A Contract-Based Computing-Charging Protocol for Electric Vehicles with Vehicular Fog Computing

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***Abstract*—Electric vehicles (EVs) are enjoying growing popularity from governments to customers. However, the development of EVs inevitably poses heavy charging and data processing burden on current smart grid. Considering the mutual demand and supply relationship between EVs and smart grid in both charging and computing tasks, we integrate vehicular fog computing and EV charging for joint optimization and propose an integrated charging-computing (IC^2) architecture for EV-included smart grid. In the proposed IC^2 architecture, EVs act as both energy consumers and computation providers. We employ contract theory to provide a multi-attribute contract-based charging protocol for EVs and charging stations in an information asymmetry scenario. To obtain the optimal contract, we derive KKT conditions and design a CCP-based contract optimization algorithm. Numerical results indicate that the proposed scheme can effectively benefit both the charging stations and EVs meanwhile improving the task computation capability in the smart grid.**

***Index Terms*—Contract theory, electric vehicle, EV charging, smart grid, vehicular fog computing.**

I. Introduction

On the pursuit of green and smart city, electric vehicles (EVs) are attracting more and more popularity from governments, industries, and customers [1]. With no regard of fossil fuel consumption and gas emission, EVs are viewed as a promising solution to face the environmental issues and are becoming one of the most appealing paradigms to realize green transportation [2]. However, the increasing adoption of EVs also poses challenging power and data processing issues (i.e., charging information collection and energy management decision) on smart grid. In order to balance the supply and demand between EVs and smart grid as well as provide reliable charging options, many works have been devoted to charging control of EVs in smart grid. Z. Wei *et al.* in [3] studied the EV charging scheduling problem of park-and-change system with the objective to minimize the battery degradation and designed a vacant charging algorithm and a dynamic power adjustment algorithm to minimize the degradation cost. In order to encourage charging behaviors of EVs, Y. Zhang *et al.* in [4] supposed charging stations can provide different charing modes to EVs and designed an optimal pricing scheme to minimize the service dropping rate of charging station. In [5], charging communities were also regarded as either energy consumers or energy providers and utilized by a three-party game for the flexibility of energy management and power trading. Y. Cao *et al.* in [6] proposed a charging management system jointly considered charging reservations and parking duration, and further designed a periodical reservation updating mechanism to tackle mobility uncertainty of EVs. Considering the individual charing intentions of EVs, an energy management protocol was proposed in [10] for the cooperative EV-to-EV charging in a distribute manner with flexibility among those rational entities. Taking the incomplete information of environments into account, the charging optimization of each EV is restricted by information asymmetry from the perspective of reality. K. Zhang *et al.* in [7] adopted contract theory to design an optimal charging policy and admission control schemes to maximize the utility of the charging station under information asymmetry. Moreover, the authors in [8] designed a mobile edge computing-supported architecture and leveraged the global controlling of EVs to the local charging stations to lower the cost for information dissemination and collection. For a similar purpose, D. A. Chekired *et al.* in [9] proposed a coordinated model for scheduling EVs charging and discharging based on the decentralized fog architecture.

However, most existing schemes inevitably pose computational burden on EV-integrated smart grid to decide charging strategy, whereas few works tried to alleviate the computation burdens of smart grid. The frequent energy transactions among EVs and charging stations in addition to intrinsic data processing requirements result in higher scheduling costs and influence the stability of the smart-grid-based system. These negative factors are likely to reduce the operating profits of the third party entities and thus hinder the development of charging control optimization [8]. Due to the potential demands of smart grid for large-scale data processing and transmission, some literatures apply fog computing architecture [8], [9] to smart charging system so as to reduce the computation requirement, but those works ignore the underutilized computation capabilities of EVs, and let alone to provide a certain incentive for EVs to tackle with the additional computing requirements. Considering the inherent features of EVs as the intelligent mobile nodes with sufficient computation resources [11], [12], EVs are capable of handling real-time management in smart cities, and thus it is appealing to apply the prominent vehicular fog computing (VFC) architecture to the EV charging problem.

In VFC, vehicles can act as fog nodes to provide services and

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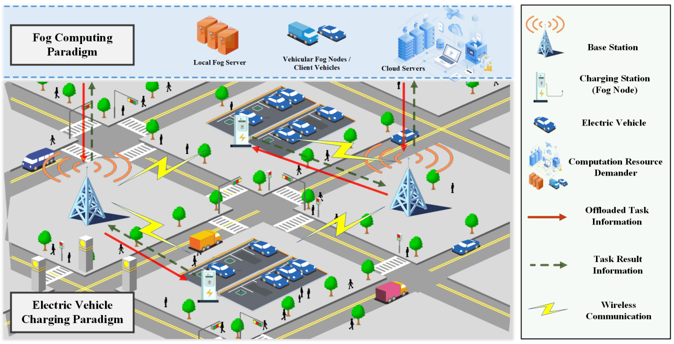

Fig. 1. IC^2 architecture: energy grid-based charging paradigm interacting with vehicular fog computing paradigm.

incentive mechanisms are designed to stimulate those vehicles to serve [13]. Considering the mutual demand and supply relationship between EVs and smart grid in both charging and computing tasks, in this paper, we propose an integrated charging and computing (IC^2) architecture for EV-included smart grid by regarding EVs as both energy consumers and computation providers to investigate the EV charging management with VFC. To the best of our knowledge, this is the first work that integrating vehicular fog computing and smart EV charging for joint optimization. Considering information asymmetry, we employ contract theory to solve the joint optimization problem, and we design a multi-attribute contract-based charging protocol taking both EVs' willingness to pay and willingness to share into account. Numerical results show not only feasibility and efficiency, but also the superiority in aggregating computation resources of our proposed protocol. Main contributions of this paper are summarized as follows.

1. We for the first time integrate vehicular fog computing and EV charging for joint optimization in EV-included smart grid. We propose a novel integrated charging and computing architecture. In the proposed IC^2 architecture, EVs act as both energy consumers that require charging from charging stations and computation providers that offer idle computation resources to help local task offloading.
2. We introduce contract theory to provide a multi-attribute contract-based charging protocol at charging station for providing charging services and enrolling computation resources of EVs. The proposed contract protocol brings both EVs and charging stations to agreements by providing two-tuple economic incentives involving the supplying charging rate, requiring CPU frequency, and the pricing of services, which poses mathematical complexity on contract formation and optimization.
3. We formulate the multi-attribute contract optimization problem with information asymmetry, and derive Karush-Kuhn-Tucker (KKT) conditions to find the optimal solution. We present a contract optimization algorithm based on convex-concave-procedure (CCP) to obtain the best contract for charging stations. Numerical results show that the charging stations with the proposed scheme can promote computation capability greatly compared with the only-charging scheme.

The rest of this paper is organized as follows. Section II introduces the overview of IC^2 architecture and formulates the objective function of charging stations. Section III designs the multi-attribute contract-based charging-computing scheme. Section IV evaluates the performance of our proposed scheme with other benchmarks and Section V concludes this paper.

II. System Model and Problem Formulation

A. System Model

The IC^2 architecture integrating charging and VFC is shown in Fig. 1. In the smart-grid-based charging system, we assume that there are N EVs in need of electric provision from power grid denoted as $\mathcal{V} = \{EV_1, EV_2, \cdots, EV_N\}$ and M charging stations distributed geographically in its dominating district denoted as $\mathcal{CS} = \{CS_1, CS_2, \cdots, CS_M\}$.

1) Energy Cost Model: The energy cost of charging station CS_j at time t is given by $\mathrm{ECost}_j(t) = q_t^G \times E_t^{CS_j} = q_t^G \times \sum_{EV_i \in CS_j} PW_i(t)$, where PW_i means the charging power provided by the charging station for EV_i and $q_t^G(E_t) = \phi_t E_t^2 + \psi_t E_t$ is unit electricity cost referring to [14]. ϕ_t, ψ_t are tariff parameters and E_t is the total energy consumption of the grid at time t.

2) Charging Behavior Model: If the state-of-charge (SOC) of an EV drops below the charging threshold, the charging demands of drivers will be triggered. The charging demand of EV_i at time t is $CD_i(t) = 1$ if $S \le S_{th}^{v_i}$, and $CD_i(t) = 0$ otherwise, where S is the SOC, $S_{th}^{v_i}$ is the SOC charging threshold of EV_i, $CD_i(t) = 1$ means that EV_i needs to charge at time t, and otherwise charging is not required. SOC threshold of drivers are determined by their charging habits S_{ha}.

3) Fog Computing System Model: We assume that the offloaded tasks assigned by cloud servers are equivalent to the computational capacity of each charging station so as to exploit the fog charging stations' potential capability and achieve computational load-balancing. The profit function of CS_i is given as $R_{CS_i}(f^{\mathrm{add}}) = r_{CS_i} \times \left(1 + \frac{f^{\mathrm{add}}}{f_i^{CS}}\right)$, where r_{CS_i} is the unit benefit brought by the reduced delay, C_i^{CS} is the computational requirements of the offloaded tasks from cloud, and f^{add} is the additional computational resources.

B. Objective Formulation

The utility of each charging station is composed of three parts: charging price received from the charging EV, computing reward from additional computational resources, and the energy cost of providing electricity. The charging station's utility at time t is designed as:

$$\mathbb{U}_{CS}(\mathbf{PW}(t), \mathbf{q}(t)) = \mathbf{1}^{\mathbf{T}}\mathbf{q}(t) + R_{CS}(f^{\mathrm{add}}) - \mathrm{ECost}(t) \qquad (1)$$

where $f^{\mathrm{add}} = \sum_{EV_i \in CS_j} f^{EV_j}$ representing the computational resources brought by the charging vehicles, $\mathbf{PW}(t)$ is the charging rate vector allocated to each charging EV at time t, and $\mathbf{q}(t)$ is the pricing vector towards each EV with different charging rate. The target of charging station is to maximize their utility.

III. Multi-Attribute Contract-Based Charging-Computing Scheme

A. Electric Vehicle Type Modeling

EVs' willingness to pay for different charging rate and the willingness to share computational resources are quantified by the EV types. Assume G types of EVs according to their willingness-to-pay parameters $\Theta = \{\theta_1, \theta_2, \cdots, \theta_G\}$ determined by the preferences of drivers. Without loss of generality, $\theta_1 \leq \theta_2 \leq \cdots \leq \theta_G$ and the θ with larger subscript implies higher preference for faster charging. Then we define the willingness-to-share parameter λ_k as follow:

$$\lambda_k = f_{\text{dev}}^{\min} + \frac{k-1}{K}\left(f_{\text{dev}}^{\max} - f_{\text{dev}}^{\min}\right) \tag{2}$$

where $f_{\text{dev}}^{\min}$ is the minimum devoted computing resources and $f_{\text{dev}}^{\max}$ is the maximum available computing resources of each EV. Subsequently, EVs' willingness to share is denoted as $\Lambda = \{\lambda_1, \lambda_2, \cdots, \lambda_K\}$ and EVs in the system are classified by the multi-attributes, denoted as a two dimension tuple (θ_g, λ_k).

B. Multi-Attribute Charging-Computing Contract Design

Since we provide a two dimension typing metrics to differentiate EVs, there exist $G \times K$ types of EVs in the system, and the charging stations sign contract items for those different types. The contract item dedicated for type (θ_g, λ_k) EV is denoted as $(PW(\theta_g), f(\lambda_k), q(\theta_g, \lambda_k))$[1], where $q(\theta_g, \lambda_k)$ is the price payed for each charging slot. The whole contract can thus be denoted as $\Phi = \{(PW_g, f_k, q_{g,k}), \forall\theta_g \in \Theta, \lambda_k \in \Lambda\}$.

1) Charging Station Utility: With $G \times K$ types of EVs and the distribution probability $\mu_{g,k}$ among N EVs in the system, the utility of charging station is modified from (1) as follows:

$$\mathbb{U}_{CS}^{C} = N \sum_{\theta_g, \lambda_k} \mu_{g,k}\left[q_{g,k} - \text{ECost}(PW_g) + R_{CS}(f_k)\right] \tag{3}$$

where $\mu_{g,k}$ is the type distribution probability following uniform distribution considering the information asymmetry.

2) EV Utility: The utility function of type (θ_g, λ_k) EV which accepts contract item $(PW_g, f_k, q_{g,k})$ is the reward offered by charging rate minus the cost of the power consumption and the charging price, denoted as:

$$\mathbb{U}_{g,k}^{EV}(PW_g, f_k, q_{g,k}) = v_g(PW_g) - \gamma f_k - q_{g,k} \tag{4}$$

where γ is the coefficient parameter meaning the power transition of CPU frequency and $v_g(\cdot)$ is the evaluation function. The evaluation function is a monotonically increasing concave function with $v_g(0) = 0$, $v_g'(PW_g) > 0$ and $v_g''(PW_g) < 0$ [15], which is defined as $v_g(PW_g) = \theta_g\left(-\frac{a}{2}PW_g^2 + bPW_g\right)$ where a and b are positive constants satisfying the derivative constraints mentioned above.

Given the utility of charging stations and EVs, we derive the social welfare of system as below:

$$SW = \sum_{CS_i \in CS} \mathbb{U}_{CS_i}^{C} + \sum_{EV_{g,k}} \mathbb{U}_{g,k}^{EV}. \tag{5}$$

[1] In the following context, we denote the contract item as $(PW_g, f_k, q_{g,k})$ for simplicity.

3) Contract Formulation: A feasible and efficient contract should guarantee individual rationality (IR), incentive compatibility (IC), and monotonicity constraints.

- *Individual Rationality (IR) constraint:* Each EV with type (θ_g, λ_k) gains nonnegative utility if it select the contract item $(PW_g, f_k, q_{g,k})$, i.e., $\mathbb{U}_{g,k}^{EV}(PW_g, f_k, q_{g,k}) \geq 0$.
- *Incentive Compatibility (IC) constraint:* In order to maximize the utility function, each EV is believed to choose the contract item which provides the maximum utility.
- *Monotonicity constraint:* The reward or demand of higher type contract item should be larger than the lower one.

The contract optimization problem with charging rate assignment and CPU frequency demands at time slot Δt is thus formulated as given:

$$\begin{aligned}
\mathbf{P1}: \quad & \max_{\mathbf{PW},\mathbf{q},\mathbf{f}} \mathbb{U}_{CS}^{C} \\
\text{s.t.} \quad & C1: v_g(PW_g) - \gamma f_k - q_{g,k} \geq 0, \forall\theta_g, \lambda_k \\
& C2: v_g(PW_g) - \gamma f_k - q_{g,k} \geq v_g(PW_{g'}) - \gamma f_{k'} \\
& \qquad - q_{g',k'}, 1 \leq g, g' \leq G, 1 \leq k, k' \leq K \\
& C3: PW_{\min} \leq PW_1 < PW_2 < \cdots < PW_G \\
& C4: f_{\min} \leq f_1 < f_2 < \cdots < f_K \\
& C5: f_k \leq \lambda_k, \forall\lambda_k
\end{aligned}$$

where $C1$ denotes the IR constraint; $C2$ denotes the IC constraint; $C3$ and $C4$ are monotonicity constraints, and $C5$ restricts the demanding frequency to the upper bound of λ_k.

C. Optimal Contract Simplification

Proposition 1 *Constraint $C2$ in* **P1** *can be substituted by the following constraints without loss of generality:*

$$-\gamma(f_{k-1} - f_k) \geq q_{g,k-1} - q_{g,k}, 1 \leq g \leq G, 1 < k \leq K$$
$$v_g(PW_g) - q_{g,k} \geq v_g(PW_{g-1}) - q_{g-1,k}, 1 < g \leq G, \forall k$$

Proposition 2 *Given any fixed $\theta_{g^\star} \in \Theta$, we have*

$$0 \leq \mathbb{U}_{g^\star,1}^{EV}(PW_{g^\star}, f_1, q_{g^\star,1}) \leq \cdots \leq \mathbb{U}_{g^\star,K}^{EV}(PW_{g^\star}, f_K, q_{g^\star,K})$$

and given any fixed $\lambda_{k^\star} \in \Lambda$, we have

$$0 \leq \mathbb{U}_{1,k^\star}^{EV}(PW_1, f_{k^\star}, q_{1,k^\star}) < \cdots < \mathbb{U}_{G,k^\star}^{EV}(PW_G, f_{k^\star}, q_{G,k^\star}).$$

Theorem 1 *The contract $\Phi = \{(PW_g, f_k, q_{g,k})\}$ is feasible if and only if the following conditions are satisfied:*

1) *$PW_{\min} \leq PW_1 < \cdots < PW_G$ and $f_{\min} \leq f_1 < \cdots < f_K$;*
2) *$v_1(PW_1) - \gamma f_1 - q_{1,1} = 0$;*
3) *For any $g \in \{1, \cdots, G\}$ and $k \in \{2, \cdots, K\}$, $-\gamma(f_{k-1} - f_k) = q_{g,k-1} - q_{g,k}$;*
4) *For any $g \in \{2, \cdots, G\}$ and $k \in \{1, \cdots, K\}$, $v_g(PW_g) - q_{g,k} = v_g(PW_{g-1}) - q_{g-1,k}$;*
5) *For any $k \in \{1, K\}$, $f_k \leq \lambda_k$.*

Proof We prove that the conditions in Theorem 1 is equivalent to the constraints mentioned in **P1**. Condition 1) is monotonicity constraint and condition 5) is the upper frequency constraint. Since the maximum utility of the charging station can be obtained under the condition that LDICs are binding for the optimization problem [7], conditions 3) and 4 are concluded by C_2^1 and C_2^2 in Proposition 1. We can also infer from Proposition 2 that $\mathbb{U}_{g,k}^{EV}(\cdot) \geq \mathbb{U}_{1,1}^{EV}(\cdot)$ given $g > 1, f > 1$ by adding g or f step-by-step. Thus condition 2) is proved to be the reduced form of IR constraint. ∎

On the basis of Theorem 1, the IC constraint is eliminated from $G \times K \times (G + K - 2)$ to $2 \times G \times K$ and **P1** is rewritten as:

$$\begin{aligned} \mathbf{P2}: \quad & \min_{\mathbf{PW},\mathbf{q},\mathbf{f}} -\mathbb{U}_{CS}^{C} \\ \text{s.t.} \quad & A1: v_1(PW_1) - \gamma f_1 - q_{1,1} = 0 \\ & A2: -\gamma(f_{k-1} - f_k) = q_{g,k-1} - q_{g,k}, \forall g, 1 < k \leq K \\ & A3: v_g(PW_g) - q_{g,k} = v_g(PW_{g-1}) - q_{g-1,k} \\ & \quad , 1 < g \leq G, 1 \leq k \leq K \\ & C3 \sim C5 \end{aligned} \tag{6}$$

D. CCP-Based Contract Optimization Algorithm

We observe that the objective function of **P2** is the weighted sum of the convex functions by analyzing the Hessian matrix. However, convex programming method cannot be directly applied to **P2** because the constraint $A3$ contains the difference of two concave functions. Therefore, we adopt CCP algorithm [16] to solve **P2** in an iterative mode as shown in Algorithm 1. We first transform the concave function $v_g(PW_g)$ into an affine function by using Taylor series with any feasible initial point $PW_{g,0}$, which is given by:

$$\begin{aligned} v_g(PW_g) &\approx \tilde{v}_g(PW_g, PW_{g,0}) \\ &= v_g(PW_{g,0}) + \nabla v_g(PW_{g,0})(PW_g - PW_{g,0}) \end{aligned} \tag{7}$$

Applying $\tilde{v}_g(PW_{g-1}, PW_{g-1,0})$ to $v_g(PW_{g-1})$ in constraint $A3$, the constraint becomes an integration of concave function and affine function, and the programming problem **P2** is transformed into the convex form which can be conveniently solved via Karush-Kuhn-Tucker (KKT) conditions. In CCP algorithm, the feasible point for the g-th type θ_g is selected iteratively. At each iteration τ, $PW_{g,0}[\tau]$ is selected by using the optimal point $PW_g^{\star}[\tau - 1]$ at the $(\tau - 1)$-th iteration. By using this selection strategy, the convex objective function series $\left\{\mathbb{U}_{CS}^{C}[\tau]\right\}$ converges to the global minimum value monotonically, and we use a positive threshold ϵ_{th} to depict the stopping criterion in Algorithm 1. The CCP-based algorithm is proved to be converge [16].

E. Optimal Contract Design Without Information Asymmetry

Since the contract item is designed for each specific EV individually, the charging station can always promote its utility by increasing price $q_{g,k}$ and CPU requirement f_k or decreasing the supplying charging rate PW_g. The optimal contract without information asymmetry should satisfy that $q_{g,k}^{\star} - \gamma f_k^{\star} = v_g(PW_g^{\star})$ for any type (θ_g, λ_k).

IV. Simulation and Results

A. Simulation Conditions

In the simulations, we consider a 10 km × 10 km urban network with 50 driving EVs and 2 charging stations. Crossroad is the road network node lined with other roads, and there are two charging stations located at (4 km, 5 km) and (7 km, 5 km). Each EV in the simulation is initialized with a starting crossroad node, a target destination node, and other attributes including velocity $v \in [2, 20]$ m/s, initial SOC $S^{\text{ini}} \in [0.1, 0.5]$, objective SOC $S^{\text{obj}} \in [0.3, 1.0]$, willingness to pay $\theta_g \in [10, 20]$, and idle CPU frequency $f_{\text{dev}} \in [0.5, 3]$ GHz. As for comparison, we evaluate the performance among four different schemes, which are the proposed scheme with information asymmetry, the contract without information asymmetry, the only-charging contract concerning information asymmetry [7], and the take-it-or-leave contract [17]. Detailed parameters are listed in Table I.

Algorithm 1 CCP-Based Contract Optimization Algorithm

Input: Initial feasible point $PW_{g,0}[0]$ and $\mathbf{PW}, \mathbf{f}, \mathbf{q}$.
Output: Optimal contract $\Phi^{\star} = \left\{\left(PW_g{}^{\star}, f_k{}^{\star}, q_{g,k}{}^{\star}\right)\right\}$.
Set $\tau = 0$, $\mathbb{U}_{CS}^{C}[\tau] = 0$, and $PW_g^{\star}[\tau] = PW_{g,0}[0], \forall g$.
Applying $\tilde{v}_g(PW_{g-1}, PW_{g-1,0})$ to $v_g(PW_{g-1})$ in constraint $A3$ to achieve convex programming problem $\tilde{\mathbf{P}}\mathbf{2}$.
Rpeat
  Update $\tau := \tau + 1$, $PW_{g,0}[\tau] = PW_g^{\star}[\tau - 1]$, $\forall g$.
  Solve the KKT equations of $\tilde{\mathbf{P}}\mathbf{2}$ to get the optimal contract, $\Phi^{\star}[\tau] = \left\{\left(PW_g{}^{\star}[\tau], f_k{}^{\star}[\tau], q_{g,k}{}^{\star}[\tau]\right)\right\}$.
  Calculate current objective function $\mathbb{U}_{CS}^{C}[\tau]$.
Until satisfying the stopping criterion: $\mathbb{U}_{CS}^{C}[\tau] - \mathbb{U}_{CS}^{C}[\tau - 1] \leq \epsilon_{th}$.

TABLE I
Simulation Parameters

EV's Habitant Charging Threshold S_{ha}	0.5
EV's Battery Capacity BC	60 KWh
Min/Maximum Charging Rate $PW_{\min}$	10/80 KW
Min/Maximum Required CPU Frequency $f_{\min}$	0/3 GHz
CC-CV Transition Threshold S_{th}^{cc}	0.6
Parameters $\phi, \psi, E^{\text{basic}}$)	0.2, 0.2, 50
Parameters a, b in $v_g(PW_g)$	10^{-5}, 0.0008
Stopping Threshold ϵ_{th} in Algorithm 1	10^{-6}
CPU Frequency Running Cost γ	5×10^{-6}
Charging Station CPU Frequency f_{CS}	5 GHz
Reward of CPU Frequency r_{CS} [13]	0.5 cent/(GHz·h)
Time Slot Length Δt	1 s

B. Contract Feasibility and Efficiency

Fig. 2a and Fig. 2b demonstrate the provided charging rate and required CPU frequency along with different types of willingness-to-pay θ and willingness-to-share λ. Fig. 2a and Fig. 2b show the contract feasibility of monotonicity constraints, while under the information asymmetric conditions, both provided charging rate PW and required CPU frequency f increase monotonically with the corresponding EV type. Without information asymmetry, the charging station provided a higher charging rate according to the EV owners evaluation function. On the other side, as shown in Fig. 2b, the required CPU frequency by charging station is always the maximum available frequency of each type of EV given the predefined γ, r_{CS}, and f_{CS}. In the take-it-or-leave scheme, the contract is designed only for type $(\theta_{th}, \lambda_{th}) = (7, 7)$ EVs. Then we show

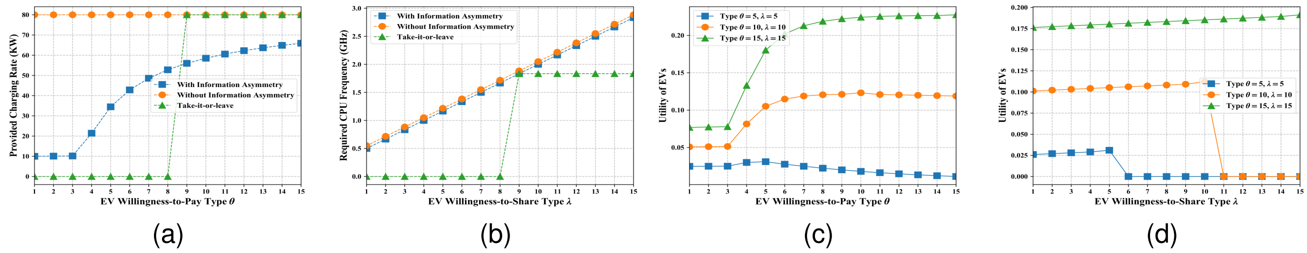

Fig. 2. Contract feasibility: (a) provided charging rate for EV, (b) required CPU frequency from EV, (c) utility of EVs versus willingness-to-pay θ with the fixed λ_5, and (d) utility of EVs versus willingness-to-share λ with the fixed θ_5.

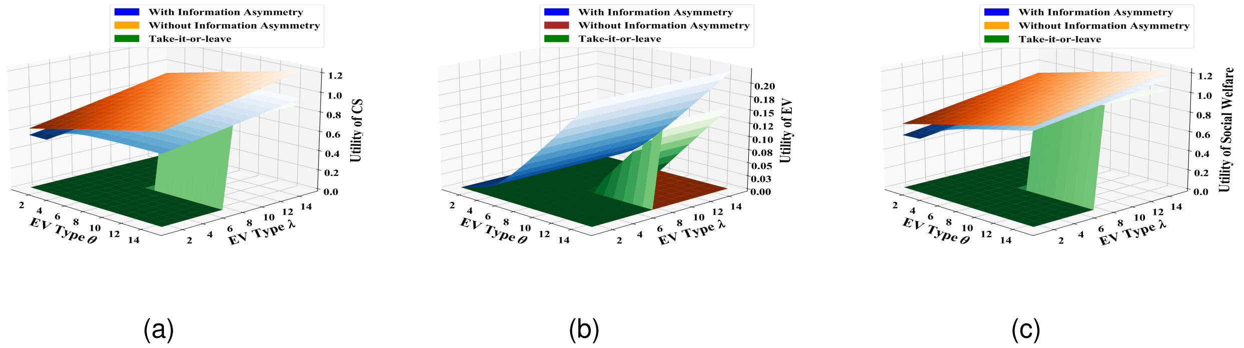

Fig. 3. Contract efficiency: (a) utility of charging stations, (b) utility of EVs, and (c) utility of social welfare versus different type of EVs

the utility comparison of three types of EV, which are $(5,5)$, $(10,10)$, and $(15,15)$, in Fig. 2c and Fig. 2d. It is verified that the proposed contract with information asymmetry obeys IC constraints. Moreover, we can also conclude from Fig. 2c and Fig. 2d that the utility of EV raises with the increment of type θ/λ given a fixed λ/θ respectively.

Fig. 3a, Fig. 3b, and Fig. 3c show the utility of charging stations, EVs, and social welfare defined in (5) versus different EV types. We plot the three-dimensional figures of the proposed contract with or without information asymmetry and the take-it-or-leave contract to illustrate the contract efficiency directly and clearly. It can be seen that the charging station achieves a higher utility without information asymmetry, in which condition that the utility of all EVs are supposed to remain zero. When it comes to the case of information asymmetry, EVs can extract more benefits from the proposed contract because of the incomplete information of charging stations. As for take-it-or-leave contract, EVs can only get utility when their types are higher than the type thresholds, and the changing in utility happens drastically from zero to the expected utility. Fig. 3c shows the relationships between social welfare and EV's types. Social welfare is a critical metric to evaluate the system performance since it offsets the payment price from EVs and charging stations. The contract without information asymmetry outperforms the one with information asymmetry in social welfare intuitively, and the proposed contract with information asymmetry exceeds the take-it-or-leave contract in performance, which demonstrates the superiority of our proposed scheme.

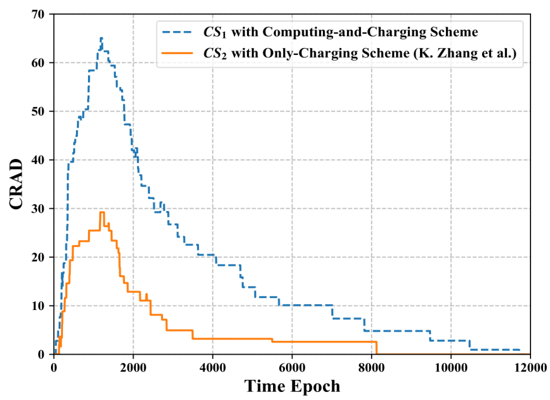

Fig. 4. CRAD varying with time epoch given two different charging stations with computing-and-charging contract and only-charging contract [7].

C. Computation Performance Evaluation

We introduce a metric to evaluate the computation resources aggregating condition in the charging-computing architecture, termed as Computation Resources Aggregating Degree (CRAD). The definition of CRAD is given by $\text{CRAD}(CS) = \sum_{EV_i \in \mathcal{V}} f_{\text{dev}}^{EV_i}/d(EV_i, CS)$, where $d(EV_i, CS)$ is the distance between charging station CS and EV_i. We can infer from the formula easily that the higher CRAD is for a charging station, the more sufficient computation resources are nearby. We suppose that one charging station in the system selects to use the proposed computing-and-charging contract, and the other one with the only-charging contract in [7]. Both of the two scheme considers information asymmetry. As shown in Fig. 4, the CRAD of the charging station with computing-and-

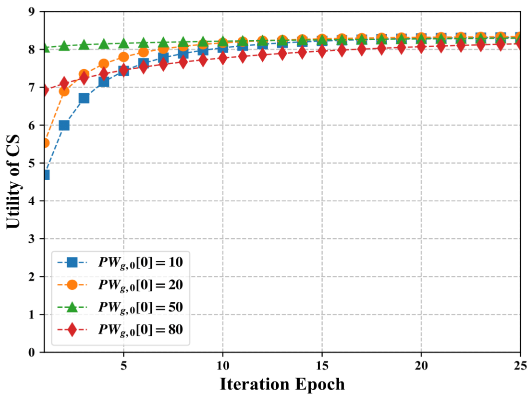

Fig. 5. The convergence of the proposed CCP-based Algorithm 1 given different feasible initial point.

charging contract is significantly higher than the one with only-charging contract in the charging peak. The numerical results reflect that our proposed computing-and-charging scheme is able to aggregate the computation resources in the fog-based paradigm, and is sure to provide stable and dependable computational services.

D. Convergence

Finally we discuss the convergence of our proposed CCP-based contract optimization algorithm. In Fig. 5, we give different value vectors as the initial charging power point, which are 10, 20, 50, and 80. It is guaranteed that all the given points are within the feasible region $[PW_{\min}, PW_{\max}]$. We can see that the proposed algorithm converges to the maximum charging station utility with different initial points within about 20 iterations with the loss of about 10^{-2}, and all four cases converge to optimal utility.

V. Conclusion

In this paper, we proposed a multi-attribute charging and computing architecture integrating charging paradigm with vehicular fog computing paradigm based on smart grid. We designed a charging-computing scheme based on multi-attribute contract and formulated the contract design problem into an optimization problem. In order to find the optimal contract of charging stations, we transformed the optimization problem into convex form and applied CCP approach to design a contract optimization algorithm. Numerical results demonstrated the feasibility and efficiency of our proposed scheme and the superiority in aggregating computation resources was also demonstrated via experiments.

VI. Acknowledgment

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