DCoE: Game-Theoretic Dynamic Coalition Extension with Micro-Grid Failure in Smart Grid

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***Abstract*— To improve reliability in energy management of smart grid, micro-grids provides electricity without any interruption and reduces the load on the main grid. However, if a micro-grid fails and cannot provide energy, the load on the main grid increases. Hence, in presence of micro-grid failure, there is a need for proper energy management scheme for uninterrupted energy service with coalition extension. In order to address this problem, we design a scheme for the *dynamic coalition extension* (DCoE) in smart grid using evolutionary game theory. The competition among the micro-grids to share the energy load and make a profit in presence of micro-grid failure is constructed as a dynamic evolutionary game, and Pareto optimal solution is ensured as an evolutionary equilibrium. From the simulation, we yield that using DCoE, energy service to the customers are ensured with proper load distribution, while paying less up to 15%. Additionally, the evolutionary equilibrium is ensured with 17-19 iterations.**

***Index Terms*—Evolutionary Game, Replicator Dynamics, Coalition Extension, Grid Failure, Micro-Grid, Smart Grid**

I. Introduction

To ensure reliability of energy management systems, traditional electrical grids is visualized to integrate with sustainable models of energy production, distribution, and usage [1]–[3], and termed as *smart grid*. Additionally, it integrates advanced techniques such as advanced metering infrastructure (AMI), automatic meter reading (AMR), distributed energy resources (DER), energy management systems (EMS), intelligent electronic devices (IEDs), and plug-in hybrid electric vehicles (PHEVs) [4]. In traditional energy management, the main grid with a centralized system distributes energy unidirectionally to the customers. However, in the presence of duplex communication infrastructure in smart grid, the large-scale traditional electrical grid is divided into micro-grids [5] having bi-directional electricity exchange facility with the substation, and the main grid. In smart grid, each customer selects one micro-grid for getting energy supply in a distributed manner. Thereby, smart grid relaxes the load on the main grid. One of the important features in a smart grid is the demand-side energy distribution, which gives the opportunity for flexible energy demand according to the requirements of the customers.

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 energy of different amounts in each slot of a day. Hence, if a micro-grid fails to distribute energy due to malfunction, the customers connected with that micro-grid cannot get any energy service. Moreover, there is a need of addressing the problem of energy distribution in presence of micro-grid failure. Additionally, the customers, who are connected with the failed micro-grid, needs to be distributed properly among the available functional micro-grids in order to ensure quality of service (QoS). However, in existing literature, there is no such work, as of our knowledge, which considers the load distribution in the presence of micro-grid failure.

In this paper, we introduce an *evolutionary game theoretic approach* for designing the scheme, *dynamic coalition extension* (DCoE), in presence of micro-grid failure in smart grid. We use a *dynamic evolutionary game* to select the appropriate strategies for the customers to choose the appropriate micro-grid in order to maintain the quality service. 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. We find out the evolutionary equilibrium solution, i.e., Pareto optimal solution of the proposed scheme, DCoE. To reach the equilibrium, we propose a centralized algorithm for DCoE, where the meter data management system (MDMS) acts as a centralized coordinator. Each customer, who is earlier connected with the failed micro-grid chooses a new micro-grid for energy service. Therefore, population share of each micro-grid is the partial value of the total amount of energy requested by the customers associated with the failed micro-grid. Additionally, each micro-grid evaluates the price per unit energy depending on the aggregated energy demanded by the customers within the coalition using dynamic pricing. In summary, our contribution in this paper as follows:

i) We present the *dynamic coalition extension* (*DCoE*) scheme for energy service to the customers in the presence of a micro-grid failure in smart grid.
ii) Dynamic evolutionary game theory is used to decide the Pareto optimal strategies, while considering the proper energy distribution to the available micro-grids.

iii) To obtain the Pareto optimal solution of DCoE, we present a centralized algorithm based on dynamic evolutionary game theory. We ensure evolutionary equilibrium of the proposed scheme, DCoE.

II. Related Works

In the past few years, many research works on smart grid emanated, viz., [1]–[3], [6]–[17]. Some of the existing literature are discussed in this section. Misra *et al.* [6] proposed a dynamic pricing scheme for PHEVs. They proposed two different types of pricing policies — local and roaming. Farzan *et al.* [3] formulated a distributed energy management scheme, while forecasting the energy consumption model of the customers based on two different schemes such as an adaptive model for short-term and a historical-data analysis model for long-term load calculations. Kamyab *et al.* [11] studied two different non-cooperative algorithms for energy distribution having multiple service providers and multiple customers. In one algorithm, the price per unit energy is decided centrally. In the other algorithm, by knowing the price decided by the data center, customers decide the optimal load profile. Samadi *at al.* [13] proposed a game theoretic scheme where the excess energy generated by customers can be supplied to micro-grids having energy deficiency, which, in turn, helps the customers to maximize their profit. Mondal *et al.* [15] proposed an energy management system, where customers are equipped with storage devices. Each customer tries to consume energy for storage, which will supply the needful energy at on-peak hours. In another work, Mediwaththe *et al.* [16] proposed a system where customers are equipped with energy generation units. Excess energy generated by customers can be supplied to the grid or a centralized energy storage. However, none of these works considers un-interrupted energy management scheme with coalition extension in presence of micro-grid failure.

In contrast to the previous works, a dynamic game theoretic model is used in this paper to explore the effects of micro-grid failure, in the smart grid. We use the evolutionary game to develop the Pareto optimal solution for deciding the coalition extension of the well-performing micro-grids in a distributed manner.

III. System Model

We consider a energy management system with multiple micro-grids and multiple customers. Each customer is connected with a single micro-grid for energy supply. In case of a micro-grid failure, the customers connected with that micro-grid needs to be connected with the available nearby micro-grids. We consider that each micro-grid $m \in \mathcal{M}$, where $\mathcal{M}$ is the set of available micro-grids in a geographical area, and the connected customers getting service, i.e., $\mathcal{N}_m \subseteq \mathcal{N}$, where $\mathcal{N}$ and $\mathcal{N}_m$ are the set of customers and the set of customers connected with micro-grid m, respectively, form a coalition. Therefore, in case of micro-grid failure, the coalition associated with that micro-grid, i.e., $\mathcal{N}_m$, needs to be dispersed among the other available coalitions of other micro-grids, i.e., $(\mathcal{M} - \{m\})$, as shown in Figure 1. We consider that each customer $n \in \mathcal{N}$ has an energy requirement of $x_n(t)$ amount at time instant t. Therefore, at time instant t, the total energy requested to each micro-grid m, $\chi_m(t)$, is defined as follows:

$$\chi_m(t) = \sum_{n \in \mathcal{N}_m} x_n(t), \quad \forall m \in \mathcal{M} \tag{1}$$

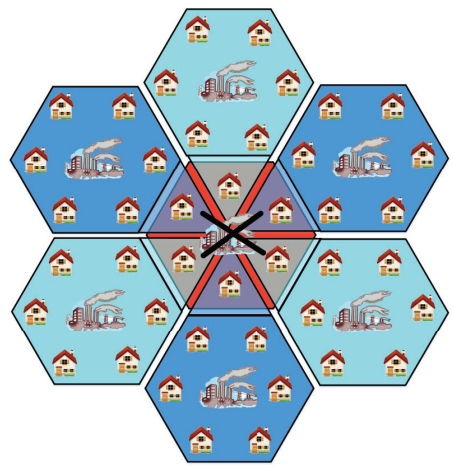

Fig. 1: Schematic Diagram of DCoE

Total energy requirement of $|\mathcal{N}|$ number customers is defined as follows:

$$\sum_{m \in \mathcal{M}} \chi_m(t) = \sum_{m \in \mathcal{M}} \sum_{n \in \mathcal{N}_m} x_n(t) \tag{2}$$

Equation (1) has to follow the following constraint:

$$\mathcal{G}_m(t) \geq \chi_m(t) \tag{3}$$

where $\mathcal{G}_m(t)$ is the amount of energy generated by micro-grid m at time instant t. $\mathcal{G}_m(t)$ varies in different time instant, as it only depends on renewable energy resources. Here, Equation (3) signifies that the amount of energy consumed by the connected customers cannot be more than the amount of energy generated by the micro-grid m. In case of failure of micro-grid m, the each customer $n \in \mathcal{N}_m$ has to choose a new energy service provider, i.e., new micro-grid $\tilde{m} \neq m$, in order to ensure uninterrupted energy service. We consider that the set of customers choosing micro-grid $\tilde{m}$ due to failure of micro-grid m is denoted as $\mathcal{N}_{m \to \tilde{m}}$, where $\mathcal{N}_{m \to \tilde{m}} \subseteq \mathcal{N}_m$. Hence, for each micro-grid $\tilde{m}$, the proposed scheme, DCoE, needs to ensure the following constraint:

$$\mathcal{G}_{\tilde{m}}(t) \geq \chi_{\tilde{m}}(t) + \sum_{n \in \mathcal{N}_{m \to \tilde{m}}} x_n(t) \tag{4}$$

On the other hand, the price per unit energy decided by micro-grid m, $p_m(t)$, is decided based on a dynamic pricing scheme [18], while considering the amount of energy requested to micro-grid m, i.e., $\chi_m(t)$. The price

per unit energy, $p_m(t)$, is calculated as follows:

$$p_m(t) = \mathcal{A}_m[\chi_m(t)]^2 + \mathcal{B}_m\chi_m(t) + \mathcal{C}_m \tag{5}$$

where $\mathcal{A}_m$, $\mathcal{B}_m$, and $\mathcal{C}_m$ are constants. Therefore, any micro-grid having high energy request will set the price per unit energy high. Thereby, among the micro-grids, the amount of energy consumed by the customers gets distributed properly. Additionally, the customers consume energy while paying less.

IV. Proposed Dynamic Coalition Extension Game

A. Game Formulation

To study the dynamics of coalition extension and interaction between the micro-grids and the customers, we use an *evolutionary game theoretic* approach [12]. In the proposed dynamic coalition extension scheme, named as DCoE, we consider that the micro-grids and customers generate the player pool. In DCoE, each micro-grid provides energy service to the customers and decides the price per unit energy to be paid the customers. On the other hand, each customer chooses the optimal micro-grid with optimum price per unit energy. The customers form a population of players. Additionally, the set of customers connected with each micro-grid forms *population share* of that micro-grid. We consider that customer $n \in \mathcal{N}$ chooses micro-grid $m \in \mathcal{M}$, and contributes in the population share of micro-grid m. Hence, we define the population share of micro-grid $m \in \mathcal{M}$, $\pi_m(t)$, as follows:

$$\pi_m(t) = \frac{\sum\limits_{n\in\mathcal{N}_m} x_n(t)}{\sum\limits_{m\in\mathcal{M}}\sum\limits_{n\in\mathcal{N}_m} x_n(t)} = \frac{\chi_m(t)}{\sum\limits_{m\in\mathcal{M}} \chi_m(t)} \tag{6}$$

In DCoE, we propose to distribute the total population, i.e., the energy demand of the customers connected with the failed micro-grid, among the available micro-grids. Therefore, we emphasize on developing a utility function for the customers in order to ensure that each micro-grid has an optimum population share. We define the utility function of each customer in the following section.

1) Utility Function of Each Customer: Utility function of each customer n, $\psi_{n,m}(t)$, signifies the payoff of customer for choosing micro-grid m. In the proposed scheme, DCoE, each customer tries to optimize his/her own payoff, while assuring the the payoff of each customer is same as the average payoff of the overall population. We define the utility function of each customer n, $\psi_{n,m}(t)$, as the difference of the quantized quality of service (QoS), i.e., $\mathcal{U}_{n,m}(t)$, and the price to be paid for consuming $x_n(t)$ amount of energy from micro-grid m, i.e., $\mathcal{P}_{n,m}(t)$. Mathematically,

$$\psi_{n,m}(t) = \mathcal{U}_{n,m}(t) - \mathcal{P}_{n,m}(t) \tag{7}$$

The quantized QoS function, $\mathcal{U}_{n,m}(t)$, varies proportionally with the amount of energy generated by micro-grid m, and the energy to be consumed, x_n. Additionally, value of the quantized QoS function, $\mathcal{U}_{n,m}(t)$, decreases with the increase in energy demand of the customers (except customer n) connected with the same micro-grid m, i.e., $\sum x_{i,m}$, where $\{x_{i,m}\} \in \boldsymbol{x}_{-n}$, and $\boldsymbol{x}_{-n} = \{x_{1,m}, x_{2,m}, \cdots, x_{n-1,m}, x_{n+1,m}, \cdots, x_{|\mathcal{N}_m|,m}\}$. Therefore, we consider that with the increase in total energy demand of the customer to the micro-grid, the payoff of the quantized QoS function decreases. Hence, we formulate $\mathcal{U}_{n,m}(t)$ as follows:

$$\mathcal{U}_{n,m}(t) = \mathcal{G}_m(t)x_n(t) - \frac{1}{2}\alpha_m[\chi_m(t)]^2 \tag{8}$$

On the other hand, the cost function, $\mathcal{P}_{n,m}(t)$, has a negative impact on utility function $\psi_{n,m}(t)$. Here, the cost function signifies the price to be paid by the customer n to micro-grid m by consuming $x_n(t)$ amount of energy. Additionally, the price per unit energy to be charged by micro-grid m is calculated using Equation (5).

$$\mathcal{P}_{n,m}(t) = p_m(t)x_n(t) \tag{9}$$

Hence, we get the utility function of customer n for choosing micro-grid m, $\psi_{n,m}(t)$, is as follows:

$$\psi_{n,m}(t) = \mathcal{G}_m(t)x_n(t) - \frac{1}{2}\alpha_m[\chi_m(t)]^2 - p_m(t)x_n(t) \tag{10}$$

2) Utility Function of Each Micro-Grid: For each micro-grid $m \in \mathcal{M}$, the utility function $\psi_m(t)$ signifies the overall payoff for providing energy service to $\mathcal{N}_m$ set of customers. Therefore, we define the utility function of micro-grid m, $\psi_m(t)$, as follows:

$$\psi_m(t) = \sum_{n\in\mathcal{N}_m} \psi_{n,m}(t) \tag{11}$$

With the increase in the payoff value of $\psi_m(t)$, the number customer served by micro-grid m increases. Thereby, the micro-grid earns high revenue by selling high amount of energy. Hence, from Equation (11), we get:

$$\psi_m(t) = \mathcal{G}_m(t)\chi_m(t) - \frac{|\mathcal{N}_m|}{2}\alpha_m[\chi_m(t)]^2 - p_m(t)\chi_m(t) \tag{12}$$

Definition 1. *The transferable utility is calculated with average payoff values of the utility function of the available micro-grids. Using the transferable utility, we consider the average payoff of the utility functions of the available micro-grids, in spite of considering the individual payoff of the micro-grids.*

Thereafter, in DCoE, we find the transferable utility, which is defined in Definition 1, for the available micro-grids $\mathcal{M}$. In DCoE, we define the transferable utility of the micro-grids, i.e., $\overline{\psi(t)}$, as follows:

$$\overline{\psi(t)} = \sum_{m\in\mathcal{M}} \psi_m(t)\pi_m(t) \tag{13}$$

Using the proposed scheme, DCoE, each micro-grid tries

to maximize the transferable utility of the micro-grids. In other words, DCoE ensures high revenue for each micro-grid, while maintaining the high quality of energy service with less price.

3) Replicator Dynamics of DCoE Scheme: We define a replicator for each micro-grid. Here, each replicator acts as a player in the evolutionary game theory based proposed scheme, DCoE. It evolves over time and has ability to reproduce itself. A replicator with high payoff value has a high preference. We model the behavior of a replicator using an ordinary differential equation, named *replicator dynamics*. We define the replicator dynamics of the proposed scheme, DCoE, as follows:

$$\frac{\partial \pi_m(t)}{\partial t} = \pi_m(t)[\psi_m(t) - \overline{\psi(t)}] \tag{14}$$

where $\frac{\partial \pi_m(t)}{\partial t}$ defines the change in population share of micro-grid m over time ∂t, i.e., $\lim_{\Delta t \to 0} \Delta t$, and $\pi_m(t)$ defines current population share of micro-grid m at time instant t.

B. Existence of Evolutionary Equilibrium Solution

We define the evolutionary equilibrium solution of the proposed scheme, DCoE, as the *Pareto optimal solution*. In DCoE, Pareto optimal solution, defined in Definition 2 is the set of tuples $< \{x_n^*(t), \boldsymbol{x}_{-n}^* | \ n \in \mathcal{N}_m\}, \ p_m(t) >$, where $\boldsymbol{x}_{-n} = \{x_{\tilde{n}} | n \neq \tilde{n}, \forall \tilde{n} \in \mathcal{N}_m\}$.

Definition 2. *The solution of DCoE, $< \ x_n^*(t), \boldsymbol{x}_{-n}^*, \ p_m(t) >$, is considered to be a Pareto optimal solution, if for every tuple $< \ x_n(t), \boldsymbol{x}_{-n}, \ p_m(t) >$, where $x_n \neq x_n^*$, we get:*

$$\psi_{n,m}(t)|_{x_n^*(t)} \geq \psi_{n,m}(t)|_{x_n(t)} \tag{15}$$

After obtaining the evolutionary equilibrium solution, we consider that there will be no change in players' strategies. Therefore, we get:

$$\frac{\partial \pi_m(t)}{\partial t} = 0 \tag{16}$$

From Equations (14) and (16), we get:

$$\psi_m(t) = \overline{\psi(t)} = \frac{\sum_{m \neq \tilde{m}} \psi_{\tilde{m}}(t) \pi_{\tilde{m}}(t)}{1 - \pi_m(t)} \tag{17}$$

For simplicity, considering that micro-grids m and $\tilde{m}$ are homogeneous in nature, we get that $\psi_m(t) = a(t)\chi_m(t) + b(t)[\chi_m(t)]^2 + c(t)[\chi_m(t)]^3$, where $a(t)$, $b(t)$ and $c(t)$ are constants; and $a(t) = (\mathcal{G}_m(t) - \mathcal{C}_m$, $b(t) = \mathcal{B}_m - \frac{|\mathcal{N}_m|}{2}\alpha_m$, and $c(t) = -\mathcal{A}_m$. Therefore, we get the evolutionary equilibrium points are as follows:

$$\chi_m(t) = \begin{cases} \frac{-(b+c\chi_{\tilde{m}}) + \sqrt{(b+c\chi_{\tilde{m}})^2 - 4c(a+b\chi_{\tilde{m}} + c_m[\chi_{\tilde{m}}]^2)}}{2c}, & \text{if } \chi_m(t) \neq \chi_{\tilde{m}}(t) \\ \chi_{\tilde{m}}, \quad \text{otherwise} \end{cases} \tag{18}$$

C. Algorithm

In order to reach the evolutionary equilibrium solution, each customers connected with the failed micro-grid needs to distribute themselves, and join coalition of other micro-grids available. Te dynamic coalition extension scheme, DCoE, handles the coalition extension in the presence of micro-grid failure using Algorithm 1. In DCoE, initially, each customer chooses a micro-grid randomly, and thereafter performs Algorithm 1. DCoE ensures proper distribution of the affected customers among the available micro-grids. Finally, using DCoE, we yield the optimal distribution vector of the affected customers, i.e., the population share at evolutionary equilibrium point.

Algorithm 1 Algorithm of the Proposed Scheme, DCoE

INPUTS:
- $x_n(t), \forall n$ ▷ Amount of energy requested by customer n
- $\mathcal{G}_m(t), \forall m$ ▷ Amount of energy generated by micro-grid m
- $\mathcal{A}_m, \mathcal{B}_m, \mathcal{C}_m, \forall m$ ▷ price constants from micro-grid m
- $\alpha_m, \forall m$ ▷ Utility constant factor of micro-grid m

OUTPUT:
- $\boldsymbol{\pi}(t) = \{\pi_1(t), \cdots, \pi_m(t), \cdots, \pi_{|\mathcal{M}|}\}$ ▷ Population share vector

PROCEDURE:

```
do
    for each m ∈ M do
        Calculate p_m(t) using Equation (5);
        Calculate π_m(t) using Equation (6);
        for each n ∈ N_m do
            Calculate U_{n,m}(t) using Equation (8);
            Calculate P_{n,m}(t) using Equation (9);
            Calculate ψ_{n,m}(t) using Equation (10);
        end for
        Calculate ψ_m(t) using Equation (11);
    end for
    Calculate transferable utility ψ̄(t) using Equation (13);
    for each m ∈ M do
        Calculate π̇_m(t) using Equation (14);
    end for
while (π̇_m(t) ≠ 0 | ∀m);
return π(t);
```

V. Performance Evaluation

A. Simulation Parameters

For performance evolution, we considered randomly generated values for the location of customers over the terrain, as shown in Table I, on a MATLAB simulation platform. For simulation, we consider the randomly generated values for amount of energy required for the customers and the amount of energy generated by the micro-grids, as shown in Table I. We vary the number of customers in the range of

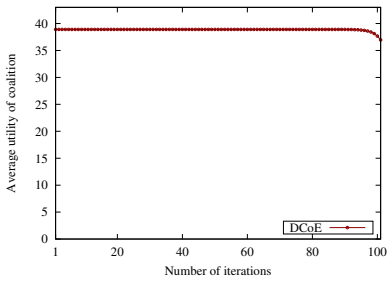

Fig. 2: Average Utility per Iteration

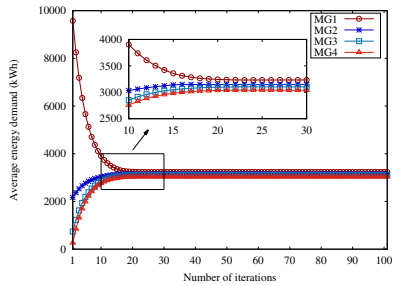

Fig. 3: Energy Demand per Iteration

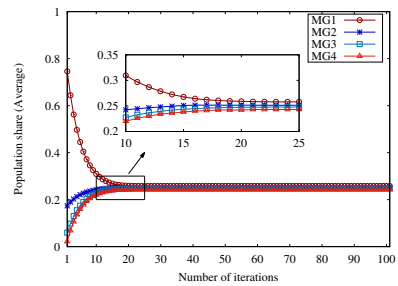

Fig. 4: Population Share per Iteration

100-250, and observe the change in profit and population share of each micro-grid.

TABLE I: Simulation Parameters

Parameter	Value
Simulation area	$10 \times 10\ km^2$
Number of micro-grids	5
Number of Customers	100-250
Customer's minimum requested energy	65 MWh
Customer's maximum requested energy	110 MWh
Micro-grid's minimum generated energy	500 MWh
Micro-grid's maximum generated energy	750 MWh
Generation cost per MWh energy	10-20 USD

B. Benchmark

The performance of the proposed scheme, DCoE, is evaluated by comparing with an scheme, WoDCoE, that is capable of coalition extension without any game theoretic approach. In WoDCoE, the customer, who belongs to the coalition of failed micro-grid, chooses the new energy service providing micro-grid based on the available energy, sequentially. However, WoDCoE does not use any game theoretic approach for coalition extension.

C. Performance Metrics

We have evaluated performance of the proposed scheme, DCoE, using following metrics.

Energy Demand: Amount of energy requested by the customers to the micro-grids. Here, the amount of requested energy to the micro-grids needs to satisfy the constraint that the micro-grid can not supply higher amount of energy than the amount of energy generated.

Population Share: In evolutionary game theory, we consider that the players or individuals form a population and decide their corresponding strategies. Thereby, the players choosing the same strategy contributes to the population share of that strategy.

Price to be paid: Each player tries to consume energy with high QoS and lower rate. Hence, each customer tries to minimize the price per unit energy to be paid for consuming energy from the micro-grids, and chooses the micro-grid for energy supply, accordingly.

Price per Unit Energy: The micro-grid decides the optimum price per unit energy in order maximize its revenue by selling the amount of generated energy to the customers. In DCoE, we consider that the price per unit energy decided by the micro-grids depends polynomially, while distributing the load among the available micro-grids in a proper fashion.

D. Results and Discussions

For simulation, we consider that each micro-grid calculates the real-time supply and energy demand of connected customers at the beginning of each time slot.

From Figure 2, we get that the average utility of the system is same in different iteration. However, we observe that the average utility reduces at the iterations close to 100 iteration. This is due to reduction in the energy requirement of the customers and the amount of energy requested to the micro-grids reduces at the same time. On the other hand, Figure 3 depicts that the customers choose the micro-grids for energy supply randomly. Hence, the average energy demand to each micro-grid varies significantly. However, within 17-19 iterations, the energy demand to the micro-grids reach the equilibrium. Hence, we claim that using the proposed scheme, DCoE, the customers reach the evolutionary equilibrium within a few iteration. Similarly, the population share of each micro-grid reaches evolutionary equilibrium with a few iteration as shown in shown in Figure 4. Hence, the proper load distribution is ensured using the proposed scheme, DCoE. Additionally, we observe that the change in population share of each micro-grid per iteration depends on the deviation from the average transferable utility. The population share of each micro-grid does not vary after reaching the evolutionary equilibrium point, which is a Pareto optimal solution of DCoE.

From Figure 5, we observe that using the proposed scheme, DCoE, the customers get the required energy while paying 12-15% less than using WoDCoE. On the other hand, we yield that the price per unit energy decided by the micro-grids are almost same using the proposed scheme, DCoE, as shown in Figure 6. However, the price decided per unit energy decided by the micro-grids using WoDCoE varies significantly. Though the schemes — DCoE and WoDCoE, use same polynomial equation while deciding the

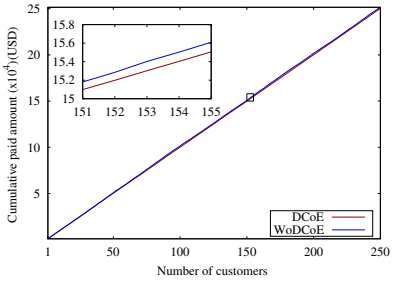

Fig. 5: Price Paid by Each Customer

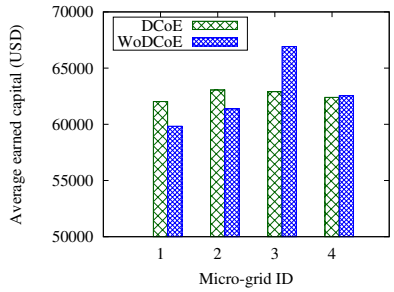

Fig. 6: Price Decided by Each Micro-Grid

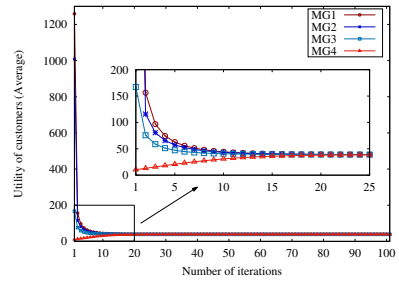

Fig. 7: Utility Value per Iteration

price per unit energy, using DCoE, the price per unit energy decide by the micro-grids is almost same, as the energy requested by the customers, who were earlier connected with the failed micro-grid, distributed properly among the available micro-grids. Figure 7 depicts the payoff value of the utility function of the micro-grids. From Figure 7, we observe that the payoff value reaches close to the equilibrium position within 10 iterations. However, using DCoE, 17-19 iterations are needed in order to reach the Pareto optimal solution.

VI. Conclusion

In this paper, we formulated an evolutionary game theoretic approach in oder to ensure proper load distribution in smart grid, in presence of micro-grid failure. Based on the proposed approach, DCoE, we yield that within 17-19 iterations, evolutionary equilibrium solution, i.e., Pareto optimal solution, is achieved. Additionally, the proposed scheme, DCoE, ensures proper distribution of the customers' demand, while paying less up to 15%. The simulation result also shows improved results.

Future extension of this work includes understanding how the presence of storage devices at the micro-grid end will influence the situation where the micro-grid fails to distribute energy. This work also can be extended while considering the presence of the plug-in electric vehicles (PEVs). Additionally, we can extend this work considering the infrastructure for vehicle to grid energy transfer in presence of PEVs and micro-grid failure.

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