{e,i}$ are integral control variables with their own lower bound $t_{smin,i}$, $t_{emin,i}$ and upper bound $t_{smax,i}$, $t_{emax,i}$ as the acceptable entering and leaving time. $t_{s,i}$ should be always earlier than $t_{e,i}$. $Q_{ub,j}(t)$ should be a non-negative value and satisfies $Q_{gap,j}(t) \leq Q_{ub,j}(t)$.

IV. Problem-solving Approach

For multi-objective optimization problem, Pareto optimal solutions (Pareto points) are the solutions that do not dominate each other, i.e., keeping the trade-off between multiple objectives. Pareto points of (7) are obtained by using the NNC method proposed in [15]. For solving each Pareto point, the problem is an NP-hard Mixed Integer Nonlinear Programming (MINLP). In the case with a large number of PEVs, it is computationally difficult to obtain the global optimal solution. Because of the high non-convexity of this problem, greedy, local search, and evolutionary algorithms may obtain local optimal solution with poor quality far away from the global optimal solution. An effective method is to use the decentralized algorithm based on Lagrangian decomposition, which is scalable as the number of PEVs increases. The primal problem is decomposed into subproblems and solved by distributed agents simultaneously. The solution quality is improved during iterations and can be evaluated from the duality gap between the tight lower bound and upper bound.

A. Normalized Normal Constraint Method

NNC first obtains two anchor points and gets the Utopia line connecting these two points. The objective costs are then normalized and M points evenly distributed on the Utopia line are selected. At each point on the Utopia line, the related Pareto point is solved by minimizing one of the two objective costs with the additional normal line constraint. Because the feasible region of (C_{pev}, C_{utl}) is non-convex, the Pareto filter proposed in [15] is used to eliminate the local Pareto optimal points among all obtained M points.

B. Decentralized Algorithm Based on Lagrangian Relaxation

1) Framework of decentralized algorithm: The framework of decentralized algorithm for solving anchor points and Pareto points of (7) is shown in Fig. 2. The primal problems consist of P1, P2, and PP$_m$ $(m = 0, ..., M-1)$ for finding two anchor points and M Pareto points. In order to make cost function block-separable for decomposition, several constraints should be relaxed. For P1, P2, and PP$_m$, their related assignment constraints should be relaxed. Besides, the normal line constraint introduced by NNC method should also be relaxed for PP$_m$. After relaxation of the normal line constrain, the cost function of its Lagrangian relaxation problem LRPP$_m$ includes components of both C_{pev} and C_{utl}. Since C_{pev} is only block-separable in terms of i, C_{utl} needs to be reformulated to become block-separable in terms of i by introducing slack variables.

After relaxation, the primal problems are decomposed into Lagrangian subproblems as LSP1$_i$, LSP2$_j$, and LSPP$_{m,i}$ for

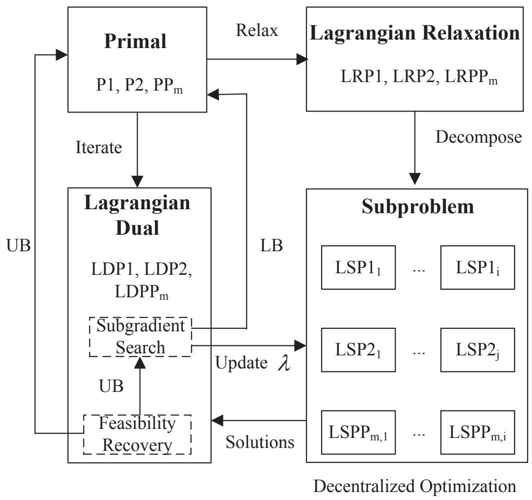


Fig. 2. Framework of the decentralized optimization with Lagrangian relaxation

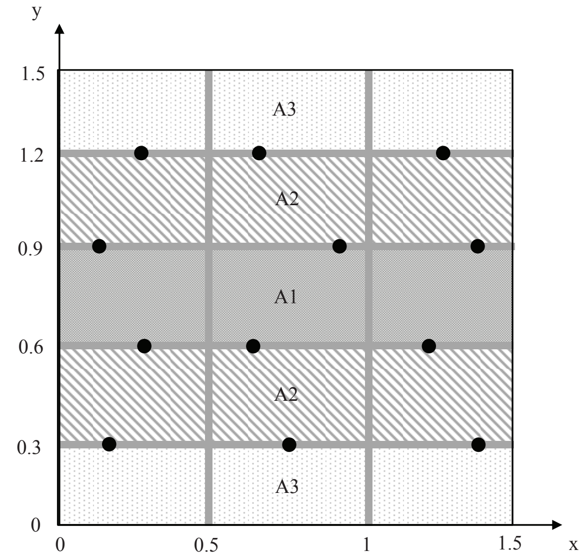


Fig. 3. Road network and charging station distribution for simulation

independent solving. The system coordinator then collects solutions of subproblems and finds lower bounds (LB) of the primal problems. It then solves the Lagrangian dual problems LDP1, LDP2, and LDPP$_m$ in order to maximize LB. With constraints relaxation, solutions from subproblems may not be feasible for the primal problem. Thus, feasibility restoration heuristics are designed to recover these solutions and also obtain upper bounds (UB). During iterations, the algorithm tries to reduce the gap between LB and UB until the termination condition is satisfied.

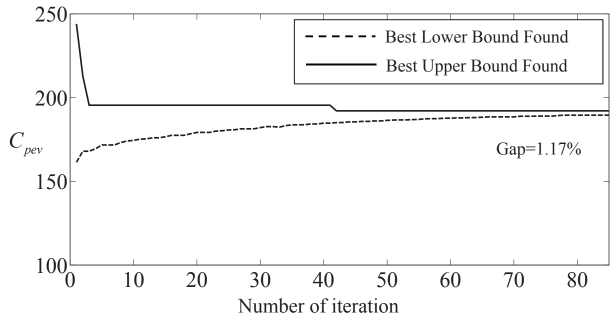
2) Subgradient search: An efficient method to solve Lagrangian dual problems is subgradient search. In order to improve the search and convergence speed, the subgradient search with deflection and average direction strategy [16] is used in this paper. In rth iteration, α_r is a scalar satisfying $\alpha_r > 0$ and with initial value 2. If none of the best found LB and UB has improvements larger than a set threshold for a number of iterations, α_{r+1} decreases as $\alpha_{r+1} = \alpha_r/2$. The algorithm terminates when α_r becomes a very small value.

3) Feasibility restoration: The feasibility of each PEV's scheduling is checked in a defined sequence. For the PEV with infeasible scheduling, it is added to the set I_R for later rescheduling. The rescheduling tries to improve the quality of restored feasible solutions by gradually adjusting their parking intervals. If one PEV cannot be rescheduled, it is then discarded without scheduling.

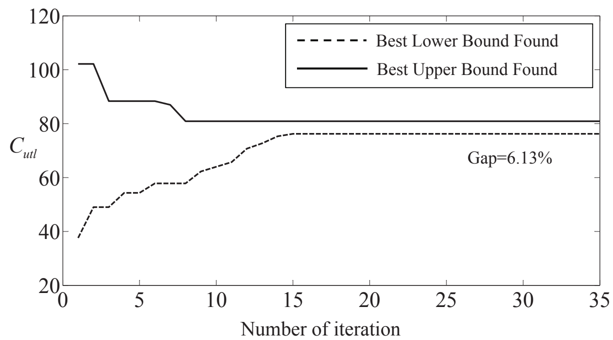
V. Results and Analysis

The designed algorithms and simulation platform are implemented with Java. Each subproblem is solved by TOMLAB optimization toolbox in MATLAB [17], which supports global MINLP. The simulation time is set from 8AM to 19PM with one hour time resolution and runs on a computer with Intel i7-2600 CPU and 8GB RAM. A $1.5km \times 1.5km$ square area is constructed for simulation with 4 horizontal roads and 2 vertical roads (gray lines) as shown in Fig. 3. 12 on-street charging stations are distributed on roads, shown as black dots. 30 PEV owners will reserve for parking and charging in this area. The location of each charging station is generated randomly. The capacity of one charging station is chosen according to the charging demand, bus power constraint, and infrastructure cost. Two reasonable configurations with capacity of 3 and 4 are evaluated in the simulation. Different charging stations are set with different time-varying charging prices within [0.1,0.5] USD/kWh. In reality, there are usually some hot areas, such as large shopping malls and office buildings, where many PEV owners' destination points locate. The whole area is divided into three parts: A1, A2, and A3 with decreasing number of PEV owners' destination points and also decreasing parking prices. In each sub-area, destination points of PEVs are generated randomly but with the guarantee that one PEV has at least one acceptable charging station. The battery charging demand of each PEV is set randomly within the capacity of 10kWh. S_{max} for each charger is set to 3 kVA. Two cases with different parking patterns are considered in the simulation. In the first case, 80% PEVs have similar commute pattern, i.e., arriving in the morning and leaving in the evening, and the remaining 20% have random patterns. This is usually true for areas like office and school areas. In the second case, the percentage of random pattern increases to 80%, which reflects the parking pattern in commercial areas. For each pattern, PEV owners' parking preferences are generated randomly.

The configuration with charging station capacity of 3 is first studied. Two anchor points are found for each case. The result for each iteration in case 1 is shown in Fig. 4. The iteration for two anchor points terminate at 85 and 35 steps, respectively. Currently we use a TOMLAB demo license, which only supports single-thread computation and solves subproblems in sequence. In this way, the 85 iteration steps take about 5 hours in total. However, when full version license is used,

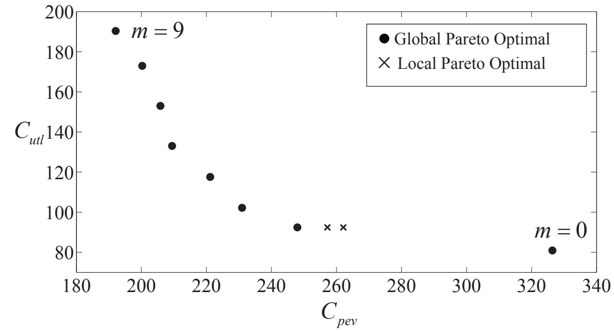


(a) Lower bound and upper bound of C_{pev} during iterations

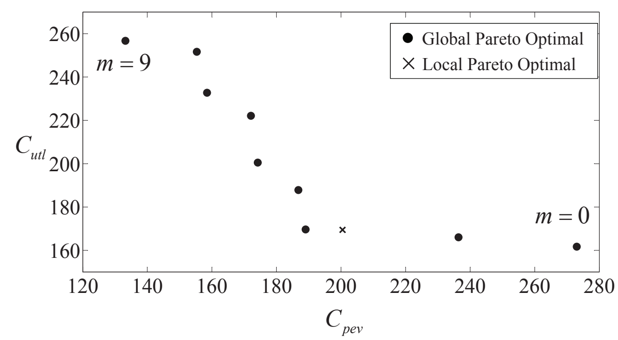


(b) Lower bound and upper bound of C_{utl} during iterations

Fig. 4. Results of solving anchor points in case 1



(a) Result of case 1



(b) Result of case 2

Fig. 5. Pareto optimal points obtained for the PEV scheduling problem in two cases

subproblems can be solved in parallel on different agents and iterations will run dramatically faster, i.e., an expected 30 times speedup in current configuration. Along iterations, both the best LB and best UB converge to steady values. The duality gap is defined as $(UB-LB)/LB \times 100\%$. For a non-convex MINLP, the duality gap is usually larger than zero. With these two anchor points and NNC method, 10 Pareto points ($M = 10$) are solved and shown in Fig. 5. C_{utl} is selected to minimize in NNC method and the duality gap for each point is shown in Table I. The points with index $m = 0$ and $m = 9$ are the two anchor points. Results show that the duality gaps of Pareto points are generally larger than those of the two anchor points because LRPP$_m$ includes the more complex normal line constraint. These gaps are all below 15%, indicating satisfying results for the complex MINLP problem. The Pareto frontier given in Fig. 5 shows that benefits of PEV owners and the utility grid are generally in conflict. Utility grid gets more benefits as m decreases.

We further analyze how different Pareto points, charging station capacities, and charging prices will affect benefits of PEV owners in detail. Three Pareto points ($m = 0, 5, 9$) with capacity 3 in case 1 are first examined. The parking interval deviation rate $\alpha_{pk,i} = (|t_{s,i} - t^*_{s,i}| + |t_{e,i} - t^*_{e,i}|)/(t_{emax,i} - t_{emin,i} + t_{smax,i} - t_{smin,i})$ is defined to describe the difference between the real scheduled parking interval $[t_{s,i}, t_{e,i}]$ and preferred parking interval $[t^*_{s,i}, t^*_{e,i}]$ for PEV owner i. Similarly, the walking distance deviation rate $\alpha_{wk,i} = (d_i - d_{min,i})/(d_{max,i} - d_{min,i})$ is used to describe the difference between actual walking distance and the ideal shortest walking distance. PEV owners are more satisfied if $\alpha_{pk,i}$ and $\alpha_{wk,i}$ are lower. Results are shown in Fig. 6 and Fig. 7. Overall, $\alpha_{pk,i}$, $\alpha_{wk,i}$, and the monetary cost decrease with the increase of m. The decrease of $\alpha_{wk,i}$ and monetary cost is more noticeable than $\alpha_{pk,i}$. This is because a relevant more fixed commute patten is assumed in case 1 and the parking interval coordination is more difficult. The zero cost for some PEVs means they are not scheduled due to the limited number of stations. Let $\overline{\alpha}_{pk}$ and $\overline{\alpha}_{wk}$ be the average value of all $\alpha_{pk,i}$ and the average value of all $\alpha_{wk,i}$, respectively. For $m = 5$, as all capacities increase to 4, all PEVs are successfully scheduled. $\overline{\alpha}_{pk}$ and $\overline{\alpha}_{wk}$ also decrease by 18.23% and 37.86%, respectively. When the time-varying price is changed to a flat one of 0.3 USD/kWh for $m = 5$ and capacity of 3, $\overline{\alpha}_{wk}$ does not change and $\overline{\alpha}_{pk}$ has a 16.68% reduction. Results show that by increasing stations' capacities or applying a flat charging rate, conflicts among users are reduced and their satisfactions are improved through scheduling. Among the obtained Pareto points, one can be selected by the system coordinator for the maximal PEV owners' benefits which meets the minimum requirement of reactive power compensation to the grid.

VI. Conclusion

This paper proposes a decentralized PEV on-street parking and charging scheduling method for V2G reactive power compensation. With on-board bidirectional AC chargers, PEVs are utilized as mobile and dispersed reactive power resources. The scheduling problem is formulated into a multi-objective

TABLE I
DUALITY GAP OF PARETO POINTS

	m									
	0	1	2	3	4	5	6	7	8	9
case 1	6.13%	11.51%	10.35%	10.27%	14.21%	11.73%	6.43%	4.95%	4.39%	1.17%
case 2	1.94%	2.62%	3.47%	4.89%	10.58%	9.80%	11.91%	7.80%	6.60%	0.12%

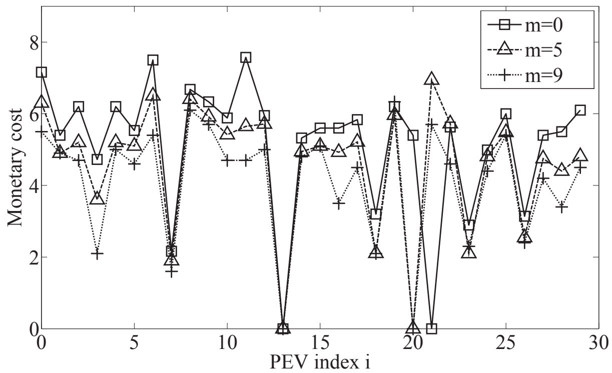
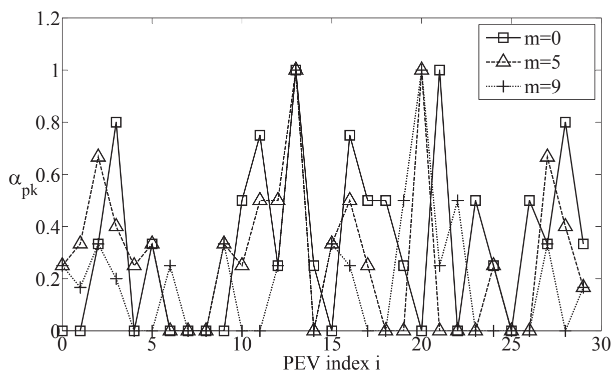
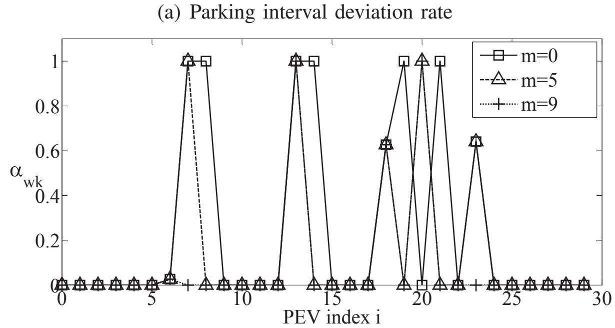


Fig. 6. PEV owners' monetary costs at different Pareto points



(a) Parking interval deviation rate



(b) Walking distance deviation rate

Fig. 7. PEV owners' parking convenience at different Pareto points

optimization problem considering benefits of both PEV owners and the utility grid. With Lagrangian decomposition and NNC method, Pareto optimal solutions are obtained in a decentralized way and the problem is also scalable in terms of the number of PEVs and charging stations. Simulation results from two test cases with different parking requirement patterns show the satisfying quality of obtained Pareto points and verify the validity of designed algorithms. The trade-off between the benefits of PEVs and grid is further analyzed.

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