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Changing the World's Energy Future

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Article

Evolutionary Game Dynamics between Distributed Energy Resources and Microgrid Operator: Balancing Act for Power Factor Improvement

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Abstract: This article investigates the intricate dynamics between Distributed Energy Resources (DERs) and the Microgrid Operator (MGO) within a microgrid interconnected with the main grid. Employing an evolutionary game framework, the study scrutinizes the strategic evolution of DERs' decision-making processes in their interactions with the MGO. Modeled as an evolutionary game, these interactions encapsulate the strategies adopted by DERs, resulting in stable equilibrium strategies over time. Motivated by direct benefits linked to increased active power production, DERs strive to sell all available power, while the MGO focuses on optimizing the microgrid's overall performance. The study assesses the microgrid's performance in terms of its power factor, emphasizing the strategic balance DERs must achieve in their active power generation to avoid penalization. This penalization results in decreased individual utility for DERs due to the overall power factor decrease resulting from their prioritization of active power generation. Additionally, the diminished overall power factor implies a decrease in MGO utility. The individual utility of each DER is further influenced by the strategies adopted by other DERs, impacting the penalization factor. Leveraging a modified IEEE 13-node distribution microgrid consisting of three DERs, the study presents case studies encompassing both cooperative and non-cooperative evolutionary game scenarios. These case studies illuminate the intricacies of interactions and the resulting equilibrium outcomes.

Keywords: distributed energy resources; evolutionary games; game theory; microgrids; power factor improvement

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1. Introduction

The integration of distributed energy resources (DERs) within microgrids has marked a pivotal shift in energy systems, introducing a paradigm where localized generation and consumption intertwine [1]. DERs, consisting of renewable energy sources, storage systems, and flexible loads, play a crucial role in enhancing the resilience and sustainability of microgrids [2]. These resources operate at smaller scales but interconnect within larger energy networks, poised to revolutionize energy generation and distribution dynamics. Amidst this transformative landscape, the strategic interactions between DERs and the microgrid operator (MGO) stand as a cornerstone [3]. These interactions delineate a complex interplay of decision-making processes, where DERs seek to maximize their individual benefits through active power generation, while the MGO endeavors to optimize the microgrid's overall performance, notably by improving its power factor. This strategic interdependence between DERs and the MGO forms the crux of this study, offering insights into the equilibrium strategies and evolutionary pathways that emerge from their interactions.

Evolutionary Game Theory (EGT), a specialized domain within game theory, serves as a crucial framework for dissecting the multifaceted interactions and evolutionary trajectories inherent in the relationship between DERs and the MGO. Fundamentally, game theory delves into mathematical models that elucidate strategic interplays among rational agents, offering invaluable tools to decipher intricate behaviors within interconnected economic settings [4]. EGT, as a methodological approach, navigates within the realm of limited rationality, spotlighting adaptive learning and strategic adjustments among participants [5]. Given the diversity in rationalities and learning capacities exhibited by these participants, the dynamic process of adjusting strategies demands a spectrum of selective mechanisms. Through its framework, EGT facilitates a quantitative exploration of how populations evolve their strategies over temporal scales, shedding light on the underlying dynamics [6]. In this context, evolutionary games emerge as the essential framework, providing a mechanism to capture the dynamic interplay, strategic adaptations, and equilibrium outcomes between DERs and the MGO in evolving energy landscapes.

Game theory and EGT have found diverse applications across various fields. In [7], an EGT-based approach was proposed to encourage collaboration among stakeholders involved in green retrofitting of China's commercial buildings. This method highlighted influential factors on developer and occupant behavior, stressing the importance of supportive policies, financial incentives, and enhanced life-cycle awareness for successful green renovations. Reference [8] investigated factors affecting the quality and safety of agricultural products within supply chains. It explored how stakeholder decisions, influenced by various parameters, affected their commitment to ensuring product quality. The study emphasized stakeholders' initial intentions and quality measure costs and highlighted the positive impact of governmental oversight, consumer feedback, and inspection penalties. In [9], the relationship between herders' livelihood constraints and grassland degradation was examined using an evolutionary game model involving local governments and herders. The paper highlighted that achieving an ideal equilibrium relied on proactive government regulation and moderate herder grazing. It stressed that policies supporting livelihood diversification motivated herders to engage in moderate grazing practices, offering insights for policymakers combating grassland degradation and enhancing herders' livelihoods. Moreover, Reference [10] introduced a three-stage energy management system for a centralized multimicrogrid operating in isolated mode. It addressed renewable energy variations caused by weather conditions, demonstrating improved performance in load, generator output, and exchanged power compared to previous methods in MATLAB Simulink simulations. Lastly, Reference [11] focused on multi-game relationships within Public–Private Partnership projects among the government, investors, and the public. Utilizing an evolutionary game model and system dynamics analysis, it revealed the pivotal role of equilibrium states, sensitivity to external variables, and the influence of security factors in shaping strategic decisions. Motivated by these works, this research explores the applications of evolutionary games in analyzing the dynamics between DERs and MGO to derive optimal strategies.

In the domain of power and energy systems, game theory serves as a robust framework for scrutinizing strategic behaviors and decision-making dynamics among interconnected agents. Reference [12] delved into the effects of DER ownership on participant benefit in peer-to-peer energy trading markets, revealing nuances such as the impact of self-sufficient rates diminishing as other agents' PV capacity grows and the potential for economic loss with high PV penetration. In [13], an edge-computing architecture utilizing an evolutionary game-based solver was proposed to optimize energy efficiency in production scheduling, addressing real-time decision-making challenges and potentially contributing to carbon reduction. Similarly, Reference [14] introduced a demand-side integration framework utilizing a prepaid energy strategy and Nash bargaining game to enhance load factor, increase net profit, and reduce total gas emissions in renewable DER-based microgrids. Moreover, Reference [15] proposed a two-stage framework that combines network reconfiguration and game-theoretic microgrid scheduling to minimize loss, voltage deviation, and operational costs while averting market power in a deregulated power market housing renewable DERs. Additionally, Reference [16] introduced a distributed energy trading mechanism among interconnected microgrids using a competitive market approach, aiming to ensure equilibrium solutions that maximize payoff and incentivize energy trading in future power grids. While these studies extensively explored interactions and strategic decision-making among

DERs within microgrids using classical game theory, understanding the nuanced dynamics, particularly concerning power factor improvement, through the lens of evolutionary games, remains an area demanding critical investigation.

This article aims to fill the aforementioned gaps by thoroughly examining the strategic interactions between DERs and the MGO within a microgrid context, leveraging evolutionary games and simulations on the modified IEEE 13-node unbalanced distribution microgrid. The research endeavors to unravel equilibrium strategies, their impact on the overall power factor, and conduct comparative analyses based on various case studies encompassing both cooperative and non-cooperative game scenarios. The main contributions of this study encompass the following aspects:

- Formulation of an Evolutionary Game Model: This work introduces an evolutionary game model designed specifically to encapsulate the intricate interactions between DERs and the MGO. This model serves as a framework to simulate and analyze the strategic behaviors and decision-making processes of DERs while engaging with the MGO within the microgrid infrastructure.
- Development of an Evolutionary Process: The study devises an evolutionary process aimed at elucidating the evolving strategies adopted by DERs during their interaction with the MGO. This process facilitates the identification and convergence toward stable strategies that characterize the equilibrium points of the interactions between DERs and the MGO within the microgrid ecosystem.
- Analysis of Game Dynamics in the IEEE 13-Node Unbalanced Distribution Microgrid: Through a series of case studies conducted on the IEEE 13-node unbalanced distribution microgrid, this research delves into the dynamics of the game between DERs and the MGO. These case studies provide a nuanced exploration of various scenarios, shedding light on the intricate dynamics, equilibrium outcomes, and strategic nuances inherent in their interactions.

The remainder of this article is organized as follows: Section 2 presents the mathematical formulation and evolutionary process of the proposed methodology. Section 3 explains the case studies conducted in the IEEE 13-node unbalanced distribution microgrid, accompanied by a discussion of the results. Finally, Section 4 offers the concluding remarks of the research along with future works. Figure 1 depicts the overall framework of the paper.

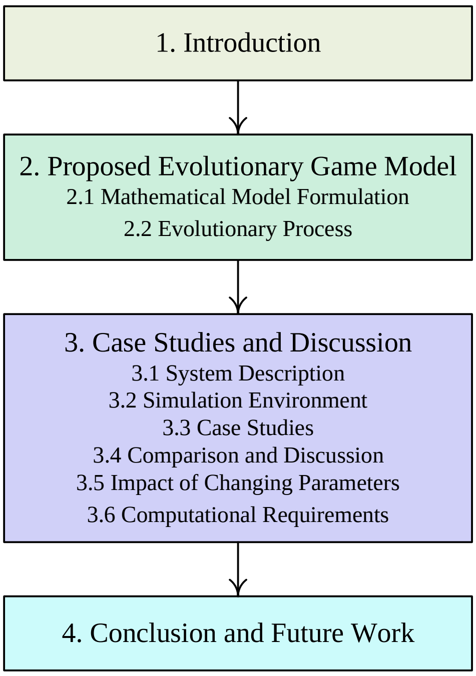

Figure 1. Framework of the paper.

2. Proposed Evolutionary Game Model

This section introduces the mathematical formulation of an evolutionary game model that captures the interaction between DERs and the MGO within the context of a microgrid. Figure 2 depicts the different ways DERs and the MGO could interact with each other. The section elaborates on the evolutionary process embedded within this game model. This evolutionary game framework serves as a dynamic representation of decision-making processes among agents, enabling the exploration of equilibrium strategies emerging from their interactions.

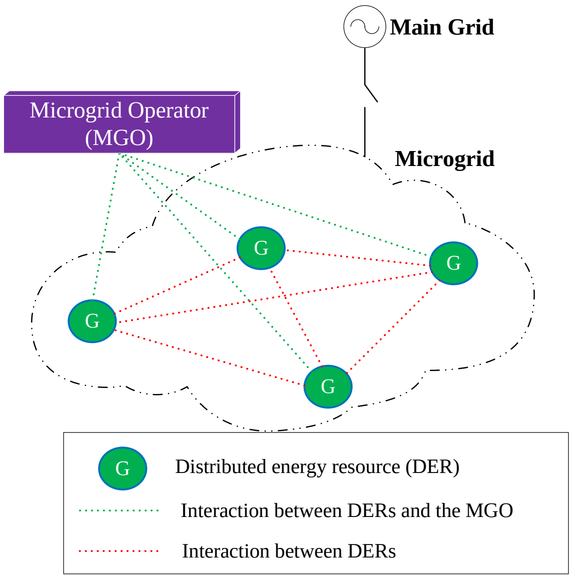

Figure 2. Interaction between DERs and the MGO.

2.1. Mathematical Model Formulation

The interactions between DERs and MGO are characterized by DERs striving to maximize their individual benefits via active power generation, while the MGO aims to optimize the microgrid's overall performance, primarily by enhancing the power factor. This interdependent strategic relationship shapes the dynamics of the evolutionary game, where DERs adapt their strategies across iterations, considering the impact on both their individual utility and the MGO's objectives.

The utility of the MGO correlates with the operational performance of the microgrid, where an improved power factor signifies higher utility. The assumption here is that the power factor consistently lags and does not lead. The utility function of the MGO is expressed as follows:

$$U_{MGO} = \cos(\phi_{MG}) = \cos\left(\tan^{-1}\left(\frac{P_{imp}}{Q_{imp}}\right)\right) \quad (1)$$

where P_{imp} and Q_{imp} denote the active power and reactive power, respectively, imported by the microgrid from the main grid.

DERs aim to maximize their active power generation within their available power capacity. However, since DERs generate solely active power without generating any reactive power, the overall power factor of the microgrid declines. Consequently, each DER incurs a penalty proportionate to its fraction of power generation concerning the total power generation by all DERs. Additionally, the strategies adopted by other DERs influence the individual utility of each DER, impacting the penalization factor. The utility function of the ith DER is expressed as follows:

$$U_{\mathrm{DER}_i} = \frac{P_{\mathrm{gen}_i}}{P_{\mathrm{cap}_i}} - \frac{P_{\mathrm{gen}_i}}{\sum_{k=1}^{N} P_{\mathrm{gen}_k}} \times (1 - U_{\mathrm{MGO}}) \tag{2}$$

where P_{gen_i} represents the active power generation of DER-i; P_{cap_i} signifies the maximum available power generation capacity of DER-i; and U_{MGO} denotes the MGO's utility function. It is important to note that the penalization term (i.e., the second term) in (2) is omitted when DERs cooperate with the MGO.

The formulation utilizes a three-phase unbalanced distribution system power flow model, based on reference [17], to compute the active and reactive power imported from the main grid in (1). This proposed model accounts for both power losses and line mutual impedance representation. The active and reactive power balance constraints at each node i and phase φ are expressed as (3) and (4).

$$P_{\varphi,i+1} = P_{\varphi,i} + P^{DER}_{\varphi,i+1} - P^{D}_{\varphi,i+1} - P^{loss}_{\varphi,i} \tag{3}$$

$$Q_{\varphi,i+1} = Q_{\varphi,i} + Q^{DER}_{\varphi,i+1} - Q^{D}_{\varphi,i+1} - Q^{loss}_{\varphi,i} \tag{4}$$

2.2. Evolutionary Process

The evolutionary process represents a methodical sequence of actions aimed at refining strategies for DERs and the MGO within a microgrid setting. Figure 3 illustrates the evolutionary process adopted in this study. Initially, the process initializes strategies randomly, fostering diverse starting points for subsequent iterations. It then evaluates the utilities of DERs and the MGO based on these strategies, determining their effectiveness in achieving objectives. Strategies yielding higher utilities are selected for reproduction, akin to natural selection favoring more successful traits. Meanwhile, occasional mutations maintain diversity, preventing premature convergence [18]. Through multiple iterations, strategies are adapted and refined, with DERs and the MGO adjusting their approaches based on past performance. This iterative framework involves multiple stages that drive the evolution of strategies toward a more optimal configuration, as outlined below.

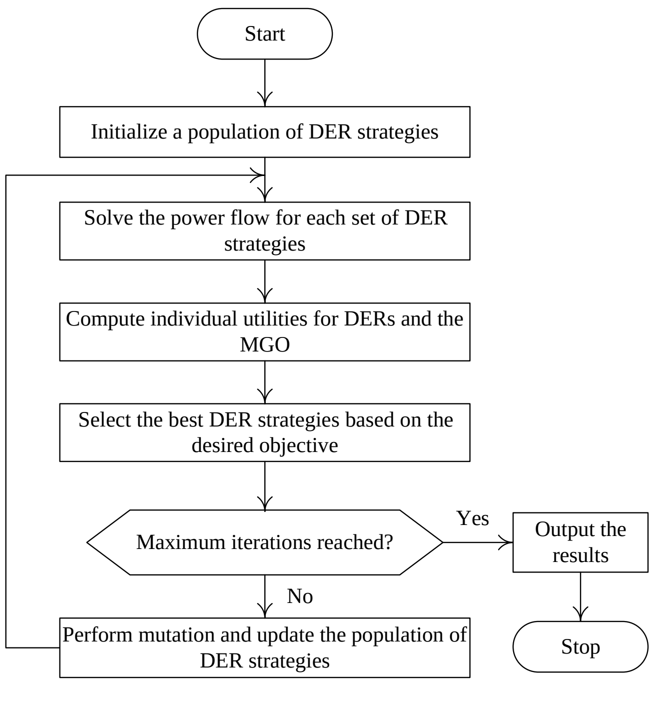

Figure 3. Flowchart of the evolutionary process.

2.2.1. Initialization of Population

At the outset, the evolutionary process commences by establishing an initial population of strategies for the DERs. This initialization phase involves generating diverse strategies randomly within the allowable capacity limits specific to each DER. The population thus comprises a spectrum of strategies, varying in their power generation distributions across the DERs.

2.2.2. Evaluation of Utilities and Interactions

Once the population is initialized, each strategy undergoes an assessment phase to evaluate its utility within the microgrid ecosystem. This evaluation process involves intricate calculations considering the power generated by individual DERs, the overall generated power from all DERs combined, and the consequential impact on the MGO's utility. The evaluation captures the complex interactions among DERs and their collective influence on the microgrid's operational dynamics.

2.2.3. Selection Based on Maximization Objective

Following the evaluation, a pivotal stage in the process involves strategy selection aligned with a specific optimization objective. This selection step is contingent upon the overarching goal, whether to maximize the utility for each individual DER or to optimize the collective utility encompassing both DERs and the MGO. Strategies are meticulously chosen based on the targeted objective, aiming to either enhance the individual benefits of DERs or optimize the overall efficiency of the microgrid system.

2.2.4. Mutation for Strategy Enhancement

The final phase of the evolutionary process introduces mutation as a mechanism to diversify strategies within the population. Non-optimal strategies undergo random alterations or mutations within their capacity boundaries. This mutation mechanism fosters exploration and innovation within the strategy pool, enabling the exploration of alternative solutions and potentially unearthing more efficient strategies. The introduction of mutations injects adaptability into the population, fostering continuous improvement in the quest for superior strategies.

3. Case Studies and Discussion

In this section, four case studies are conducted on a microgrid based on the IEEE 13-node distribution system to illustrate the evolutionary game dynamics of interaction among DERs and MGO under various scenarios. Furthermore, the section analyzes the impact of changing various parameters of the proposed evolutionary game along with DER locations.

3.1. System Description

The 4.16 kV-rated IEEE 13-node distribution test system serves as a compact feeder with a notable load capacity and encompasses various integral components. This system configuration includes a substation featuring a star-connected voltage regulator comprising three 1-phase units. Noteworthy elements within this system include shunt capacitor banks, an in-line transformer, and a mix of spot and distributed loads, potentially exhibiting imbalances. According to the data sourced from [19], the total active load and reactive load for this system are 3577 kW and 1725 kVAr, respectively. Furthermore, Figure 4 portrays the integration of three DERs into this system, each assumed to have total available capacities of 500 kW (DER-1), 600 kW (DER-2), and 700 kW (DER-3), respectively.

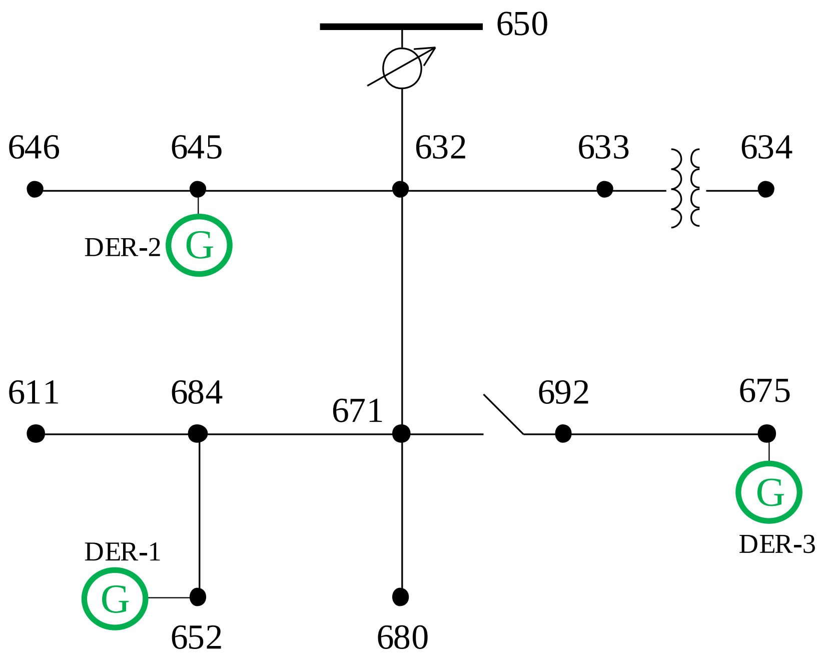

Figure 4. IEEE 13-node unbalanced distribution system.

3.2. Simulation Environment

The simulation environment is established within a Python framework, utilizing specialized modules to model the interactions between DERs and the MGO. To facilitate power flow calculations and system analysis, a dedicated Python-OpenDSS interface is developed, harnessing the capabilities of OpenDSSDirect [20]. This interface enables seamless communication between Python and OpenDSS, facilitating efficient and precise distribution system simulations. The integration with OpenDSSDirect streamlines the automation of power flow calculations within the microgrid, thereby enhancing the analysis of evolutionary game dynamics between DERs and the MGO.

3.3. Case Studies

Four distinct case studies are formulated to investigate the evolutionary game dynamics between DERs and the MGO across diverse scenarios. The evolutionary process spans 250 iterations, employing a mutation rate set at 0.5 and a population size of 20. Case 1 examines the scenario of non-cooperation among all DERs and MGO. Case 2 delves into the analysis of DERs' cooperation to maximize their collective utility. Case 3 investigates DERs' collaboration aimed at maximizing MGO's utility. Finally, Case 4 scrutinizes the collaboration among all DERs and MGO to maximize the collective utility of both DERs and MGO. The specifics of each case study are elaborated below.

3.3.1. Case 1: Non-Cooperation among All DERs and MGO

In this case, neither the DERs nor the MGO engage in cooperation with each other. Without any collaboration, each entity strives to maximize their individual utility function. Figure 5 depicts the evolution of optimal DER strategies throughout the iterations in this scenario. The illustration showcases the strategies adopted by the DERs that maximize their individual utilities at each iteration.

Initially, from the pool of randomly generated DER strategies, the best strategies identified for DER-1, DER-2, and DER-3 were 500 kW, 510 kW, and 650 kW, respectively, in the first iteration. Correspondingly, Figure 6 showcases the evolution of individual utilities for both DERs and the MGO when employing these optimal strategies in each iteration. In the initial iteration, the individual utilities for the DERs were 0.9295, 0.7781, and 0.8370, while the MGO exhibited an individual utility of 0.7661.

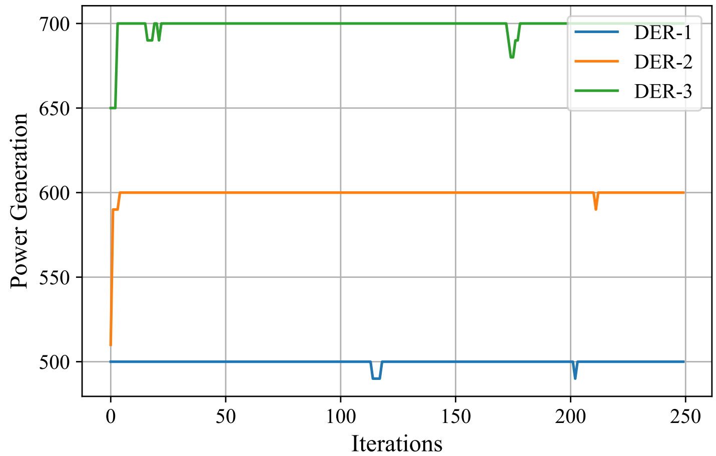

Figure 5. Evolution of DER strategies for Case 1.

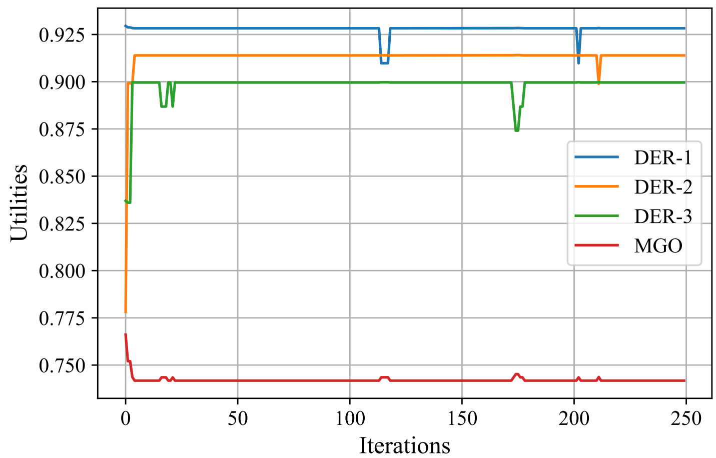

Figure 6. Evolution of DER and MGO utilities for Case 1.

As the iterations progress, DER-2 and DER-3 undergo significant strategy changes, resulting in increased individual utilities for these entities, subsequently impacting the individual utility of the MGO, leading to its decline. The stabilized strategies for DER-1, DER-2, and DER-3 are at their maximum capacity generating 500 kW, 600 kW, and 700 kW of active power, respectively. At this stage, the individual utilities for DER-1, DER-2, DER-3, and MGO stand at 0.9283, 0.9139, 0.8996, and 0.7418, respectively.

3.3.2. Case 2: DERs' Cooperation to Maximize Collective Utility

In this scenario, all DERs collaborate exclusively among themselves to maximize their collective utility, without engaging in cooperation with the MGO. Figure 7 illustrates the evolution of the most optimal DER strategies across iterations for this specific case, portraying the strategies adopted by the DERs to maximize their collective utility in each iteration.

Initially, from the pool of randomly generated DER strategies, the most optimal strategies identified for DER-1, DER-2, and DER-3 were 500 kW, 510 kW, and 320 kW, respectively, in the first iteration. Similarly, Figure 8 demonstrates the evolution of individual utilities for both DERs and the MGO with the employment of these optimal strategies in each iteration. In the initial iteration, the individual utilities for the DERs were 0.9283, 0.7768, and 0.4112, while the MGO exhibited an individual utility of 0.8092.

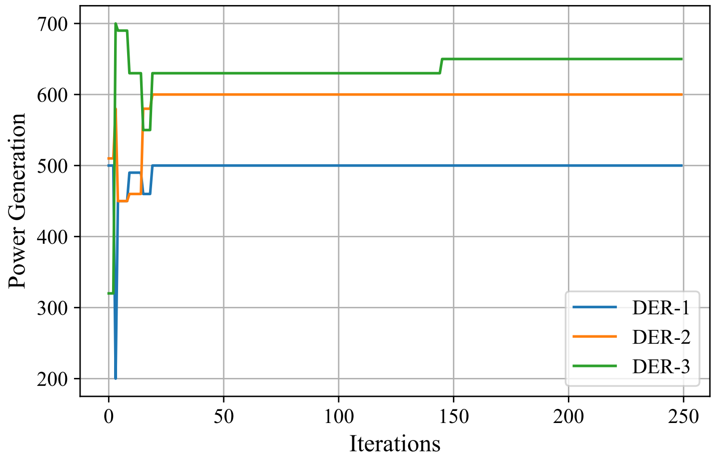

Figure 7. Evolution of DER strategies for Case 2.

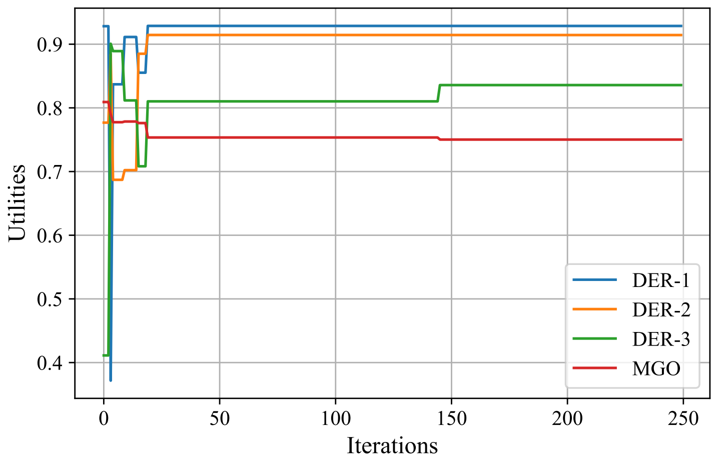

Figure 8. Evolution of DER and MGO utilities for Case 2.

As the iterations progress, the DERs adapt their strategies to converge upon final stable strategies that lead to the maximization of their collective utility. However, this pursuit results in a decrease in the individual utility of the MGO. The stabilized strategies for DER-1, DER-2, and DER-3 operate at 500 kW, 600 kW, and 650 kW, respectively. At this stage, the individual utilities for DER-1, DER-2, DER-3, and MGO amount to 0.9286, 0.9144, 0.8258, and 0.7502, respectively.

3.3.3. Case 3: DERs' Cooperation to Maximize MGO's Utility

In this scenario, all DERs collaborate among themselves to optimize the individual utility of the MGO. This particular situation of DERs cooperating to enhance the MGO's utility is feasible when the DERs are owned by the MGO, aiming to bolster the overall system performance. Figure 9 depicts the evolution of the most optimal DER strategies across iterations for this case, showcasing the strategies adopted by the DERs to maximize the individual utility of the MGO in each iteration.

Initially, from the pool of randomly generated DER strategies, the most optimal strategies identified for DER-1, DER-2, and DER-3 were 10 kW, 180 kW, and 0 kW, respectively, in the first iteration. Similarly, Figure 10 illustrates the evolution of individual utilities for both DERs and the MGO with the utilization of these optimal strategies in each iteration. In the initial iteration, the individual utilities for the DERs were 0.02, 0.3, and 0, while the individual utility of the MGO was 0.8805.

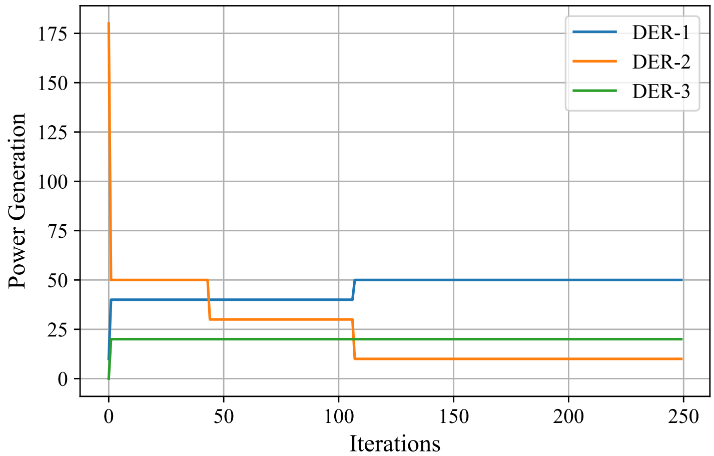

Figure 9. Evolution of DER strategies for Case 3.

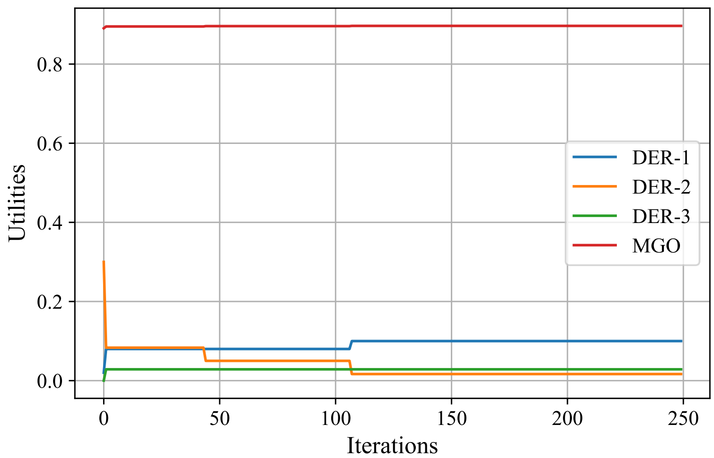

Figure 10. Evolution of DER and MGO utilities for Case 3.

As the iterations progress, the DERs adapt their strategies to converge upon final stable strategies that lead to the maximization of the individual utility of the MGO. However, this optimization results in considerably low individual utilities for the DERs. The stabilized strategies for DER-1, DER-2, and DER-3 operate at 50 kW, 10 kW, and 20 kW, respectively. At this stage, the individual utilities for DER-1, DER-2, DER-3, and MGO amount to 0.1, 0.0167, 0.0286, and 0.8965, respectively.

3.3.4. Case 4: Cooperation of All DERs and MGO to Maximize Collective Utility

In this scenario, all DERs and the MGO collaborate to maximize their collective utility. Figure 11 illustrates the evolution of the most optimal DER strategies across iterations for this case, demonstrating the strategies adopted by the DERs and MGO to maximize their collective utility in each iteration.

Initially, from the pool of randomly generated DER strategies, the most optimal strategies identified for DER-1, DER-2, and DER-3 were 500 kW, 510 kW, and 320 kW, respectively, in the first iteration. Correspondingly, Figure 12 portrays the evolution of individual utilities for both DERs and the MGO with the utilization of these optimal strategies in each iteration. In the initial iteration, the individual utilities for DERs were 1, 0.85, and 0.4571, while the individual utility of the MGO was 0.8092.

As the iterations progress, the DERs adapt their strategies to converge upon final stable strategies that lead to the maximization of the collective utility of both DERs and the MGO. The stabilized strategies for DER-1, DER-2, and DER-3 operate at 500 kW, 600 kW, and 650 kW, respectively. At this stage, the individual utilities for DER-1, DER-2, DER-3, and the MGO stand at 1, 1, 0.9286, and 0.7502, respectively.

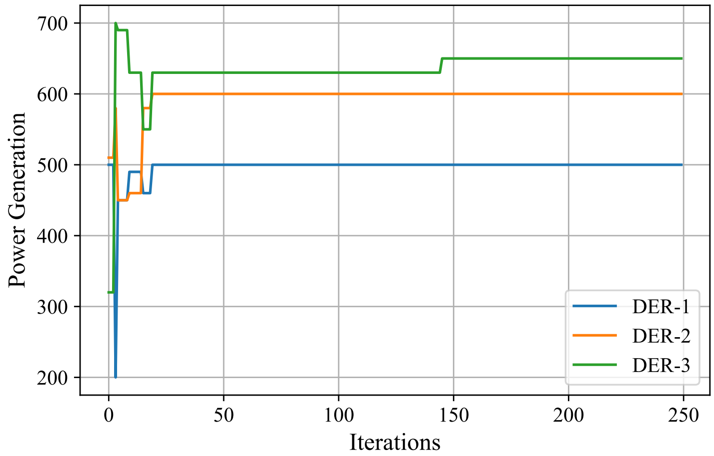

Figure 11. Evolution of DER strategies for Case 4.

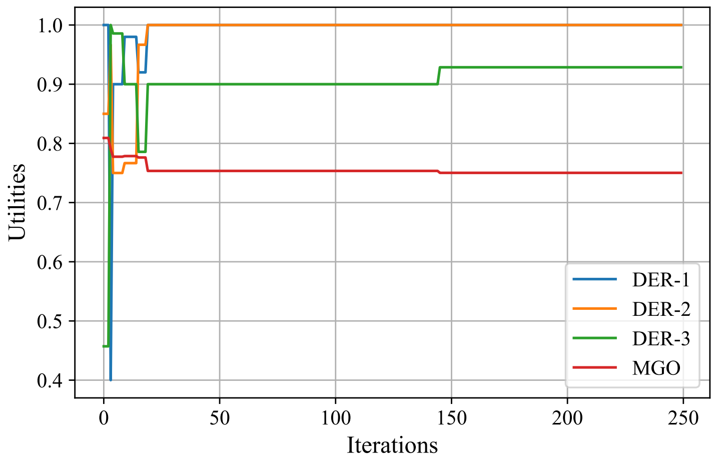

Figure 12. Evolution of DER and MGO utilities for Case 4.

3.4. Comparison and Discussion

Table 1 presents the stable strategies and corresponding individual utilities of DERs and the MGO for all four cases, while Figure 13 displays a bar plot depicting the individual utilities of all four players. Analysis of these stable strategies suggests that non-cooperation among all DERs and the MGO, as explored in Case 1, could seemingly benefit DERs by allowing them to maximize their active power set points. However, despite operating at maximum power points, DERs face penalization by the MGO due to the microgrid's low overall power factor, resulting in reduced individual utilities. Notably, in this scenario, the MGO exhibits the lowest individual utility compared to all cases.

Table 1. Stable strategies and corresponding individual utilities for different cases.

Cases	**Stable Strategies (i.e., Power Generations)**			**Individual Utilities**			
	DER-1	**DER-2**	**DER-3**	**DER-1**	**DER-2**	**DER-3**	**MGO**
Case 1	500 kW	600 kW	700 kW	0.9283	0.9139	0.8996	0.7418
Case 2	500 kW	600 kW	650 kW	0.9286	0.9144	0.8358	0.7502
Case 3	50 kW	10 kW	20 kW	0.1	0.0167	0.0286	0.8965
Case 4	500 kW	600 kW	650 kW	1	1	0.9286	0.7502

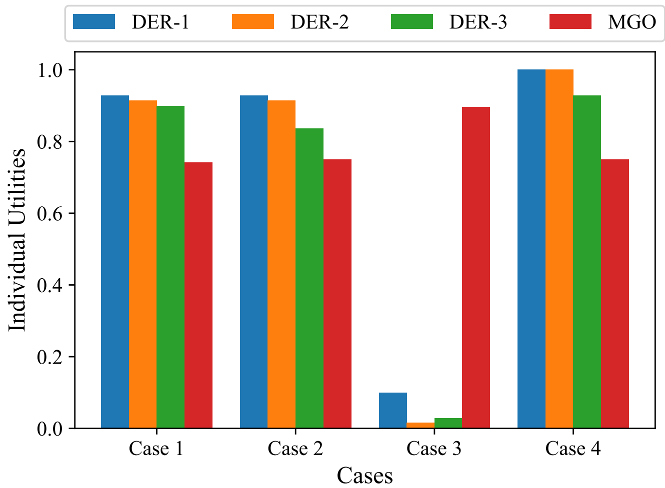

Figure 13. Comparison of four cases in terms of individual utilities of the players.

In Case 2, where DERs form coalitions to maximize their collective utility without collaborating with the MGO, the individual utilities of all DERs do not improve significantly compared to Case 1, where they operate independently. DERs with higher capacities experience lower individual utilities due to the higher penalization term in the utility function (2), directly linked to their active power generation. Thus, higher-capacity DERs need to compromise some available capacity when collaborating.

Case 3, where DERs cooperate to maximize the MGO's utility, lacks substantial interactions or competitive dynamics—rendering it an impractical scenario for rational economic agents. In practical terms, this case is feasible only in a vertically integrated monopolistic microgrid setting, where the primary objective is to meet specific technical performance requirements.

In Case 4, where all DERs and the MGO collaboratively aim to maximize their collective utility, the individual utilities of DERs display significant improvement. As DERs work towards collective utility maximization, the MGO refrains from penalizing these DERs, even as part of a coalition. However, it appears that the MGO's individual utility remains unchanged compared to Case 2, where DERs collaborated without involving the MGO.

3.5. Impact of Changing Various Parameters

In order to analyze the impact of parameters of the evolutionary process such as mutation rate and population size, the case of DERs' cooperation to maximize collective utility (Case 2) is simulated with different parameters' values from that presented in Section 3.3. Additionally, the effect of varying DER locations is examined, using parameter values different from those outlined in Section 3.3. For specific parameter configurations used in this analysis, refer to Table 2.

Table 2. Various parameters of cases analyzed for the impact.

Cases	Mutation Rate	Population Size	Location of DER-1	Location of DER-2	Location of DER-3
Case 2a	0.8	20	675	645	685
Case 2b	0.2	20	675	645	685
Case 2c	0.5	10	675	645	685
Case 2d	0.5	30	675	645	685
Case 2e	0.5	20	685	645	675

3.5.1. Case 2a and Case 2b: Impact of Mutation Rate Variation

In Case 2a, the mutation rate is increased to 0.8 while maintaining the number of iterations at 250 and the population size at 20, consistent with Case 2. Figure 14 illustrates the evolution of the most optimal DER strategies across iterations for this specific case, depicting the strategies adopted by the DERs to maximize their collective utility in each iteration.

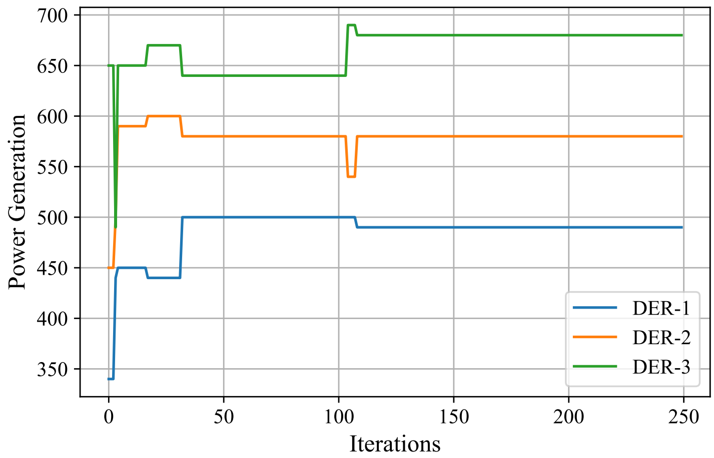

Figure 14. Evolution of DER strategies for Case 2a.

Similarly, Figure 15 demonstrates the evolution of individual utilities for both DERs and the MGO using these optimal strategies in each iteration. Table 3 presents the stable strategies and corresponding individual utilities of DERs and the MGO for this case. The collective utility of DERs in Case 2a is 2.6687, comparable to that of Case 2, which is 2.6788.

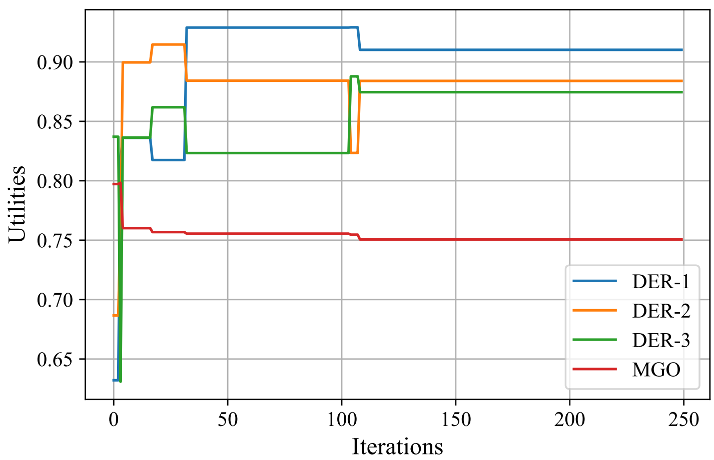

Figure 15. Evolution of DER and MGO utilities for Case 2a.

Compared to Case 2, Case 2a shows comparable collective utility among DERs, with faster convergence but less pronounced evolutionary dynamics during initial iterations.

In Case 2b, the mutation rate is decreased to 0.2 while maintaining the number of iterations at 250 and the population size at 20, consistent with Case 2. Figure 16 illustrates the evolution of the most optimal DER strategies across iterations for this specific case, showcasing the strategies adopted by the DERs to maximize their collective utility in each iteration.

Similarly, Figure 17 demonstrates the evolution of individual utilities for both DERs and the MGO using these optimal strategies in each iteration. Table 3 displays the stable strategies and corresponding individual utilities of DERs and the MGO for this case. The collective utility of DERs in Case 2b is 2.6281, slightly lower than that of Case 2, which is 2.6788.

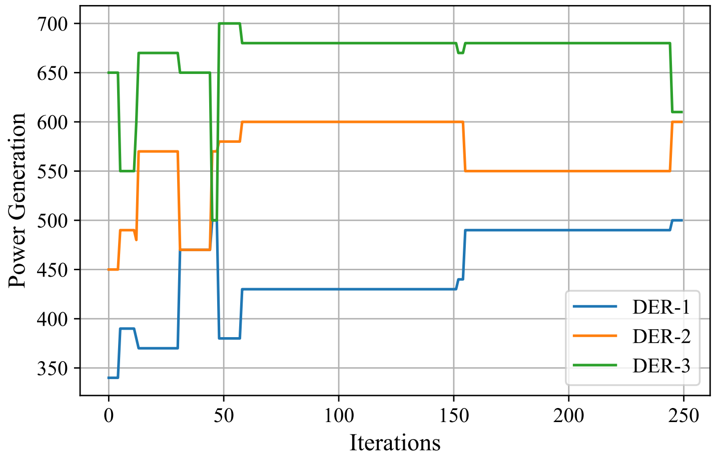

Figure 16. Evolution of DER strategies for Case 2b.

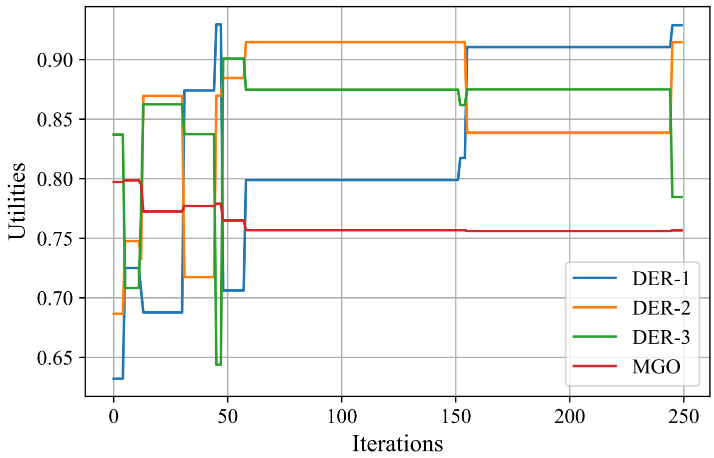

Figure 17. Evolution of DER and MGO utilities for Case 2b.

Compared to Case 2, Case 2b demonstrates lower collective utility among DERs, with slower convergence but more prominent evolutionary dynamics during initial iterations.

In summary, both Case 2a and Case 2b indicate that higher mutation rates may yield better final strategies but with less pronounced evolutionary dynamics. Conversely, lower mutation rates require more iterations to reach the final equilibrium. However, the primary conclusion of Case 2, stating that DERs with higher capacities will have lower individual utility, remains consistent. Thus, the primary conclusion remains unchanged.

Table 3. Analysis of impact of various parameters on stable strategies and corresponding individual utilities.

Cases	Stable Strategies (i.e., Power Generations)			Individual Utilities			
	DER-1	**DER-2**	**DER-3**	**DER-1**	**DER-2**	**DER-3**	**MGO**
Case 2a	490 kW	580 kW	680 kW	0.9102	0.8840	0.8745	0.7506
Case 2b	500 kW	600 kW	610 kW	0.9288	0.9146	0.7846	0.7567
Case 2c	500 kW	520 kW	700 kW	0.9292	0.7931	0.9009	0.75661
Case 2d	490 kW	590 kW	680 kW	0.9101	0.8991	0.8743	0.7488
Case 2e	490 kW	580 kW	650 kW	0.8363	0.8844	0.9105	0.7559

3.5.2. Case 2c and Case 2d: Impact of Population Size Change

In Case 2c, the population size is decreased to 10 while maintaining 250 iterations and a mutation rate of 0.5 identical to Case 2. Figure 18 illustrates the evolution of the most optimal DER strategies across iterations for this specific case, depicting the strategies adopted by the DERs to maximize their collective utility in each iteration.

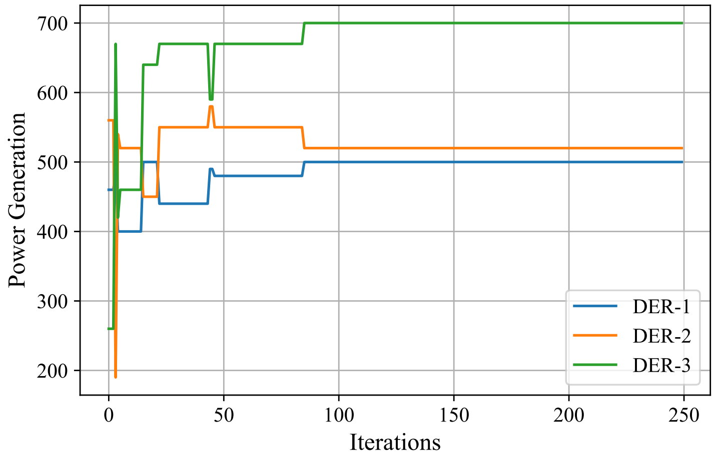

Figure 18. Evolution of DER strategies for Case 2c.

Similarly, Figure 19 demonstrates the evolution of individual utilities for both DERs and the MGO employing these optimal strategies in each iteration. Table 3 displays the stable strategies and corresponding individual utilities of DERs and the MGO for this case. The collective utility of DERs in this case is 2.6233, lower than that of Case 2, which is 2.6788.

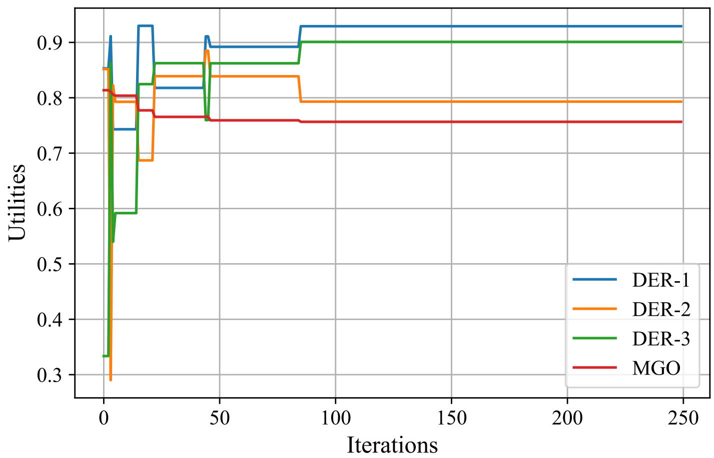

Figure 19. Evolution of DER and MGO utilities for Case 2c.

Compared to Case 2, Case 2c shows lower collective utility among DERs, with slower convergence but more prominent evolutionary dynamics during initial iterations.

In Case 2d, the population size is increased to 30 while keeping 250 iterations and a mutation rate of 0.5 identical to Case 2. Figure 20 illustrates the evolution of the most optimal DER strategies across iterations for this specific case, showcasing the strategies adopted by the DERs to maximize their collective utility in each iteration.

Similarly, Figure 21 demonstrates the evolution of individual utilities for both DERs and the MGO employing these optimal strategies in each iteration. Table 3 presents the stable strategies and corresponding individual utilities of DERs and the MGO for this case. The collective utility of DERs in Case 2d is 2.6835, comparable to that of Case 2, which is 2.6788.

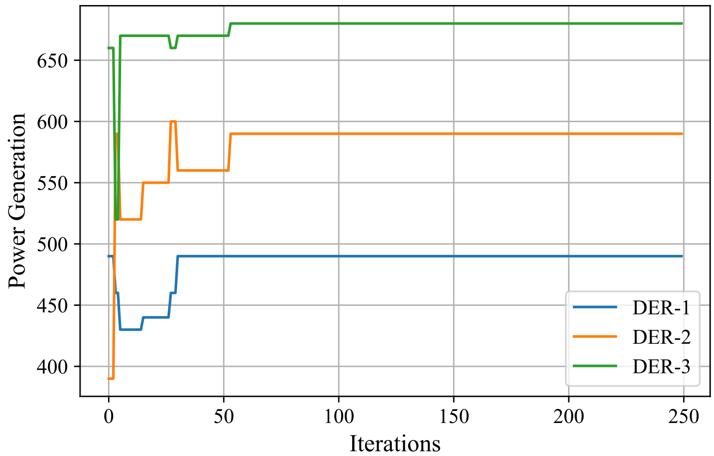

Figure 20. Evolution of DER strategies for Case 2d.

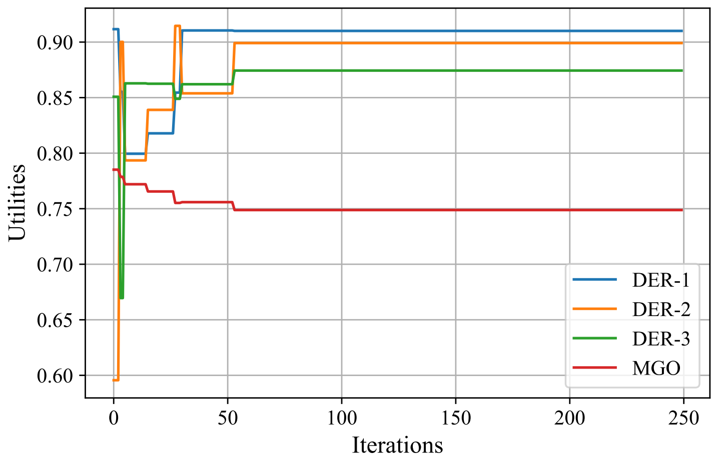

Figure 21. Evolution of DER and MGO utilities for Case 2d.

Compared to Case 2, Case 2d demonstrates similar collective utility among DERs, with faster convergence but less pronounced evolutionary dynamics during initial iterations.

In summary, both Case 2c and Case 2d suggest that higher population sizes may yield better final strategies but with less prominent evolutionary dynamics. Conversely, lower population sizes require more iterations to reach the final equilibrium. However, the primary conclusion from Case 2, stating that DERs with higher capacities will have lower individual utility, remains consistent. Thus, the primary conclusion remains unchanged.

3.5.3. Case 2e: Impact of Changing DER Locations

In this case, the locations of DER-1 (capacity 500 kW) and DER-3 (capacity 700 kW) are interchanged compared to Case 2. Figure 22 illustrates the evolution of the most optimal DER strategies across iterations for this specific scenario, demonstrating the strategies adopted by the DERs to maximize their collective utility in each iteration.

Similarly, Figure 23 shows the evolution of individual utilities for both DERs and the MGO using these optimized strategies in each iteration. The stable strategies and corresponding individual utilities of DERs and the MGO for this case are detailed in Table 3.

As a result of the change in DER locations, there are alterations in the stable strategies and the individual utilities of DERs and the MGO, as anticipated. However, the fundamental conclusion drawn in Case 2, stating that DERs with higher capacities will have lower utilities, remains unchanged despite the shift in DER locations.

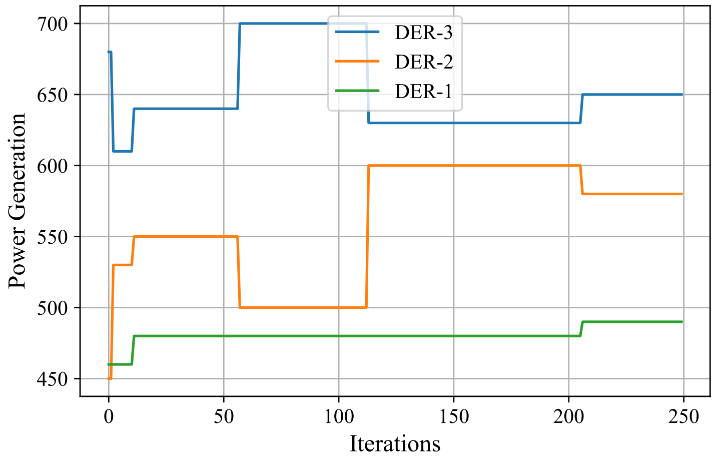

Figure 22. Evolution of DER strategies for Case 2e.

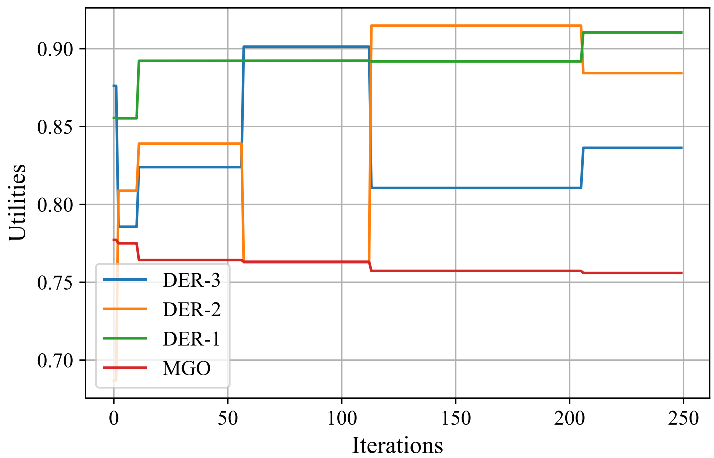

Figure 23. Evolution of DER and MGO utilities for Case 2e.

3.6. Computational Requirements of the Proposed Approach

The proposed approach has been executed on a personal computer featuring a 64-bit 12th generation Intel i5 core processor clocked at 1.6 GHz, 16 GB of RAM, and operating on the Windows 10 platform. The execution time required for the proposed approach to complete 250 iterations with a population size of 20 ranged between 12 to 14 min.

4. Conclusions and Future Work

The evolutionary game dynamics between DERs and the MGO have been analyzed in this study, elucidating their roles as players with conflicting objectives within the microgrid ecosystem. Despite the alignment of DERs' individual goals, they engage in competitive behaviors, influencing each other's utility functions based on their adopted strategies. The evolutionary analysis of DERs' strategies was conducted via four case studies executed on a modified IEEE 13-node distribution microgrid, shedding light on the resultant stable strategies in each scenario.

In non-cooperative scenarios, DERs can benefit from optimizing their individual utility functions but at the expense of degrading the microgrid's overall power factor, subsequently diminishing the MGO's utility. Cooperative settings marginally favored the MGO; however, the enhancement in the MGO's individual utility was limited. Notably, the scenario where all DERs are owned by the MGO exemplified the attainment of maximum individual utility by the MGO, a common occurrence in microgrids managed by a single entity. Conversely, in deregulated settings, competition or mutual cooperation among DERs and the MGO prevails.

The cooperation among DERs revealed a tradeoff: higher-capacity DERs adjusted their strategies to generate less power due to penalties in their utility functions. This underscores the complexity of tradeoffs in pursuing collective gains. These findings highlight intricate dynamics and interactions within microgrid environments, emphasizing the importance of understanding DERs' strategic behaviors for efficient and sustainable energy management in regulated and deregulated settings.

Potential future work could involve an in-depth analysis of evolutionary game dynamics considering various types of DERs, such as PV systems, wind energy sources, batteries, and other emerging technologies. Exploring these diverse DER types could offer a comprehensive understanding of their distinct strategic behaviors and interactions within microgrids.

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Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DER	Distributed Energy Resource
EGT	Evolutionary Game Theory
IEEE	Institute of Electrical and Electronics Engineers
MGO	Microgrid Operator

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