Noncooperative Distributed Social Welfare Optimization with EV Charging Response

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***Abstract*—This paper presents a novel non-cooperative strategic game-theoretic framework to model electric vehicle (EV) aggregators (such as fast-charging stations and aggregated building charging infrastructures) and enable their participation in integrated economic dispatch and demand response, as known as social welfare optimization. Each EV aggregator acts as a selfish and independent player with focus on only its own benefits. A special type of non-cooperative strategic game, called potential game, is applied to model the interaction between all palyers. Spatial adaptive play (SAP) is applied to for the players to learn and react in the proposed game, with guaranteed convergence to a Nash equilibrium (NE) which is also a global optimizer to the social welfare optimization problem. Simulations on a 15-bus IEEE network have been conducted to validate the framework. Results match expected outcomes and dynamics of the proposed EV charging response game.**

***Index Terms*—EV charging, demand response, social welfare, economic dispatch, strategic game**

I. Introduction

U.S. Department of Energy (DOE) expects that there will be over 2.3 million new total-battery electric vehicles (EVs) sales per year in U.S. [1]. Current EV charging infrastructures include fast-charging stations and building-level chargers. At (residential and commercial) building level, level-2 charging at 240 single-phase VAC dominates the market, with power consumption range between 3.4kW and 19.2kW (typical 7kW in current practice). On the other hand, fast-charging stations typically converts three-phase AC to DC and charge EVs at typically 60KW to 100KW range. For instance, Tesla currently has 1,229 Supercharger Stations with 9,623 Superchargers. Therefore, in the near future, a penetration rate of EVs charging needs will constitute a significant part of the overall electricity demand [2].

Although EV charging infrastructures are trending towards higher voltage and higher power level, it remains an unlikely scenario for individual EV charging infrastructure to participate into system-level operations along with system operators. The main reasons are two-fold: 1) individual EV charging infrastructure capacity is below the required minimum to participate in power system markets, even for fast-charging stations; and 2) there will be a huge number of market participants as well as gigantic volume of individual transactions to manage [3]. Therefore, EV charging aggregators have been proposed to facilitate the interactions between EV fleets and power grids, whose primary role is to group EVs according to their owners economic benefits and then to exploit opportunities [4]. With large-scale system-wide EV charging profiles (starting time, charging period, and initial SOC) identified [5], accurate load profile modeling and demand forecasting can be achieved for distribution system operators (DSOs) to incorporate EV charging as an important flexible load with EV owners allow EV charging aggregators to manage their charging activities in a predefined and pre-scheduled manner.

Traditionally, economic dispatch (ED) and demand response (DR) problems are considered separately on different ends of power demand and supply.On power generation and distribution end, ED is well-studied problem which optimizes an system-wide objective function, such as generation cost minimization, transmission loss minimization, or profit maximization, over the generation and transmission network under a given set of constraints. The solution of ED is an allocation of generation amount amount generation units. Many aspects make the ED problem complex. For instance, the objective function is nonsmooth and nonconvex if the valve-point effect or multi-fuel scenario is considered [6], [7]. On customer end, DR refers to participation of end-users into distribution network operations, especially during peak hours to help DSOs to reduce peak demand, reshape load profile, and improve grid reliability [8]. DR enables customers to make informed decisions in terms of scheduling and rescheduling their energy consumption with respect to timed energy tariffs.

Recently, DR and ED are proposed to be combined to form a closed-loop system [9], [10]. With active participation of DR, load models will be revised and demand will be reduced, which in turn result in revisiting the ED corresponding to the updated load and demand. Therefore, a number of recent work [10]–[12] proposed to formulate these two problems into an integrated framework, which is called a (constrained) *social welfare optimization* (SWO) problem.

This paper proposes to formulate the SWO problem as a specific type of non-cooperative strategic game, i.e., potential game. To reflect the nature of DR, each EV aggregated is formulated as an independent and selfish player whose object is to maximize its own utility/payoff function. For the ED problem, each generator is also modeled as a selfish player whose actions are its own power generation, and its utility function can be the loss, cost, or revenue [13], [14]. Therefore, in the proposed SWO game, both EV aggregators and generating units active independently only to maximize each individual's utility. The proposed formulation alleviates the computational burden introduced by inequality constraints as they are converted to feasible action sets of players. Therefore, both the formulation and solution process of the constrained SWO problem are greatly simplified. A learning algorithm with guaranteed convergence to Nash equilibrium for potential games, called Spatial Adaptive Play (SAP) [15], is applied to solve the SWO game. Analytic analysis on how players act as best responses to others is provided to investigate the economic reasoning of generator operations.

This paper is organized as follows. Section II defines objective functions and constraints for the SWO problem and Section III introduces potential games and the SAP algorithm for potential games. The potential game formulation of the SWO problem is described in Section IV. Section V presents simulation results on a 15-generator system. Finally, Section VI summarizes major contribution of this paper and proposes some future work.

II. Problem Formulation

In this section, the social welfare optimization problem (SWO) is presented. The objective function is defined at first and some physical operation constraints are provided later.

A. Objective Function

The prototype of the SWO problem is economic dispatch (ED) problem and demand response (DR) problem. The objective of the former is to minimize the total generation cost of generators and that of the latter is to maximize the overall benefit of users. Normally, DR and ED are realized separately. Before ED allocates the power generation economically, DR needs to reshape load profile. This interactive process will be implemented some rounds until it goes to convergence, which will probably take long time. Here, the two problems are formulated in a unified form and solved simultaneously, of which the optimization objective is to maximize the social welfare as shown in (1).

$$\max_{P_i} \sum_{i\in\mathcal{E}} U_i(P_i) - \sum_{i\in\mathcal{G}} C_i(P_i) \tag{1}$$

In our paper, we assume that the customers participating in DR are only the owners of EVs. Compared with other load, EV charging load has prominent potential to help to reduce the peak demand and increase grid reliability. So the first term in (1) represents the sum of the utility function of EV customers. For simplification, $\mathcal{E} := \{k+1, ..., k+m\}$ denotes the set of EV aggregators. The utility function of EV aggregator i is formulated as [16]

$$U_i(P_i) = \frac{\eta}{1 + e^{-P_i + \rho_i \hat{P}_i}} \tag{2}$$

where $P_i(i \in \mathcal{E})$ is the demand of the ith EV aggregator, that is charging rate. η is used for scaling, and ρ_i and forecasted EV demand $\hat{P}_i$ are used for demand profile modeling. The interesting thing in (2) is that the coefficient ρ_i can indicate the level of range anxiety, which means that the higher the ρ_i is, the more energy the customer needs to cover his driving needs at that time. So we call $\rho_i \hat{P}_i$ the weighted forecasted EV demand. The choice of sigmoid utility function unlike traditional utility function in [17] is based on the fact that the satisfaction level or marginal utility of customers increase until they have enough battery capacity to drive.

Let $\mathcal{G} := \{1, ..., k\}$ denote the set of generators. The generation cost function of $C_i(P_i)$ in (1) is formulated as follows

$$C_i(P_i) = \alpha_i P_i^2 + \beta_i P_i + \gamma_i \tag{3}$$

where $P_i(i \in \mathcal{G})$ is the real power output of generator i. α_i,β_i and γ_i are coefficients of the quadratic function.

B. Operation Constraints

1) Constant Power Charging Property: Most of current charging mode is constant power charging. Therefore, the demand of the ith EV aggregator can be formulated as

$$P_i = n_i \widetilde{P}_i \qquad (n_i \in \mathcal{N}, i \in \mathcal{E}) \tag{4}$$

where n_i is the number of EVs that the ith EV aggregator contains and $\widetilde{P}_i$ is the value of charging power.

2) Active Power Balance:

$$\sum_{i\in\mathcal{G}} P_i = P_D + P_{loss} + \sum_{i\in\mathcal{E}} P_i \tag{5}$$

where P_D is the total demand except EV charging load and it is uncontrollable. P_{loss} is the total transmission loss which is a function of $P_i(i \in \mathcal{G})$ with Kron's $\boldsymbol{B}$ coefficients [18]

$$P_{loss} = \sum_{i\in\mathcal{G}} \sum_{j\in\mathcal{G}} P_i B_{ij} P_j + \sum_{i\in\mathcal{G}} B_{0i} P_i + B_{00} \tag{6}$$

3) Generator Output Limits:

$$\underline{P}_i \le P_i \le \overline{P}_i \quad (i \in \mathcal{G}) \tag{7}$$

where $\underline{P}_i$ and $\overline{P}_i$ denote the lower bounds and upper bounds of P_i, respectively.

4) Ramp Rate Limits:

$$P_i^0 - DR_i \le P_i \le P_i^0 + UR_i \quad (i \in \mathcal{G}) \tag{8}$$

where P_i^0 denotes previous power output of generator i. DR_i and UR_i denote down-ramp and up-ramp limits for generator i, respectively.

5) Prohibited Zone Limits: Some thermal generators may not operate in the valve points and thus they should avoid zones which contain those points. Feasible operation regions for generator i can be written as

$$\begin{cases} \underline{P}_i \leq P_i \leq P_{i,1}^L \\ P_{i,s}^U \leq P_i \leq P_{i,s+1}^L \\ P_{i,N_i}^U \leq P_i \leq \overline{P}_i \\ (i \in \mathcal{G}, s = 1, ..., N_i - 1) \end{cases} \tag{9}$$

where N_i is the total number of prohibited zones for generator i.

6) Charging Rate Limits:

$$\underline{P}_i \leq P_i \leq \overline{P}_i \quad (i \in \mathcal{E}) \tag{10}$$

where $\underline{P}_i$ and $\overline{P}_i$ denote the lower bounds and upper bounds of P_i, respectively.

C. SWO with EV Charging Response

For $i \in \mathcal{G}$, define the set of candidate power output as

$$\mathcal{F}_{i\in\mathcal{G}} := \{P_i \in \mathcal{R} | (7), (8), (9)\} \tag{11}$$

For $i \in \mathcal{E}$, define the set of candidate amount of EVs the aggregator can provide charging service to as

$$\mathcal{F}_{i\in\mathcal{E}} := \{n_i \in \mathcal{N} | (4), (10)\} \tag{12}$$

Substituting $P_i(i \in \mathcal{E})$ in (1),(5) and (10) with n_i in (4), the complete SWO with EV Charging Response can be reformulated as

$$\begin{aligned} &\max_{n_i, P_i} \sum_{i\in\mathcal{E}} U_i(n_i) - \sum_{i\in\mathcal{G}} C_i(P_i) \\ \text{s.t.} \quad &\sum_{i\in\mathcal{G}} P_i = P_D + P_{loss} + \sum_{i\in\mathcal{E}} n_i \widetilde{P}_i \\ &P_i \in \mathcal{F}_{i\in\mathcal{G}}, \quad n_i \in \mathcal{F}_{i\in\mathcal{E}} \end{aligned} \tag{13}$$

Obviously, (13) is a mixed integer nonlinear programming (MINLP) problem. The Fig. 1 shows the framework for SWO with EV charging response. Using the collected historical data, the data center does load forecasting and solves the SWO problem. After the solution is achieved, the data center assigns decision instructions to aggregators and generators. Generators will output real power according to informed decision and we expect that ev consumers can make informed decision regarding consumption in order to reshape their charging profile. This process is repeated at a certain interval. It should be noted that the SWO does not involve uncontrolled load because its utility is fixed, which means that its demand can be always satisfied.

III. Potential Game

In this section, we review the potential game theory by Monderer and Shapley [19] and an exsiting learning algorithm for potential games.

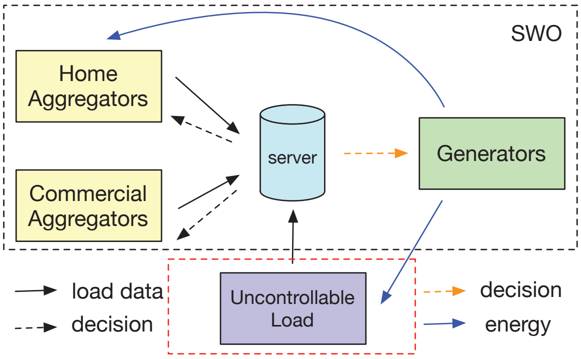

Fig. 1. SWO with EV charging response framework.

A. Non-cooperative Strategic Games

A typical non-cooperative strategic game consists of some basic elements as follows

1) A set of players: $\mathcal{P} := \{1, ..., N\}$

2) A set of actions for each player $i \in \mathcal{P}$: $\mathcal{A}_i$

3) A payoff function for each player $i \in \mathcal{P}$: $u_i : \mathcal{A} \to \mathcal{R}$ where $\mathcal{A} := \times_{i\in\mathcal{P}} \mathcal{A}_i \subseteq \mathcal{R}^N$ denotes the set of action profiles for all players.

4) $\forall a \in \mathcal{A}$ can be written in a compacted way as $a = (a_i, a_{-i})$, which means that an action profile is the combination of the ith player's action and everyone else's.

5) $\exists a^* \in \mathcal{A}$ is an nash equilibrium (NE) $\iff u_i(a^*) = u_i(a_i^*, a_{-i}^*) \geq u_i(a_i, a_{-i}^*)$ for $i \in \mathcal{P}$, $a_i \in \mathcal{A}$. Note that there can be multiple NEs, unique NE, or no NE in a game.

6) The best response is defined as $BR_i(a_{-i}) \in \{a_i | u_i(a_i, a_{-i}) \geq u_i(\grave{a}_i, a_{-i}), a_i \in \mathcal{A}\}$. So $a_i^* = BR_i(a_{-i}^*)$.

B. Potential Game

A potential game is a special non-cooperative strategic game. In a potential game, the change in a player's payoff resulting from a unilateral change in strategy equals the change in the global utility named potential function. Specifically, the potential function $\phi : \mathcal{A} \to \mathcal{R}$ conforms to the following condition: for every player $i \in \mathcal{P}$, for every $a_{-i} \in \mathcal{A}_{-i}$ and for every a_i,$\grave{a}_i \in \mathcal{A}_i$

$$u_i(a_i, a_{-i}) - u_i(\grave{a}_i, a_{-i}) = \phi(a_i, a_{-i}) - \phi(\grave{a}_i, a_{-i}) \tag{14}$$

When such a function exists, this game is called a potential game with the potential function ϕ. Obviously, any action profile maximizing the potential function in a potential game is a pure NE and thus every potential game must possess at least a NE.

C. Spatial Adaptive Play

Although the optimal action profiles are NE, not every NE is an optimal action profile. Spatial Adaptive Play (SAP) [15] is a learning algorithm in games which can guarantee the convergence to the optimal action profiles with an arbitrarily high probability. The practice in SAP is to randomly select a updating player, his action is updated according to the softmax distribution from exploring to exploiting.

IV. Potential Game Method For SWO Problem

In this section, we formulate the SWO problem as a potential game described in section III, propose a SAP based distributed algorithm and analyze the best response of the crafted game.

Under our problem formulation, the EV aggregators and generators can be considered as players who will not co-operate. The action of EV aggregators and generators is consumption and generation decison, respectively. Before we design our potential function, we do need to relax the equality constraint first. By involving the lagrangian multiplier, the objective function in (13) becomes

$$\begin{aligned}\max_{n_i, P_i} \sum_{i\in\mathcal{E}} U_i(n_i) - \sum_{i\in\mathcal{G}} C_i(P_i) \\ -\lambda|P_D + P_{loss} + \sum_{i\in\mathcal{E}} n_i \widetilde{P}_i - \sum_{i\in\mathcal{G}} P_i|\end{aligned} \tag{15}$$

where the lagrangian mutiplier λ should be a extremely large positive number so that the absolute term behind the lagrangian mutiplier is forced to approach zero, which indirectly meets the active power balance. Note that a slight active power unbalance might be allowed with reserves or storages.

In this work, the potential function is designed as the objective function in (15). For convenience of later analysis, we replace n_i with $P_i (i \in \mathcal{E})$ here and there is no conflict incurred. So the potential function is written as follows

$$\begin{aligned}\phi(P_i, P_{-i}) = \sum_{i\in\mathcal{E}} U_i(P_i) - \sum_{i\in\mathcal{G}} C_i(P_i) \\ -\lambda|P_D + P_{loss} + \sum_{i\in\mathcal{E}} P_i - \sum_{i\in\mathcal{G}} P_i|\end{aligned} \tag{16}$$

The payoff function for each player is designed as

$$\begin{aligned}u_i(P_i, P_{-i}) = -(\alpha_i P_i^2 + \beta_i P_i) \\ -\lambda|P_D + P_{loss} + \sum_{i\in\mathcal{E}} P_i - \sum_{i\in\mathcal{G}} P_i| \quad (i \in \mathcal{G})\end{aligned} \tag{17}$$

$$\begin{aligned}u_i(P_i, P_{-i}) = U_i(P_i) \\ -\lambda|P_D + P_{loss} + \sum_{i\in\mathcal{E}} P_i - \sum_{i\in\mathcal{G}} P_i| \quad (i \in \mathcal{E})\end{aligned} \tag{18}$$

It is straightforward to see that

$$\begin{aligned}u_i(P_i, P_{-i}) - u_i(P_i', P_{-i}) &= \phi(P_i, P_{-i}) - \phi(P_i', P_{-i}) \\ &= \alpha_i(P_i'^2 - P_i^2) + \beta_i(P_i' - P_i) \\ &-\lambda|P_D + P_{loss} + \sum_{i\in\mathcal{E}} P_i - \sum_{i\in\mathcal{G}} P_i| \\ &+\lambda|P_D + P_{loss} + \sum_{i\in\mathcal{E}} P_i - P_i' - \sum_{-i\in\mathcal{G}} P_i| \\ &(i \in \mathcal{G})\end{aligned} \tag{19}$$

$$\begin{aligned}u_i(P_i, P_{-i}) - u_i(P_i', P_{-i}) &= \phi(P_i, P_{-i}) - \phi(P_i', P_{-i}) \\ &= U_i(P_i) - U_i(P_i') \\ &-\lambda|P_D + P_{loss} + \sum_{i\in\mathcal{E}} P_i - \sum_{i\in\mathcal{G}} P_i| \\ &+\lambda|P_D + P_{loss} + P_i' + \sum_{-i\in\mathcal{E}} P_i - \sum_{i\in\mathcal{G}} P_i|\end{aligned} \tag{20}$$

Therefore, a potential game is formed in the context of SWO problem with the potential function ϕ. The proposed algorithm 1 for SWO problem is shown as follows

Algorithm 1 SAP based algorithm for SWO problem

Read in system parameters and generators' previous output;
For all $i \in \mathcal{G}$, find $\mathcal{F}_{i\in\mathcal{G}}$;
For all $i \in \mathcal{E}$, find $\mathcal{F}_{i\in\mathcal{E}}$;
repeat
  Randomly select $i \in \mathcal{G} \cup \mathcal{E}$;
  if $i \in \mathcal{G}$ **then**
    Update $P_i \sim softmax(u_i(P_i \in \mathcal{F}_{i\in\mathcal{G}}, P_{-i}); T)$; {$T$: a predefined parameter for SAP}
  else
    Update $P_i \sim softmax(u_i(P_i \in \mathcal{F}_{i\in\mathcal{E}}, P_{-i}); T)$; {$T$: a predefined parameter for SAP}
  end if
until Converge to NE
return P_i

The following part presents the analytical form of the best response.

If $P_D + P_{loss} + \sum_{i\in\mathcal{E}} P_i - \sum_{i\in\mathcal{G}} P_i > 0$, then for player $i \in \mathcal{G}$,

$$\begin{aligned}\frac{\partial u_i(P_i, P_{-i})}{\partial P_i} = -2\alpha_i P_i - \beta_i \\ -\lambda(2 \sum_{j\neq i, j\in\mathcal{G}} B_{ij} P_j + 2B_{ii} P_i + B_0 i - 1)\end{aligned} \tag{21}$$

$$\frac{\partial^2 u_i(P_i, P_{-i})}{\partial P_i} = -2(\alpha_i + \lambda B_{ii}) < 0 \tag{22}$$

From (21) and (22), we can infer that the stationary point of $u_i(P_i, P_{-i})$ should be a local maximum. So by Fermat's theorem, global extrema must occur on the boundary or at stationary points. That is the best response in this case should check boundary and stationary points.
for player $i \in \mathcal{E}$,

$$\frac{\partial u_i(P_i, P_{-i})}{\partial P_i} = \frac{\eta e^{(-P_i + \rho \hat{P}_i)}}{(1 + e^{-P_i + \rho \hat{P}_i})^2} - \lambda < 0 \tag{23}$$

When $\lambda \gg \eta$, (23) is always less than 0 and $u_i(P_i, P_{-i})$ is monotone decreasing. So We can deduce that the global extrema must occur on the boundary, which means there exists best response on the boundary.

Similarly, we can investigate the analytical form of the best response if $P_D + P_{loss} + \sum_{i \in \mathcal{E}} P_i - \sum_{i \in \mathcal{G}} P_i < 0$ and here we no longer elaborate on it.

V. Simulation Results

In this section, we validate the effectiveness of our algorithm in Matlab. We assume that our algorithm is applied to the distribution system where there are two different kinds of aggregator as shown in the Fig. 1: 3 home aggregators and 12 commercial aggregators. The charging rate for the former is 10 kW and the one for the latter is 100 kW. 15 generators whose parameters are given in table I and table II are considered.

TABLE I
Generators Data of The 15-Generator System

i	$\underline{P}_i$	$\overline{P}_i$	α_i	β_i	γ_i	UR_i	DR_i	P_i^0
1	150	455	0.000299	10.1	671	80	120	400
2	150	455	0.000183	10.2	574	80	120	300
3	20	130	0.001126	8.8	374	130	130	105
4	20	130	0.001126	8.8	374	130	130	100
5	150	470	0.000205	10.4	461	80	120	90
6	135	460	0.000301	10.1	630	80	120	400
7	135	465	0.000364	9.8	548	80	120	350
8	60	300	0.000338	11.2	227	65	100	95
9	25	162	0.000807	11.2	173	60	100	105
10	25	160	0.001203	10.7	175	60	100	111
11	20	80	0.003586	10.2	186	80	80	60
12	20	80	0.005513	9.9	230	80	80	40
13	25	85	0.000371	13.1	225	80	80	30
14	15	55	0.001929	12.1	309	55	55	20
15	15	55	0.004447	12.4	323	55	55	20

TABLE II
Prohibited Zones of Generators

i	**Prohibited Zones (MW)**
2	[185 225] [305 335] [420 455]
5	[180 200] [305 335] [390 420]
6	[230 255] [365 395] [430 455]
12	[30 40] [55 65]

The solution under near-full loading levels to the SWO problem shown in table III is based on the formulation with $\lambda = 3000$, $\eta = 15$ and $T = 80000$. It should be noted that the setting of η is critical to the performance of our algorithm. An appropriate setting should satisfy the following condition:

$$\eta < 4 \min \{2\alpha_i \underline{P}_i + \beta_i, i \in \mathcal{G}\} \tag{24}$$

Figure 2 shows simulation results.

- Fig. 2(a) shows that the global potential function increases quickly and converge to a near steady final value after around 50 iterations;
- Fig. 2(b) shows that the total social welfare of all EV aggregators and generating units converges along with the global potential function;

TABLE III
Solutions Under Near-full Loading Level

i	ρ_i	$\hat{P}_i$	$P_{i \in \mathcal{G}}$	n_i
1	1	13	449.68	999
2	1	12.5	378.97	1235
3	1	13	128.06	738
4	1	9	128.12	57
5	1	10	167.99	64
6	1	10	459.53	99
7	1	6	429.65	35
8	1	8	157.42	70
9	1	10	149.64	97
10	1	9	155	59
11	1	10	77.32	91
12	1	9	75.75	89
13	1	10	80.16	58
14	1	8	47.73	48
15	1	10	49.44	88

- Fig. 2(c) shows that the total utility of all EV aggregators decreases along with the decrease of the total EV charging demand, which is shown in Fig. 2(e);
- Fig. 2(d) shows that the total generator cost drops along with the decrease of of the total EV charging demand shown in Fig. 2(e) as well as the total generation shown in Fig. 2(i);
- Fig. 2(e) shows that EV aggregators have participated in DR in terms of reducing total charging demand, although it decreases EVs' total utility;
- Fig. 2(f) shows the player which is randomly selected at each iteration of the SAP learning process;
- Fig. 2(g) shows that the total generation drops as EV aggregators participating in DR to reduce peak demand;
- Fig. 2(h) shows that the total transmission loss converges as the SAP learning in progress;
- Fig. 2(i) shows that the total load/demand drops as EV aggregators participating in DR;
- Fig. 2(j) shows that the power balancing converges as the SAP learning in progress.

VI. Conclusions and Future Work

This paper presented a novel non-cooperative strategic game-theoretic framework to model EV and enable their participation in integrated SWO problem. Both EV aggregators and generating units act as selfish and independent players with focus on only its own benefits. The SWO problem is formulated as a potential game with SAP applied to for the players to learn and react in the proposed game. The proposed SWO game can be solved by SAP with guaranteed convergence to a NE which is also a global optimizer to the SWO problem. Simulations on a 15-bus IEEE network were conducted to validate the framework.

For future work, the proposed formulation can be improved with more effective way to handle the power balance equality

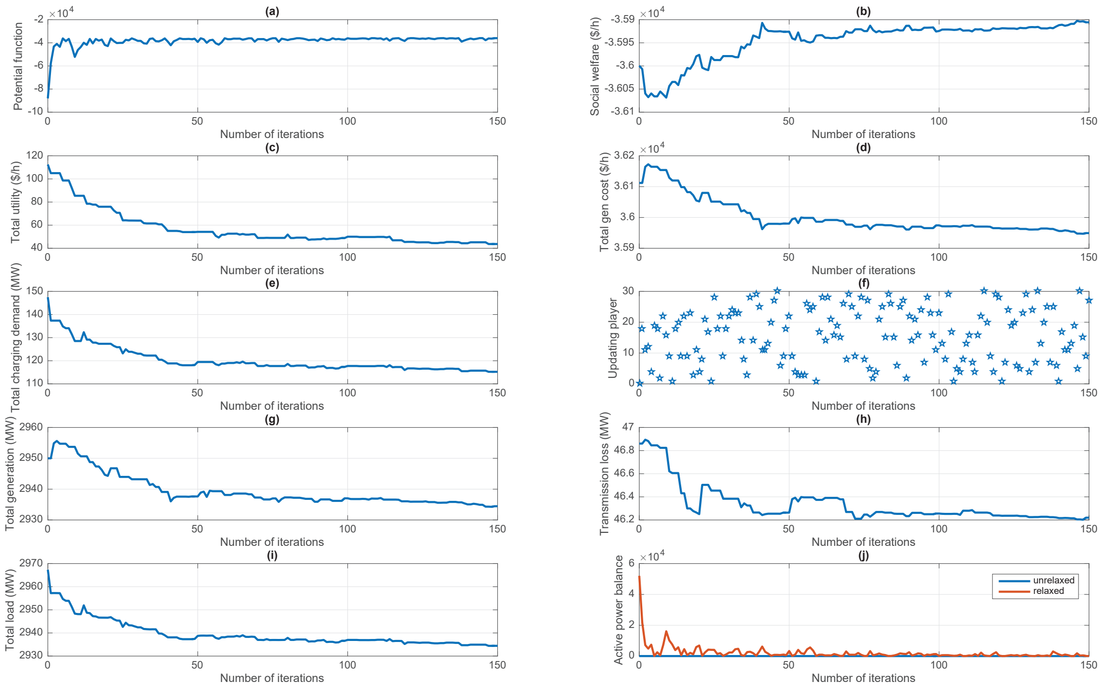

Fig. 2. Update of all indicators of the near full-load scenario

constraints. Also, the proposed formulation can be extended to vector-based action profiles to consider a long-duration SWO problem. Finally, the proposed formulation can be combined with data-driven EV charging profiles identification and forecasting to achieve accurate large-scale EV management and incorporation of EV charging profiles into future Distributed Energy Resource Management Systems (DERMS).

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