Dynamic Micro-Grid Selection by Plug-In Electric Vehicles in Smart Grid: An Evolutionary Game

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***Abstract*—In this work, the problem of dynamic micro-grid selection by the plug-in electric vehicles (PEVs) in smart grid is studied as an evolutionary game theoretic approach. In the proposed dynamic micro-grid selection game, named DMSG, each PEV chooses an optimal micro-grid for energy consumption with an optimum price. In DMSG, the PEVs act as the players and form the population. The micro-grids are considered as strategies. The amount of energy requested to each micro-grid is considered as the population share of the micro-grid. Each PEV selects the micro-grid, based on prediction, for charging, and decides the amount of energy to be consumed. Thereby, the PEVs select the Pareto optimal solutions and ensure the proper energy-load distribution. Through simulation, we observe that within 20-25 iterations, Pareto optimal solution is accomplished. Additionally, DMSG ensures proper distribution of energy demand of the PEVs, while the PEVs pay less.**

***Keywords*—Evolutionary Game Theory, Replicator Dynamics, Dynamic Selection, Plug-In Electric Vehicles, Smart Grid**

I. INTRODUCTION

With the integration of sustainable models of energy production, distribution, and usage [1], the traditional electrical grid is visualized to ensure high reliability, and termed as *smart grid*. In smart grid, a group of micro-grids serves a group of PEVs in a distributed manner, and relax the load on the main grid. In smart grid, each micro-grid uses renewable energy resources — biomass energy, solar energy, wind power, and geothermal heat for generating energy. Therefore, each micro-grid generates different amount of energy in each slot of a day. Therefore, the PEVs [2] either have to pay high or have to wait for a finite time duration to get energy service. In the last few years, a lot of research work on smart grid emerged, viz., [2]–[4]. Some existing works are discussed in this Section. Misra *et al.* [3] proposed a dynamic pricing scheme for PEVs. Farzan *et al.* [1] formulated a distributed energy management scheme for energy forecasting. Mondal *et al.* [4] proposed an energy management system, where users are equipped with storage devices. Mondal and Misra [2] have proposed to use a multi-leader multi-follower Stackelberg game for distributing the energy among the PEVs, non-cooperatively. However, there is need to design a cooperative scheme for PEVs, such that the Pareto optimal solution can be achieved by selecting a suitable micro-grid in a distributed manner.

In this paper, we introduce an *evolutionary game theoretic approach* for designing of *dynamic micro-grid selection* (DMSG) for PEVs in the presence of multiple predicted micro-grids in smart grid. We use a *dynamic evolutionary game* to select the appropriate strategies for the PEVs to choose the appropriate micro-grid in order to maintain the quality service and proper load distribution. On the other hand, the strategies for the micro-grids to maximize their profit by supplying the requested energy, while assuring proper utilization of the generated energy. The evolutionary equilibrium solution, i.e., Pareto optimal solution of DMSG is ensured. MDMS predicts the next location of each PEV and distributes the energy accordingly. On the other hand, each micro-grid evaluates the price per unit energy depending on the aggregated energy demanded by the PEVs using dynamic pricing.

II. SYSTEM MODEL

We consider an energy management system having multiple micro-grids and multiple PEVs. Each PEV can get connected to a single micro-grid for energy supply. Thereby, we consider that at time instant t, the set of PEVs getting energy service from micro-grid m is denoted as $\mathcal{V}_m$. Each PEV v having residual energy E_v^{res} chooses one of the available set micro-grids $\mathcal{M}_v$ calculated based on *order 2* ($O(2)$) *Markov predictor with fallback* [5] in the duration ΔT_v. We consider that the energy consumption rate for PEV v is denoted as $\alpha_v(\nu_v)$, while considering that the velocity of the PEV v is ν_v. We consider that each PEV v requests $x_v(t)$ amount of energy to micro-grids m. Hence, the total amount of energy requested $\mathcal{X}_m(t)$ to micro-grid m, which has generated $\mathcal{G}_m(t)$ amount of energy, follows the equations given below:

$$\mathcal{X}_m(t) = \sum_{v \in \mathcal{V}_m} x_v(t), \text{ and } \mathcal{G}_m(t) \geq \mathcal{X}_m(t) \tag{1}$$

In this work, in order to ensure proper distribution of requested energy among the micro-grids, we use a dynamic pricing mechanism [3] for deciding the price per unit energy $p_m(t)$, which is calculated as follows:

$$p_m(t) = A_m(\mathcal{X}_m(t))^2 + B_m\mathcal{X}_m(t) + C_m \tag{2}$$

where A_m, B_m, and C_m are constants for micro-grid m.

III. PROPOSED DMSG GAME

To study dynamic micro-grid selection by the PEVs, and the energy trading between the PEVs and the micro-grids, we use an *evolutionary game theoretic* approach [6]. In the proposed dynamic micro-grid selection scheme, named DMSG, we consider that the PEVs are the players and form the population of DMSG. Using DMSG, we propose to distribute the total population among the available strategies. On the other hand, the micro-grids are considered as the strategies.

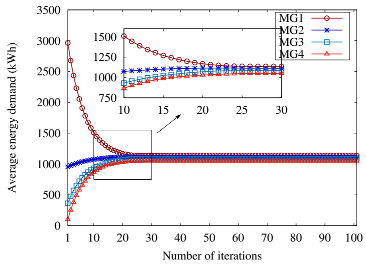

Fig. 1: Energy Demand using DMSG

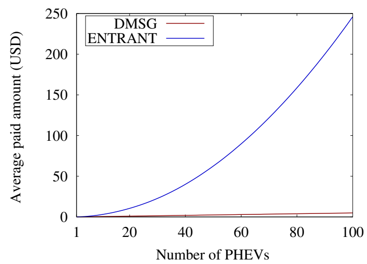

Fig. 2: Price Paid by the PEVs

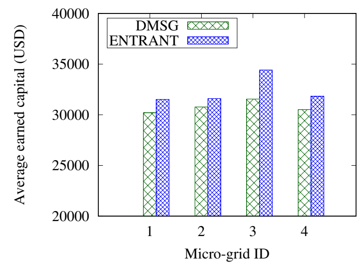

Fig. 3: Profit per Micro-Grid

We define the population share of micro-grid m as follows:

$$\omega_m(t) = \mathcal{X}_m(t) / \sum_{m \in \mathcal{M}} \mathcal{X}_m(t) \quad (3)$$

1) Utility Function of a PEV: The utility function $\mathcal{U}_v(\cdot)$ signifies the satisfaction of a PEV v by consuming $x_v(t)$ amount of energy. In DMSG, each PEV tries to maximize its payoff, while ensuring that the transferable utility of the population gets maximized. The payoff of utility function $\mathcal{U}_v(\cdot)$ — (a) increases with the increase in $x_v(t)$, (b) decreases with the increase in p_m and satisfaction factor $\mathcal{S}_v(t)$, where $\mathcal{S}_v(t) = x_v(t)(E_v^{max} - E_v^{res})$ with constant λ. Hence, the utility function $\mathcal{U}_v(\cdot)$ of PEV v is defined as follows:

$$\mathcal{U}_v(\cdot) = E_v^{max} x_v(t) - \lambda \mathcal{S}_v(t) x_v(t)^2 - p_m x_v(t) \quad (4)$$

2) Utility Function of a Micro-Grid: The utility function $\mathcal{B}_m(\cdot)$ of micro-grid m signifies the profit of the micro-grid m earned by distributing $\mathcal{X}_m(t)$ energy, and defined as follows:

$$\mathcal{B}_m(\cdot) = \sum_{v \in \mathcal{V}_m} x_v(t) p_m(t) \quad (5)$$

Each micro-grid m tries to maximize its payoff value of $\mathcal{B}_m(\cdot)$, while satisfying the constraint given in Equation (1).

3) Replicator Dynamics of DMSG: Each micro-grid m acts as a replicator in the evolutionary game theory-based DMSG scheme. We define the replicator dynamics of the proposed scheme, DMSG, as follows:

$$\dot{\omega}_m(t) = \sigma \omega_m(t) \left(\mathcal{B}_m(\cdot) - \overline{\mathcal{B}}(\cdot) \right) \quad (6)$$

where σ is a constant. $\overline{\mathcal{B}}(\cdot)$ is the transferable utility of the micro-grids, where $\overline{\mathcal{B}}(\cdot) = \sum_{m \in \mathcal{M}} \mathcal{B}_m(\cdot) \omega_m(t)$.

IV. Performance Evaluation

For performance evaluation, we generated random values for initial locations of the PEVs over a terrain, as shown in Table I, using MATLAB simulation platform. We consider that each micro-grid calculates the real-time supply and energy demand of connected PEVs at the beginning of each time slot. The performance of DMSG scheme is evaluated by comparing with ENTRANT [2]. In ENTRANT, Mondal and Misra [2] proposed to use a multi-leader multi-follower Stackelberg game for distributing the energy among the PEVs. However, they have not considered cooperativeness of the PEVs.

Initially, each PEV selects one of the available micro-grids in DMSG. Thereafter, based on the replicator dynamics, the energy demand to each micro-grid gets modified in each iteration. From Figure 1, we observed that the energy demand to each micro-grid reaches to the evolutionary equilibrium within 20-25 iterations using DMSG. Additionally, we observed that strategy with high population share has a high rate of change in population share. From Figure 2, we observed that average price per unit energy reduces significantly using DMSG than using ENTRANT. On the other hand, the price decided by each micro-grid is almost same using DMSG as shown in Figure 3. However, the price per unit energy decided by each micro-grid while using ENTRANT varies significantly, due to varied the energy requested to each micro-grid.

TABLE I: Simulation Parameters

Parameter	Value
Simulation area	$10 \times 10\ km^2$
Number of micro-grids	4
Number of PEVs	1-250
PEV's requested energy	35-65 MWh
Micro-grid's generated energy	500-750 MWh
Generation cost per MWh energy	10-20 USD

V. Conclusion

In this paper, the evolutionary game theory-based DMSG scheme ensures proper load distribution in the presence of PEVs. We observed that Pareto optimal solution is accomplished using DMSG. The simulation results also show significant improvement. Future extension of this work includes understanding how the presence of storage devices at the micro-grid will influence the situation, where the PEVs are present with finite storage capacity. This work can be extended in the presence of malicious PEVs, which intend to increase the price per unit energy with the false-high energy demand.

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