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Vehicle-to-Grid Integration for Enhancement of Grid: A Distributed Resource Allocation Approach

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ABSTRACT In the future grids, to reduce greenhouse gas emissions Electric Vehicles (EVs) seems to be an important means of transportation. One of the major disadvantages of the future grid is the demand-supply mismatch which can be mitigated by incorporating the EVs into the grid. The paper introduces the concept of the Distributed Resource Allocation (DRA) approach for incorporating a large number of Plug-in EV (PEVs) with the power grid utilizing the concept of achieving output consensus. The charging/discharging time of all the participating PEVs are separated with respect to time slots and are considered as strategies. The major aim of the paper is to obtain a favorable charging strategy for each grid-connected PEVs in such a way that it satisfies both grid objectives in terms of load profile smoothening and minimizing of load shifting as well as economic and social interests of vehicle owners i.e. a fair share of the rate of charging for all connected PEVs. The three-fold contribution of the paper in smoothening of load profile, load shifting minimization, and fair charging rate is validated using a representative case study. The results confirm improvement in load profile and also highlight a fair deal in the charging rate for each PEV.

INDEX TERMS Distributed resource allocation, plug-in electric vehicle, output consensus problems.

I. INTRODUCTION

In the future smart grids, electric vehicles (EVs) offer more attractive transportation options in concern with increasing gasoline prices and environmental issues [1], [2]. In the case of plug-in hybrid EVs (PHEVs) for powering the electric motor, batteries are used whereas, in the case of an internal combustion engine the power is supplied using different fuel such as diesel or gasoline. The plug-in EVs (PEVs) can be operated in two possible operating modes, one in grid-to-vehicle (G2V) mode wherein the vehicle uses power from the grid to charge batteries and other in vehicle-to-grid (V2G) mode in which the grid receive power by discharging the vehicle's batteries [3]. The introduction of the V2G concept has captivated curiosity from grid operators as well as PEVs owners. However, for realizing the benefits of the V2G concept convenient recharging options and availability of electricity supplies are mandatory. In the V2G concept, the residual energy of the EV batteries is generally utilized for facilitating the requirement of grids.

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The total charging demand of EVs when integrated into the grid constitutes a significant load. The total load on grid increases by an average of 18% due to EVs charging and this unpredictable load lead to the unreliability of the grid [4], [5]. In [6], the recharging time of EV and its effects on utilities was studied. The effects of batteries long charging cycle were highlighted by [7]. To avoid peak load time intervals of load cycles a time-shifted fast charge at night time is proposed by [8]. Designing appropriate controllers for stabilization of frequency and modeling of PHEVs with a micro-grid system was studied in [9].

The enhancement of power grid operating conditions such as increasing load factor and reducing power losses by determining the optimal charging profile is claimed by [10]. In [11], an optimization technique based on a genetic algorithm for maximizing the benefits of EVs batteries utilization as an energy storage system in the grid was presented. In a V2G market, the authors of [12] highlighted the modeling of interactions among aggregators and EVs. For charging pattern, an optimization mechanism to concurrently minimize the total degradation of battery health and also the total cost of fuel and electricity over a naturalistic drive cycle of 24 hours was derived by [13].

With the introduction of V2G technology various services with respect to grid like valley-filling [14], peak shaving [14], [15], compensating reactive power [16], [17], regulation of voltage and frequency [18], [19], and spinning reserve [20] can be achieved. In view of grid peak shaving, the power loss of the distribution network reduces, power quality improves, with a probable increase in the life of transformers. With these improvements, utilities can handle more number of loads without any further extension in the existing network.

In a centralized approach of energy trading [21], [22] a control center or aggregator is responsible for coordinating the discharging of each EVs to meet the demand of network. This approach results in a bidirectional flow of power between the PEVs and the aggregator. However, in contrast to the centralized approach, EVs can decide its own discharging pattern in case of the decentralized approach [23]–[25]. The authors in literature [14], [15], [26]–[28] highlighted the strategies available for peak shaving, wherein [15] and [26] a decentralized approach was adopted for PEVs discharging strategies. However, these approaches fail to guarantee the desired peak shaving, and hence there is a strong need for well-coordinated charging/discharging strategies. The V2G schemes described in [14], [27], [28] supplies the load demand by discharging PEVs into the grid with proper tracking of the reference line (load demand). The peak shaving achieved in [27] is limited whereas, in the case of [14], [28] the satisfactory performance of the algorithm is only possible if there is a high penetration of PEVs. In [29] an algorithm for peak shaving is proposed which provides desired characteristics even at low penetration rates of PEVs. Similarly, [30] designed an algorithm for the implementation of the V2G concept with the consideration of reactive power management. Moreover, the authors of [14] and [28] fail to incorporate PEV stochastic nature in terms of mobility leading to inaccurate tracking of the reference line. Furthermore, literature [14], [15], [26], [28] overlooks the requirement of minimum charge required for PEVs to drive back in case of an emergency.

As described in [23] and [31] for a decentralized approach, the complete system is divided into small sub-parts, where each small sub-parts based on the information available from the rest of sub-parts of the complete system solves an optimization problem. One of the methods which utilize such an approach is the Distributed Resource Allocation (DRA) which uses output consensus. In DRA, for achieving a desirable global state the sub-parts coordinate with each other and make decisions based on the information available locally. The authors in [32] and [33] has explored the DRA approach for PEV integration with the grid, however, the number of PEVs considered is only six.

In this article, the problem of finding the optimal charging strategy of the large number of PEVs integrated with a microgrid is considered. PEVs are connected to the microgrid for charging their batteries to the desired capacity. The microgrid supplies power to residential and industrial regions in addition to the charging of PEVs. The concept of DRA is used to calculate the optimal charging strategy of each PEV taking into consideration the load profile smoothening of the grid. A payoff function is formulated for each PEV using smoothening and commitment factors such that reaching of consensus of payoff function of every PEVs gives us the optimal charging strategy in terms of objectives of the grid such as load profile smoothening and prevention of load shifting. The commitment factor is decided by each PEV individually and the smoothening factor is decided by the utility grid.

The major contributions of the paper are as follows:

i) DRA approach is applied to obtain a charging strategy that guarantees smoothening of load profile considering all PEVs plugged into the microgrid.
ii) By implementing the error variable in the defined payoff function for the DRA approach gives a fair deal to each PEV with respect to charging rates based on their commitment factors.

The rest of the paper is organized as follows: Section II focuses on the problem statement and the associated analogies for the DRA approach. Section III introduces the prerequisite for understanding the load management problem. Section IV presents the features of the DRA approach considering the output consensus. Section V highlights the proposed approach application for PEV load management. Section VI provides the representative case studies and results to confirm the claim and Section VII concludes with the possible future extension of the work

II. PROBLEM STATEMENT AND ANALOGIES

For supplying power to two different types of customers i.e. fixed and transient as shown in Figure 1 a distribution type of transformer has been considered. The industrial regions and occupational areas are considered fixed customers and have a load profile which is constant for a long-period of time. In contrast, PEVs are designated as transient customers and have load profile varying with respect to time.

In view of electricity demand variation, for different time instants, different payoff functions are proposed thus there are k time slots for equivalent k different payoff functions and also a PEV charger can be a single-phase or three-phase. Consider an array A where each element represents the active power supplied to the customer by the grid at time slot k. The elements of arrays A is given as follows:

$$A_k = a_k + \sum_{i=1}^{N} x_k^i / t_k^i \tag{1}$$

where a_k represents active power supplied by the distribution transformer at k^{th} time slot when no PEVs are present. Similarly x_k^i represents active power of i^{th} PEV at time slot k.

For the energy population, the proposed analogies can be illustrated in terms of strategies [34]. In short, there are k strategies that depend on the values of k, where each strategy

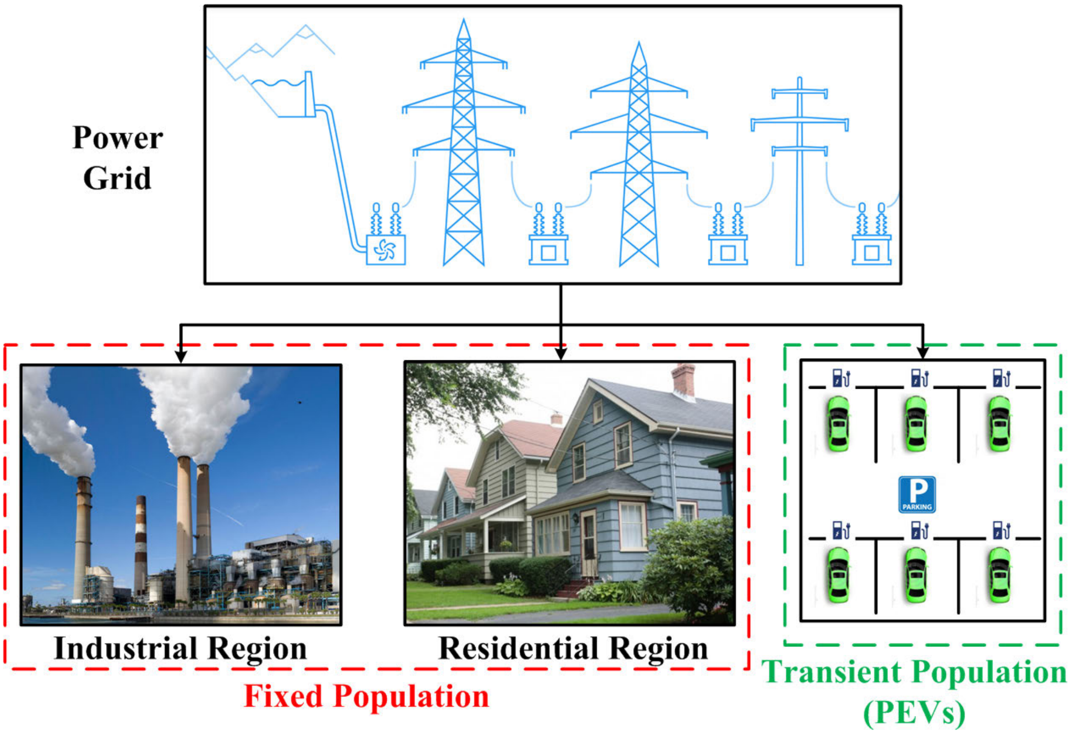

FIGURE 1. The connection of Power Grid with the transient and fixed population.

provides a defined payoff so that individuals can settle on it. As described earlier, fixed customers have strategies constant over a period of time. However, transient customers have the goal of minimizing their cost by changing their strategies from time to time and hence described as transient. In order to satisfy its objectives PEVs if required can discharge their batteries for a certain time period. The discharged energy of the PEV with help of grid can be supplied to the fixed population and in return, the part of the payoff for that particular time slots will be provided to defined PEV. This results in the transient population forcing a fixed population for mitigating to other strategies. Even though the time changes, the whole population covering all strategies remains the same.

As the grid has imposed different payoff functions for different time slots, it is desired to compute the energy consumption of each PEV for different time slots in such a way that all the PEVs act together for providing the grid with several beneficiary services. The beneficiary services range from grid load profile smoothening and load shifting minimization as well as obtaining the fair share of charging scheme where each PEV is able to get their rate of charging close to their expected rate of charging in the defined time frame.

III. PRELIMINARIES FOR DRA APPROACH AND BARRIER FUNCTION FORMULATION

A. GRAPH THEORY

The multi-agent system considered in the paper allows the agents to exchange their information using a communication graph which is modelled with the help of a graph. The triplet $\mathcal{C} = (\mathcal{S}, \mathcal{L}, \mathcal{A})$ is used for the mathematical representation of the graph. In the graph, the set of nodes is represented by $\mathcal{S} = \{1, ..., K\}$, the set of edges connecting the nodes is represented by $\mathcal{L} \subseteq \mathcal{S} \times \mathcal{S}$ and $\mathcal{A}$ represents a $K \times K$ non-negative matrix. The values of the elements of $\mathcal{A}$ are such that $a_{kj} = 1$ for all $(k, j) \in \mathcal{L}$, and $a_{kj} = 0$ for all $(k, j) \notin \mathcal{L}$. The agents and communication channels of the multi-agent system are represented by the nodes and edges of the graph respectively. Hence, agents k and j are connected and can communicate with each other if and only if $(k, j) \in \mathcal{L}$. The neighbours of node k i.e. all the nodes that can communicate and share information with node k are represented by $\mathcal{N}_k = \{j \in \mathcal{S} : (k, j) \in \mathcal{L}\}$.

The following assumptions are considered for the graphical modeling of the multi-agent system:

i) $a_{kk} = 0 \quad \forall k \in \mathcal{S}$ i.e. no self-loops are present.
ii) $a_{kj} = a_{jk}$ i.e. communication channels are bidierctional.

The matrix $L(\mathcal{C}) = [l_{kj}]$ is the $K \times K$ graph Laplacian matrix of $\mathcal{C}$ and can be defined as follows:

$$l_{kj} = \begin{cases} \sum_{j \in \mathcal{S}} a_{kj}, & \text{if} \quad k = j \\ -a_{kj}, & \text{if} \quad k \neq j \end{cases} \tag{2}$$

B. SYSTEM PASSIVITY STRUCTURE

The convergence of the DRA algorithm using consensus protocol can be done utilizing the concept of the passivity framework. The concept of passivity theorem as described in [35] is given as follows.

A dynamical system can be represented by the state model as follows:

$$\begin{aligned} \dot{x} &= f(x, u) \\ y &= h(x, u) \end{aligned} \tag{3}$$

where $f : R^n \times R^p \rightarrow R^n$ is locally Lipschitz, $h : R^n \times R^p \rightarrow R^p$ is continuous, $f(0,0) = 0$, and $h(0,0) = 0$. The total number of inputs of the system is equal to the total number of outputs. The system represented by (3) would be passive if there exists a continuously differentiable positive semidefinite function $V(x)$ (called storage function) such that

$$u^T y \geq \dot{V} = \frac{\partial V}{\partial x} f(x,u), \quad \forall (x,u) \in R^n \times R^p \tag{4}$$

Moreover, it is said to be

- lossless if $u^T y = \dot{V} \quad \forall (x,u) \in R^n \times R^p$.
- strictly passive if $u^T y \geq \dot{V} + \psi(x)$ for some positive definite function ψ, and for $\forall (x,u) \in R^n \times R^p$.

C. BARRIER FUNCTION FRAMEWORK

In many practical applications, limited resource availability, system design limitations, etc. impose various restrictions on the state of system. Hence, for the proper operation, it is crucial that the dynamics evolution (3) should be bounded to predefined feasible region of the state space. Consider constraints in the form of upper and lower bound on the state value x given as (l, m). To incorporate this constraint, this article utilizes barrier formulation $\beta(x)$ provided in [36].

$$\beta(x) = \frac{1}{l-x} + \frac{1}{m-x} \tag{5}$$

The barrier function $\beta(x)$ has the following properties:

- $\beta(x)$ is monotonically increasing continuous function defined in (l, m).
- $\beta(x) \rightarrow -\infty$, when $x \rightarrow l$.
- $\beta(x) \rightarrow \infty$, when $x \rightarrow m$.

Barrier function is considered as the derivative of a convex function which obstructs the control signal from violating its feasible domain.

IV. FEATURES OF DRA

A multi-agent system of n agents is considered which is connected by a communication network. The weighted graph $\mathcal{C} = (\mathcal{S}, \mathcal{L}, \mathcal{A})$ is used to characterize this system. The dynamical model of the system is represented by the following differential equations:

$$\Gamma_k^S : \begin{cases} \dot{x}_k = f(x) \\ y_k = g(x) \end{cases} \tag{6}$$

where the system as a whole is represented as Γ_k^S, the output of subsystem k is represented by $y_k \in R$ and the state of subsystem k is represented by x_k. Driving the system to a desired global state where grid objectives are met is the main objective of all agents as mentioned in Section II and Section III. However, each agent has only partial information of the system. A situation is considered where the agent only knows the information of its output and the output of its neighbours i.e., the value of y_k and that of y_j for all $j \in \mathcal{N}_k$ is known by the k^{th} agent. The control law of each agent is formulated by utilizing all the available information which drives their $\dot{x}$. This is shown in the following equation:

$$\Gamma_k^C : \dot{x}_k = u_k(y_k, y_j), \quad \forall j \in \mathcal{N}_k \tag{7}$$

A. CONTROL OBJECTIVE

In many applications, the desired global state in a multi-agent system can be achieved by reaching consensus, i.e., all subsystems reaching the same output. Such problems are called output consensus problems. The definition of output consensus as defined in [36] is:

Definition 1: Consider the set of subsystems given in (6) and (7). It can be said that output consensus is reached if $lim_{t\rightarrow\infty} \mid y_k(t) - y_j(t) \mid = 0$, for all $i, j = 1, \ldots, n$ where $y_k(t)$ is the output of the subsystem i at time t.

In this article, output consensus is achieved utilizing the constraint applied to the state variables:

$$\sum_{k=1}^{n} x_k^i = X \tag{8}$$

where the sum of all the state values in the given time frame is represented by $X \in R$. The electrical energy transferred between the PEVs and the grid is represented by x_k^i and the total amount of electrical energy required to completely charge the battery of each PEV is represented by X. The control objective of the multi-agent system can be summarized as follows:

i) Satisfying the constraint (8).
ii) Driving (6) to output consensus.

B. DYNAMICS OF RESOURCE ALLOCATION

The desired global state is achieved by designing local control laws $u_1, u_2, \ldots, u_n$ to be applied to the multi-agent system. The proposed DRA dynamic equation is:

$$u_k(y_k, y_j) = \sum_{j \in \mathcal{N}_k} a_{kj}(y_j - y_k), \ \forall k = 1, \ldots, K \text{ and } \forall j \in \mathcal{N}_k \tag{9}$$

The constraint (8) easily satisfies (9) if following conditions are met:

i) $\sum_{k=1}^{K} x_k^i(0) = X$

ii) $\sum_{k=1}^{K} \dot{x}_k^i = 0$

C. CONVERGENCE TO OUTPUT CONSENSUS

The multi-agent system represented by (6) utilizing the control law (7) can be thought of as a feedback interconnection outlook as displayed in Figure 2. The proposed DRA dynamical equation (9) and its equilibrium point (x^*) of the feedback interconnection must satisfy the Statement 1 which is adapted from [36]:

Statement 1: Consider the feedback interconnection shown in Figure 2 having its equilibrium point at x^* and let the steady state output of Γ^S be $y^* = g(x^*)$. If $u(y_k, y_j) \quad \forall j \in \mathcal{N}_k$ is given by (9) and the communication graph $\mathcal{C}$ is connected, then $y_k^* = y_j^* \quad \forall k, j = 1, \ldots, K$ where y_k^* is the k^{th} element of the vector y^*. Using the definition of output consensus problem, Statement 1 states that if the equilibrium point x^* is asymptotically stable then the output consensus will be obtained. To check the stability of x^* the dynamics of Γ^S and Γ^C are expressed in error coordinates.

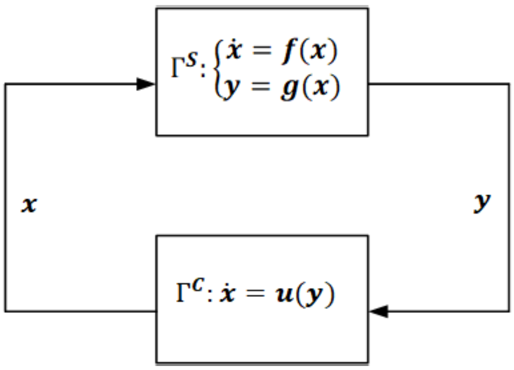

FIGURE 2. Representation of (6) and (7) via feedback interconnection outlook.

The system Γ^S is written in error coordinates as,

$$\Gamma^S_e : \begin{cases} \dot{e}_x = f^e(e_x) \\ e_y = g^e(e_x) \end{cases} \tag{10}$$

where $e_x = x - x^*$ and $e_y = y - y^*$. Also $f^e(e_x) = f(x)$ and $g^e(e_x) = g(x) - g(x^*)$ for all $x \in R^n$. Since x^* is an equilibrium point of (6), it can be seen that $f^e(0) = 0$, and $g^e(0) = 0$. Assumption 1 is made on (10):

Assumption 1: Consider the dynamical system (10). If $f^e(0) = 0$, then $e_x = 0$.

The *Assumption 1* guarantees the existence of unique rest points for (6). Similarly, the dynamics of (7) that implements (9) is also expressed in error coordinates using Laplacian of $\mathcal{C}$ as:

$$\dot{e}_x = -L(\mathcal{C})e_y \tag{11}$$

Now consider the Statement 2 given in [36] reformulated as:

Statement 2: The multi-agent system expressed in error coordinates given by (9) is passive and lossless from the input e_y to the output $-e_x$, if $x(0)$ and x^* satisfies the resource constraint (8), i.e., $\sum_{k=1}^{K} x_k^* = X$ and $\mathcal{C}$ is connected. The concept of passivity can be explored along with Statement 2 to validate the stability of equilibrium points of (6) as described in [36]. Feedback interconnection of two passive systems generally results in stable rest points. This property of passivity is utilized to ensure output consensus is achieved under the configuration as shown in Figure 2. The Theorem 2 adapted from [36] is used to summarize the requirements to reach output consensus.

Theorem 2: Consider the feedback interconnection of system (6) and (7) having its equilibrium point at x^* where (8) defines the $u(y)$. Following conditions are assumed:

i) The connectivity of the communication graph $\mathcal{C}$ of the system given by (7) is assured.
ii) The resource constraint (8) is satisfied by x^* and $x(0)$.
iii) Assumption 1 is satisfied by the system (6) expressed in error coordinates with respect to x^*. Moreover it is strictly passive from the input e_x to the output e_y with radially unbounded storage function.

Then (6) reaches output consensus.

V. APPLICATION OF DRA FOR LOAD MANAGEMENT OF PEV

Based on the proposed DRA dynamical equation (6)- (7) and properties of output consensus problem, the application of PEVs inclusion with a microgrid is presented.

A. PEV VARIABLES ENERGY CONSTRAINTS

The energy constraints listed are considered in the application of PEV incorporation similar to the constraints given in [34]

$$\sum_{k=1}^{K^i} x_k^i = soc_K^i - soc_0^i \tag{12}$$

$$x_k^i \leq \overline{soc}^i - (soc_0^i + \sum_{\omega=1}^{\Omega} x_\omega^i - x_k^i),$$
$$\forall \Omega = \{1, 2, \ldots, K^i\}, \forall k = \{1, 2, \ldots, \Omega\}, \tag{13}$$

$$x_k^i \geq \underline{soc}^i - (soc_0^i + \sum_{\omega=1}^{\Omega} x_\omega^i - x_k^i),$$
$$\forall \Omega = \{1, 2, \ldots, K^i\}, \forall k = \{1, 2, \ldots, \Omega\}, \tag{14}$$

$$-t_k^i \overline{p}^i \leq x_k^i \leq t_k^i \overline{p}^i, \quad \forall k = \{1, 2, \ldots, K^i\} \tag{15}$$

where soc_0^i represents initial state of charge (SOC) (in Watt-hour), soc_K^i is represented as desired SOC (in Watt-hour) at the end of time window, t_k^i is the length of k^{th} time step (in hours), and $\overline{p}^i$ is the nominal power of the charger. The constraint (12) can be considered equal to the state variable constraint define by (8). The constraints (13) and (14) describes the accumulated SOC for a particular time period and has a limitation for crossing upper limit $\overline{soc}^i$ and lower limit $\underline{soc}^i$. The constraint (15) defines the limits for energy consumption rate as well as injection rate by PEV which in turn depends upon the limits of charger and also on length of time steps.

B. OUTPUT FUNCTIONS FORMULATION

The payoff function of each time step would be the output function of this particular resource allocation problem. Payoff functions are defined in such a way that the objectives of both PEVs owner and grid are met simultaneously. In view of this, a commitment factor μ^i and a smoothing factor η are introduced. The commitment factor μ^i is controllable by the owners of PEV and gives a level of choice to them i.e. time duration in which PEV battery should be fully charged. The sudden variation in the profile of active power while transitioning from one time step to next is monitored by η, the parameter which is controlled by a power grid manager. These factors are defined as

$$\underline{\mu} \leq \mu^i < 1, \quad 0 \leq \eta \leq 1 \tag{16}$$

where $0 < \underline{\mu} < 1$ is defined as the minimum allowable limit of commitment. For strategies corresponding to active power the payoff functions are defined as:

$$f_k^i(x_k^i) = -(1-\mu)(x_k^i - x_k^{i*})/t_k^i - \mu\eta A_k$$
$$-\mu(1-\eta)(2A_k - A_{k-1} - A_{k+1}) \tag{17}$$

where x_k^{i*} is the desired charging rate of the PEV owner's at the k^{th} time step and the μ is the mean value of all μ^i.

The total output profiles, as well as the profile of active power, are affected by variation in the value of μ and η. When $\mu = 0$, then smoothening/flattening objectives are neglected, while payoff functions give importance to local references of load distribution. When $\eta = 0$ and $\mu > 0$, then importance is given to smoothening objective while flattening objectives are ignored. Lastly, when $\eta = 1$ and $\mu > 0$ then importance is given to flattening objectives while the smoothening objective is neglected. Thus it can be seen from the above cases that there is direct or indirect control of these parameters by a utility grid manager. These parameters are used as an agreement between grid objectives and also social and economic benefits to owners of PEV. For active power strategies the constraints (12)-(15) are incorporated in the output function by adding the barrier function developed in Section III-C to the payoff function described in (17) Thus, for active power strategies the modified output function is given as:

$$l_k^i(x_k^i) = f_k^i(x_k^i) + \beta(x_k^i) \tag{18}$$

For active power strategy:

$$x_k^i \in (a, b) \tag{19}$$

where

$$a \in max[\underline{soc}^i - (soc_0^i + \sum_{\omega=1}^{\Omega} x_\omega^i - x_k^i), -t_k^i \bar{p}^i] \tag{20}$$

$$b \in min[\overline{soc}^i - (soc_0^i + \sum_{\omega=1}^{\Omega} x_\omega^i - x_k^i), t_k^i \bar{p}^i] \tag{21}$$

The working of the barrier function to satisfy the constraints given in (12)-(15) for active power strategies can be understood from the example:

Assume the active power strategy x_k^i to be very close to the upper bound. As a result, the corresponding payoff function value will be higher than that of other function values. This is because $\beta(x_k^i)$ is present in the payoff function, given by (5), and is a monotonically increasing function that tends to $+\infty$ when x_k^i gets closer to the upper bound. $\dot{x}_k^i$ becomes negative (according to (7) and (9) when the above condition occurs and therefore the value of x_k^i will decrease and upper bound is not violated. As a result, it can be ensured that the proposed consensus algorithm does not generate a charging rate which is not feasible by the PEV batteries which would make the DRA approach using Consensus protocol not applicable to the present scenario.

C. INFORMATION CONNECTIVITY GRAPH OF PROPOSED PROBLEM

There are K strategies in the PEV power grid incorporation problem. For achieving output consensus as described in Section III-A, the connectivity of the strategies is necessary. The equations (1), and (17), governs the connectivity graph of the proposed strategies. An example of the connectivity graph is shown in Figure 3 for three PEVs connected to the grid, i.e., $i = \{1, 2, 3\}$ and grid providing payoff functions for four time slots i.e., $k = \{1, 2, 3, 4\}$ where (k, i) represents the strategy with k^{th} time slot for i^{th} PEV.

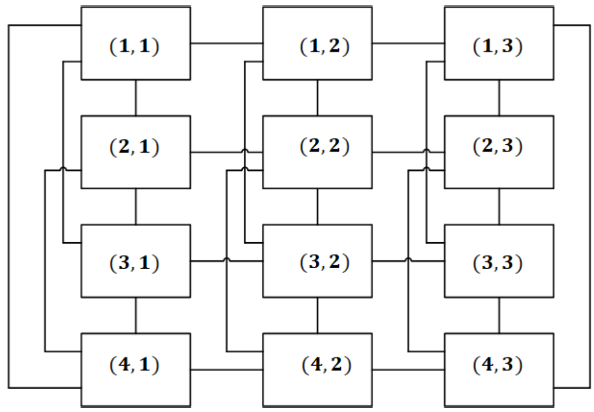

FIGURE 3. Partial information connectivity diagram for a system of three PEVs connected to the grid with grid providing payoff functions for four time slots.

The Figure 4 represents the implementation steps. The procedure initiates by determining the total number of PEVs involved in load sharing. Parking lot equipped with such charging functionalities can be one such scenario. Each participating PEV declares its SOC need along with its tendency do aid load sharing in terms of parameter values μ and η. The owner can decide these parameters based on various factors such as urgency, total parking period, required SOC, etc. Once all the parameters are finalized, the output function is calculated for each PEV over every time slot. Using this output function value each PEV then evaluates its charging and discharging strategies using the DRA algorithm. This process is repeated until the output consensus is reached.

VI. REPRESENTATIVE CASE STUDY AND RESULTS FOR GRID ENHANCEMENT USING PEVs

The representative case study comprises of virtual simulation for a fleet of 40 PEVs over the span of 24 hours. Every PEV is considered to arrive and depart from the charging station according to its own preference. Figure 5 represents the cumulative load profile and the respective feature is represented using the black horizontal segments in the start and at the end of every trajectory in Figure 6 which denotes the absence of the respective PEV due to late arrival and early departure, respectively. Moreover, each PEV is assumed to have different charging requirements. The minimum allowable state of charge $SOC_{downlimit}$ for every vehicle is bounded within the band $14kWh$ to $16kWh$ while the maximum limit of the batteries $SOC_{uplimit}$ is restricted between $18kWh$ and $20kWh$. The values of the initial SOC SOC_0 and desired SOC SOC_K for each PEV is bounded by its respective $SOC_{downlimit}$ and $SOC_{uplimit}$. Wherein, the value of SOC_K is greater than the respective PEV's SOC_0. Moreover, the charger power limit at any given instance is considered to be $3kW$.

In Figure 5, a comparison is provided between the DRA approach and constant rate approach wherein the PEVs are continuously charged at a constant rate. The load profile

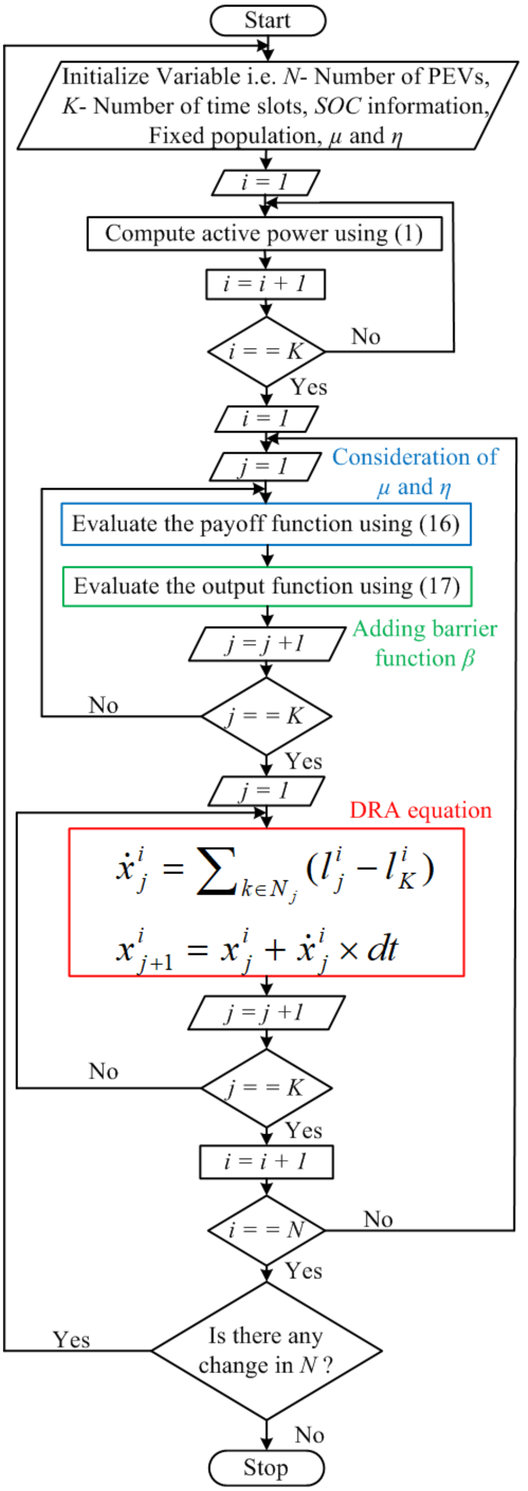

FIGURE 4. Flowchart for implementation of DRA approach in grid profile enhancement using PEVs.

in yellow specifies the outcome of the DRA implementation whereas the load profile in red represents the outcome of the application of a constant rate approach. The overall sedentary population in the absence of PEVs over the duration of 24 hours is represented by the blue color graph represents. In the approach with the constant charging rate, the discharging capability of batteries is not utilized. Compared to the

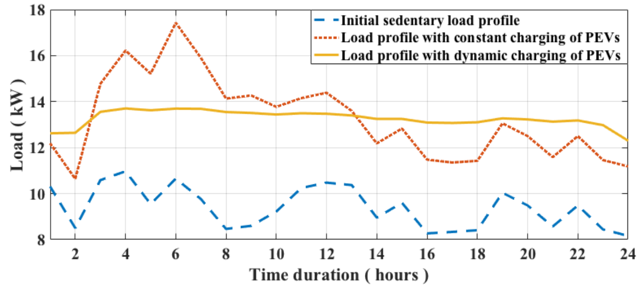

FIGURE 5. Cumulative load profiles.

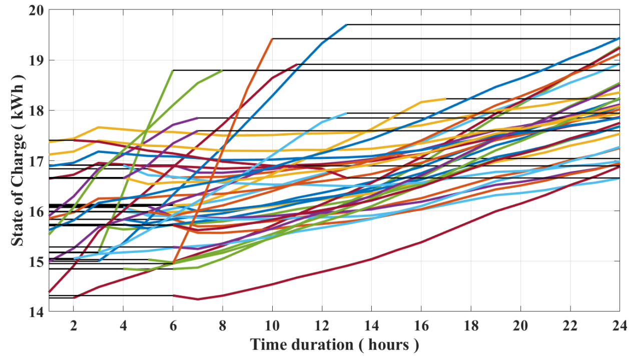

FIGURE 6. PEV charging and discharging profiles.

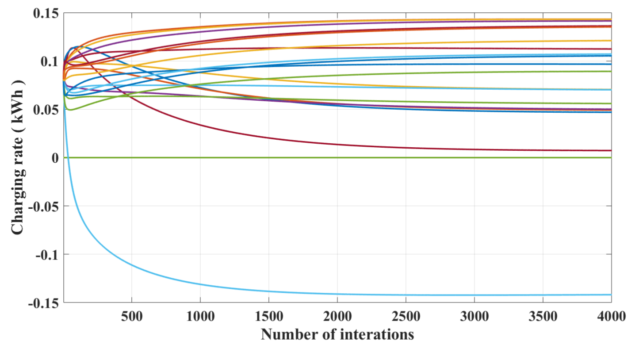

FIGURE 7. Charging strategies for different PEVs.

respective implementation result yellow the graph depicting the result of the DRA approach is smooth and flat. This approach not only charges but also discharges the PEV batteries to provide ancillary support to the grid. In Figure 6, it can be seen that not every trajectory is monotonous, the random troughs in the individual trajectory represent the process of battery discharging to share the high demand of the sedentary population, similarly, crest region represents the charging process of PEVs when the cumulative load on the grid is below average. The convergence of this approach is represented in Figure 7. In this, each line corresponds to the particular time slot, *i.e.* the total number of trajectories in Figure 7 is equal to 24.

A. IMPORTANCE OF DESIGN PARAMETERS μ AND η

The traditional way of charging with approximately constant charging rate results into the additive load at each time step as shown in Figure 5 red graph. This approach is referred to as customer-centric implementation because in this no

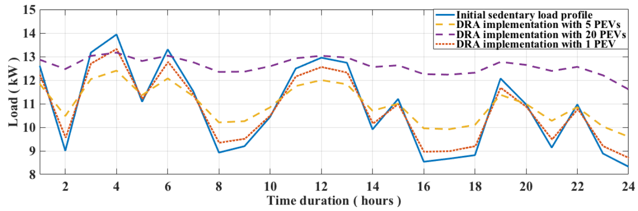

FIGURE 8. Effect of number of PEVs.

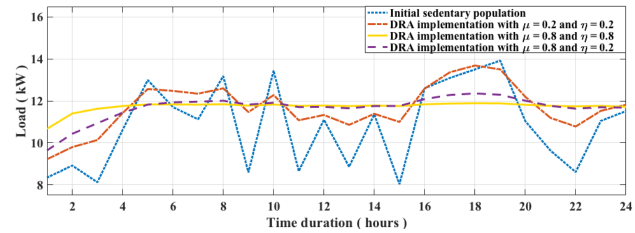

FIGURE 9. Variation in design parameters.

adjustments in the charging process are introduced to have smooth load variations over time. On the other hand, with the DRA methodology, it is possible to adjust charging behavior to have trade-off among the customer-centric implementation and grid assisting implementation. The careful selection of design parameter μ and η within the constraints (16) can provide different grid assessing implementation approaches while satisfying end-user requirements. Figure 9 shows one such implementation scenario. here, the yellow line represents the load profile after implementation of the DRA approach in which the flattening objective is maximized. On the other hand, the violet line represents DRA implementation in which the smoothening objective is preferred.

B. EFFECT OF NUMBER OF INTERACTING PEVs

The DRA exploits the availability of the total time period along with the lower and upper constraints of individual PEVs which allows PEV to not only be a power sink but also a power source. However, in comparison to the overall power grid load profile, the individual PEV contribution is minuscule due to the comparatively low operational band of $SOC_{downlimit}$ and $SOC_{uplimit}$. However, the number of participating PEVs increased their combined contribution can be quantified. In Figure 8 each plot corresponds to a different number of interacting PEVs aiding the power grid by constructing a smooth and flat load profile. In this case the value of design parameters μ and η is assumed to be 0.5 each. It is evident from (1) that as the number of PEVs increases, one obtained a comparatively more smooth and flat grid load profile.

VII. CONCLUSION

In this article, the incorporation of PEVs into the grid for overcoming the problem of demand-supply mismatch is addressed. The paper proposed an output consensus which is an application of DRA for managing distributed integral load of PEVs connected to the power grid. The concept of DRA and passivity approach is feasible for providing active power load and load shifting minimization through a fair scheme of PEV charging. The representative case study results highlight the effectiveness of the proposed approach in grid supply smoothening as well as confirms the desired performance in load management of PEV. The future aim is to conduct a case study considering variation in performance parameters of PEVs participating in grid enhancement activities.

APPENDIX

The following abbreviations are used in this manuscript:

Symbol	Description
$\mathcal{S}$	Set of nodes of a multi-agent system
$\mathcal{L}$	Set of edges connecting the nodes of a multi-agent system
$\mathcal{A}$	A nonnegative matrix whose elements satisfy the following: $a_{kj} = 1$ if $(k, j) \in \mathcal{L}$; $a_{kj} = 0$ if $(k, j) \notin \mathcal{L}$
$\mathcal{N}_k$	Set of neighbours of node k
A_k	Total active power supply of grid at k^{th} time slot
β	Barrier function
x_k^i	Active power charging strategy at k^{th} time step of i^{th} PEV
	of i^{th} PEV
K^i	Number of time steps allotted to i^{th} PEV
soc_K^i	Desired state of charge of i^{th} PEV
soc_o^i	Initial state of charge of i^{th} PEV
$\overline{soc}_o^i$	Upper limit of i^{th} PEV charger
$\underline{soc}_o^i$	Lower limit of i^{th} PEV charger
t_k^i	Time width of k^{th} time step of i^{th} PEV
$\overline{p}^i$	Nominal power of i^{th} PEV charger
μ	Commitment factor controlled by the PEV owner
η	Smoothing factor controlled by the power grid manager
s^i	Auxillary slack variable of i^{th} PEV

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