Evolutionary Stable Strategy enabled Resource Allocation in 6G: A Strategy Integration based Game Theoretic Approach

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***Abstract*—In the rapidly advancing era of 6G networks, an efficient resource allocation (RA) is necessitated. Consequently, our paper reveals a sophisticated mathematical model based on Evolutionary Game Theory and replicator dynamics designed to optimize and stabilize resource distribution. The model delineates how Evolutionary Stable Strategies (ESS) can be systematically identified and employed to enhance network efficiency and fairness significantly. Further, strategic interaction analysis and dynamic modelling integration demonstrate that ESS respond adeptly to changing network conditions and robustly guards against inefficiencies caused by signal degradation and user demand variability. Furthermore, we proposed a few algorithms, such as ESS sustainability and stabilization criteria for ESS, to depict the change in strategy population, which turns into the strategy fitness change and convergence of strategic population, respectively. Lastly, our empirical simulations validate the model's effectiveness in fostering resilient and equitable RA, setting a foundation for future 6G network designs prioritizing adaptability and sustainability. In conclusion, our paper aims to highlight the innovative approach succinctly, as well as the theoretical foundation and practical outcomes of our research, focusing on engaging and addressing a more expansive audience effectively in the upcoming era of next-generation communication technologies.**

***Index Terms*—Evolutionary Stable Strategies, 6G, Resource Allocation, Evolutionary Game Theory**

I. Introduction

Pioneering a new era of 6G wireless networks, future advancements are set to revolutionize the communications landscape, characterized by ultra-low latency, high reliability, and data rate. Furthermore, intelligent and innovative resource allocation (RA) tactics are needed due to the extensive increase in enormous end-user demands. In wireless communication scenarios, mobile networks experience variability, resulting in dynamic network requirements and adaptive resource management strategies. Thus, it necessitates the emergence of innovative, intelligent and adaptive mechanisms capable of addressing and predicting the network's complexity. Moreover, traditional flow control methods need a balance where abundant network throughput is achieved at the expense of the user resources [1]. Owing to this, imbalance can result in a condition that affects the entire network because some nodes are starved of the resources they need, and others are overloaded with the same resource. In wireless networks, there is a hazard of interference and signal strength loss, mainly due to several devices and services, each having different resource demands. In this context, strategies such as Evolutionary Stable Strategies (ESS), often used in the Evolutionary Game Theory (EGT), are helpful in these complex scenarios. ESS are strategies which, once integrated in some populations, cannot be defeated by any other tactic as long as the conditions of the environment are preserved. This theoretical framework is more attractive for understanding and organizing resources in wireless network environments. In our proposed model we exploit Replicator Dynamics (RD) as a method of strategy selection based on conventional selection from evolutionary theory. Consequently, we can distinguish similar strategies that dominate and stabilize under conditions of competition.

Hence, this paper is focused on utilizing ESS for resource management in next-generation of communication era [2]. The proposed methodology ingress to identify ways that a node in a network can modify and improve its approaches to improve the prevailing network's stability. On the other hand, the application of ESS facilitates direct performance optimization for RA. It improves the overall network fairness and robustness against jamming perturbation, including a rise in the number of BSs or signal destruction. Furthermore, our paper demonstrates the application of ESS in conventional real-world networks through both theoretical and simulation analysis. Our Proposed work is intended to make a significant research contribution to shape the forthcoming 6G wireless network that offers fair and efficient access to available resources for all diverse end users while leveraging the overall network capacity, performance, and adaptability to alter the network's dynamics in next-generation wireless communication networks.

TABLE I: Acronym Table

Acronym	Interpretation
ESS	Evolutionary Stable Strategy
EGT	Evolutionary Game Theory
$\mathcal{F}$	Satisfaction derived from a Specific Strategy
QoS	Quality of Service
KPI	Key Performance Indicator
DR_i^p	Demand Resource of i^{th} BS during Time-Period p
AR_i^p	Allocated Resource to i^{th} BS during Time-Period p
TR_{is}^p	Total Requests from s^{th} Peer to i^{th} BS
$\Delta\mathcal{FC}_i$	Change in Fitness of i^{th} Strategy
SP_i	Strategic Population of i^{th} Strategy
$F_{\overline{S}_u}(t)$	Cumulative Distribution Function of the Delay Constraint $\overline{S}_u$
$\delta\mathcal{P}_i$	Rate of Change in the Population of i^{th} Strategy
$\varpi(t)$	Vector Representing Different Strategic Distribution over t
$\overline{\Omega}$	Average Payoff across all the Strategies
$\eta(t)$	Total Population over Time
$\Upsilon(e^i, \varpi(t))$	Utility of i^{th} Evolutionary Strategy

II. SYSTEM MODEL

There is little understanding of the practical application of RA methods in the rapidly evolving 6G wireless networks. Consequently, this paper addresses the proposed model framework. The presented model is a superior mechanism for identifying the ESS of various RA configurations in highly dynamic and distributed networks by drawing on the concepts of EGT and RD. The concept of ESS immune to interference by other strategies in certain conditions is essential for our proposed method [3]. The model implements differential equations for the changes of strategy frequencies across the population and employs RD for the dynamic generation of strategies for network nodes [4]. One of the tools exploited in our approach is the strategy interaction matrix, which reflects the outcome of interactions between strategies within the network. The information arriving at the nodes in the network in real-time is fed into the matrix so that changes can be made according to the situation, and nodes can be steered towards the most favourable outcome. To ensure the practical implementation of the proposed strategy, we evaluate the strategy fitness with data rate, latency, fairness, and RA rate key performance indicator (KPI). However, certain KPIs are important for the network's sustainability and for ensuring the quality of service (QoS). When combined with RD, the above measurements ensure that the computational evolutionary models mean improvement in the overall network functionality and evaluate the strategies' feasibility at evolutionary stable states.

Furthermore, it allows changing strategies for network nodes according to observed outcomes and expected further circumstances. This is referred to as adaptive strategy evolution. We run experiments to mimic actual network environments to confirm the suggested paradigm. Our simulations demonstrate how ESS emerges and is sustainable under different network configurations. They are carried out with the help of strategies $S_i \in$ (Reputation-based RA [5], Demand-based RA [6], Auction-based RA [7], QoS-based RA) at any given time. The mathematical foundation of our model is designed to specify how strategies transform in the context of 6G networks, thus enhancing our understanding of how ESS emerge and become dominant. The mathematical concepts underlying the evolutionary aspects of the model and the strategic interaction analysis are presented. The primary focus of our model is the reward matrix Φ that contains the immediate reward or utility received when using some strategies within the network. Some of the monetary value received when the strategy i plays against the strategy j is Φ_{ij}. These payoffs capture the intricate interdependence of strategy interactions by considering various network-specific characteristics, such as signal quality, interference levels, and bandwidth allocation. These payoffs capture the intricate interdependence of strategy interactions by considering various network-specific characteristics, such as signal quality, interference levels, and bandwidth allocation.

A. Utility Function Vector ($\mathcal{F}$)

The utility vector $\mathcal{F}$ represents the performance or satisfaction that a small base station (SBS) or network component derives from a particular strategy or action and is given by

$$\Upsilon_i(x) = \alpha_i U_{BS_i}(x),\ i \in [1, \ldots, n] \tag{1}$$

$$U_{BS_i}(x) = \frac{1}{TR_{is}^p} \sum_{t \in T_{is}^p} \frac{AR_{is}^t}{DR_{p_{is}}^p} \tag{2}$$

Here in (1) and (2), α_i is a scaling constant for every node, TR_{is}^p is the total requests from s^{th}peer to i^{th} BS, AR_i^p is the allocated resource of i^{th} BS during period p, and DR_i^p is the demand resource of i^{th} BS during p [8]. This vector is crucial for assessing the population dynamics under replicator equations, as shown below

$$\mathcal{F} = [\Upsilon_1, \Upsilon_2, ..., \Upsilon_n] \tag{3}$$

In (3), each Υ_i non-negative value representing the proportion of resource satisfaction allocated to i^{th} BS with all the proportions summing to one, under normalization process, thereby ensuring a balanced and efficient RA within the network.

B. Replicator Framework for Strategy Evolution

The core of our model lies in understanding how strategies evolve over time, which is governed by RD [9]. The RD describes how strategies outperform in terms of generating high payoffs. Consequently, it increases utility within the population while less effective strategies diminish. Further, we detailed the mathematical modelling using RD, which can be seen below. Let $\varpi(t)$ = [$\varpi_1(t)$, $\varpi_2(t)$, $\varpi_3(t)$, $\varpi_4(t)$] be the vector representing different strategic distribution at time t, and $\eta(t)$ denotes the total population. Further, we detailed the corresponding equation as follows

$$\eta(t) \cdot \varpi_i(t) = \eta_i(t) \tag{4}$$

Here in (4), $\eta_i(t)$ represents the actual number of individuals in the population, following strategy i at time t. The product $\eta(t) \cdot \varpi_i(t)$ avails the number by multiplying the total population $\eta(t)$ by the distribution of the i^{th} strategy $\varpi_i(t)$. Thus, we identify that the rate of change in the population adopting strategy i, denoted by $\dot{\eta}_i(t)$, is proportional to the utility of that strategy, represented by $\Upsilon(e^i, \varpi(t))$ and detailed below

$$\dot{\eta}_i(t) = \Upsilon(e^i, \varpi(t)) \cdot \eta_i(t) \quad (5)$$

In (5), $\Upsilon(e^i, \varpi(t))$ is the utility of strategy i when it is played against the population's current strategy distribution $\varpi(t)$. This equation indicates that the growth rate of the population adopting strategy i depends directly on its current fitness. Moreover, the total population $\eta(t)$ is the sum of all $\eta_i(t)$ across all strategies and can be represented as follows

$$\eta(t) = \sum \eta_i(t) \quad (6)$$

In (5) and (6), the average payoff across the population, denoted $\Upsilon(\varpi(t), \varpi(t))$, is the sum of the payoffs weighted by the distribution of each strategy and can be shown as below

$$\sum \varpi(t)\Upsilon(e^i, \varpi(t)) = \Upsilon(\varpi(t), \varpi(t)) \quad (7)$$

Further, we differentiate both sides of the (4) to analyze how the strategy distribution changes over time. Hence, the following equation can be seen below

$$\dot{\eta(t)}.\varpi_i(t) + \dot{\varpi}_i(t) \cdot \eta(t) = \dot{\eta}_i(t) \quad (8)$$

Here in (8), $\dot{\eta}(t)$ represents the rate of change of the total population after each time period, and $\dot{\varpi}_i(t)$ is the rate of change of the distribution of strategy i. The equation shows how these rates interact with the population growth rate. Indicating that $\dot{\eta}(t) = \sum \dot{\eta}_i(t)$, therefore we simplify the (8) as presented below

$$\dot{\varpi}_i(t) \cdot \eta(t) = \dot{\eta}_i(t)[1 - \sum \varpi_i(t)] \quad (9)$$

Using (5) and (9), since the sum of the distribution $\varpi_i(t)$ across all strategies equal to one, the change of strategy i is given as

$$\dot{\varpi}_i(t) \cdot \eta(t) = \eta_i(t)[\Upsilon(e^i, \varpi(t)) - \sum \varpi_i(t)\Upsilon(e^i, \varpi(t))] \quad (10)$$

Equation (10) indicates that the change in strategy i is proportional to the difference between its utility and the average utility in the population. Finally, by dividing both sides by $\eta(t)$, we attain the RD equation such as

$$\dot{\varpi}_i(t) = \varpi_i(t)[\Upsilon(e^i, \varpi(t)) - \Upsilon(\varpi(t), \varpi(t))] \quad (11)$$

Equation (11) confirms that the strategy change rate is driven by the difference between the strategy's utility and the average utility, scaled by its current distribution. If a strategy performs better than average, its BS will increase; otherwise, it will decrease. This dynamic ensures that strategies leading to higher payoffs become more prevalent over time, guiding the population toward an evolutionary stable state.

C. Fitness Criteria ($\mathcal{FC}$)

In our model, the fitness of each strategy is evaluated using three key parameters [10]: These measures include Delay Rate (DLR), Jain's Fairness Index (JFI) and Data Rate (DR). These criteria are fundamental in assessing the appropriateness of the RA strategies in the context of the 6G wireless network environment and can be formulated as mentioned below

$$\text{FC} = \frac{[\text{DLR} \times \text{JFI} + \text{DR}]}{2} \quad (12)$$

$$\mathcal{FC}(x) = [\text{FC}(x)_i], \ \forall \varpi_i \ i \in [1, \ldots, n] \quad (13)$$

For each parameter in the aforementioned Equation (12), it is clearly seen that the proposed approach emphasises an aspect of network performance that completes an overall picture of the strategy's effectiveness in the given evolutionary processes.

1) DLR: This parameter determines the degree of network interaction through the time it takes for data packets to be transmitted from the source to the destination application. In high-performing networks, the DLR is used to facilitate performance improvements where such networks are used to conduct real-time activities such as video conferencing and telemeters [11]. In this model, we determine the probability that the delay of a given packet exceeds a given limit and, hence, is dropped, thereby affecting the QoS of the network. In our study, we consider the delay constraint $\overline{S}_u$ for a given SBS, where the following expression characterizes the delay. In this work, we consider the delay constraint $\overline{S}_u$ for a given SBS, where the following expression characterizes the delay and can be seen as below

$$\overline{S}_u = \frac{1}{\nu_u} - \frac{1}{1 - \rho_u} \quad (14)$$

In (14), ν_u is the service rate while ρ_u is the occupational rate of the network. The cumulative distribution function (CDF) of the delay $\overline{S}_u$ is represented as

$$F_{\overline{S}_u}(t) = 1 - e^{-\nu_u(1-\rho_u)t} \quad (15)$$

The probability that the delay constraint surpasses a critical threshold $\mathcal{V}$ can be represented as follows

$$P(\overline{S}_u > \mathcal{V}) = 1 - F_{\overline{S}_u}(\mathcal{V}) \quad (16)$$

Consequently, results in a probability where delay lies within the critical threshold $\mathcal{V}$ and denoted as given below

$$\text{DLR} = e^{-\nu_u(1-\rho_u)\mathcal{V}} \quad (17)$$

This framework also offers a thorough assessment of delay constraints and delay reliability in BS, which are vital for guaranteeing low-latency communication in BS networks. The derived expressions provide the frame of reference for assessing the performance of different RA schemes, especially in situations where delay-sensitive applications are in role.

2) JFI: It is one of the most commonly used metrics in RA network to determine the extent of the fairness of RA to the users in a system [12]. It is beneficial in applications where there are several users who are sharing resources and competing for them, such as bandwidth in wireless networks. The index gives a numerical value for fairness; this is advantageous because it prevents one user from hogging the resources and therefore makes the system to be fairer and can be expressed as below

$$\text{JFI} = \frac{\left(\sum_{\nu\in u} \tau \log_2\left(1+\frac{\rho_\nu\cdot h_\nu}{\sigma^2}\right)\right)^2}{n\cdot\sum_{\nu\in u}\left(\tau\log_2\left(1+\frac{\rho_\nu\cdot h_\nu}{\sigma^2}\right)\right)^2} \tag{18}$$

Here $\tau\log_2(1+\frac{\rho_u\cdot h_u}{\sigma^2})$ is the throughput that represents the data transmission rate of user u, τ is the allocated time slot during uplink, an important measure of data transmission rate that depends on other parameters such as allocated power ρ_i, uplink gain h_i and additive white gaussian noise σ^2 [13]. The sum of the throughputs($\sum_{\nu\in u}\theta_u$) across all users captures the total data transmission capability of the network. The sum of the squared throughputs ($\sum_{\nu\in u}\theta_u^2$) considers the distribution of throughputs, penalizing scenarios where certain users receive disproportionately high data rates compared to others.

3) DR: It represents the capacity of the network to transmit data efficiently, which is a key performance indicator in wireless communications. A higher data rate corresponds to a more efficient use of the available spectrum, allowing for faster data transfers and better overall network performance. The expression for the DR [14], is given by

$$\text{DR} = \text{BW}\log(1+\gamma_u) \tag{19}$$

$$\gamma_u = \frac{\sum|h_{u,b'}|^2 P_{max}}{\sum|h_{u,b'}|^2 P_{max}+\sigma_u^2} \tag{20}$$

In (20), P_{max} is maximum transmit power, σ_u^2 is white guassian noise, $|h_{u,b'}|$is small scale fading parameter.

D. Strategic Payoff Analysis

In the context of EGT, payoffs play a crucial role in determining the success of different strategies within a population. By calculating the payoff for each strategy, we gain insights into which strategies are more successful in the current environment and are thus more likely to proliferate. To evaluate the overall performance of the population, we compute the average payoff ($\overline{\Omega}$) across all strategies. This average payoff is not a simple mean but a weighted average that accounts for the utility of each strategy within the population. The formula for the average payoff is given by

$$\overline{\Omega} = \mathcal{F}^T\cdot(\Phi\cdot\mathcal{F}) \tag{21}$$

Here $\mathcal{F}$ is the vector of strategy utilities, and Φ is the payoff matrix. This formula determines the expected payoff of the population by factoring the payoffs of all strategies and the frequency of their use. The average payoff is a reference point through which the effectiveness of individual strategies is determined. If the payoff is greater than the average, the strategy is likely to enhance the utility, and if the payoff is below the average, the utility will be reduced.

E. Replicator Dynamics

This is the primary idea in EGT that defines the process of change in the distribution of strategies in a population. Mathematically, the change in the population of strategy i over time, denoted as $\delta\mathcal{P}_i$, is expressed as follows $\delta\mathcal{P}_i$, is given by

$$\delta\mathcal{P}_i = \mathcal{P}_i\left(\Phi_i - \overline{\Omega}\right), \tag{22}$$

$$\Phi_i = \frac{\Phi_{i1}+\Phi_{i2}+\cdots+\Phi_{in}}{n} \tag{23}$$

In (22), $\delta\mathcal{P}_i$ depicts the rate of change in the population of strategy i, $\mathcal{P}_i$ is the current population of strategy i and Φ_i is the payoff of strategy i. Altogether, these terms denote how the value of a strategy in the population evolves over time, depending on whether the payoff of the strategy is more or less than the average payoff of the population. Consequently, this shows that the rate of growth of the usefulness of a strategy is directly proportional to the difference between the payoff of the strategy and the average payoff. If the payoff of a strategy surpasses the average, the utility of the strategy will elevate, indicating that it is more effective in the current environment. On the other hand, if the payoff of a strategy is lower than the average, the usefulness of the strategy will be reduced.

F. Strategy Proportion Update

The next step after identifying the rate of change of the population of each strategy is to adjust these utilities to the new population distribution. The updated population $\mathcal{P}_i(new)$ for each strategy is calculated using the following equation

$$\mathcal{P}_i(new) = \mathcal{P}_i(old) + \delta\mathcal{P}_i \tag{24}$$

Equation (24) reflects how the strategy distribution evolves in the population over time. However, the adjustment is not solely based on payoffs; it also considers $\mathcal{FC}$, which measure key performance metrics such as DLR, JFI, and DR. Once utilities are updated, the $\mathcal{FC}$ for each strategy, $\mathcal{FC}_{i-new}$ are re-calculated such as

$$\mathcal{FC}_{i-new} = \mathcal{FC}(\mathcal{P}_{i-new}) \tag{25}$$

Further, the change in fitness ($\Delta\mathcal{FC}_i$), is assessed as mentioned below

$$\Delta\mathcal{FC}_i = \mathcal{FC}_{i-new} - \mathcal{FC}_{i-old} \tag{26}$$

If $\Delta\mathcal{FC}_i$ across all strategies fall below a certain threshold, it suggests that the strategy frequencies are stabilizing, indicating that the population is moving toward an ESS. This process is iterated until the population reaches stability. It is essential in EGT as it models the dynamic nature of strategy evolution, explores different possible distributions of strategies and converges toward an equilibrium where no strategy can improve its payoff by unilaterally changing its behaviour.

The threshold ensures that the strategies have converged sufficiently close to an ESS, where the population can maintain

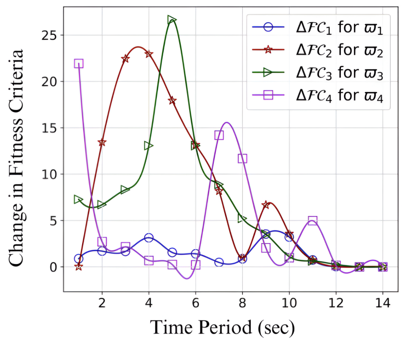

Fig. 1: Fitness Stabilization vs Time

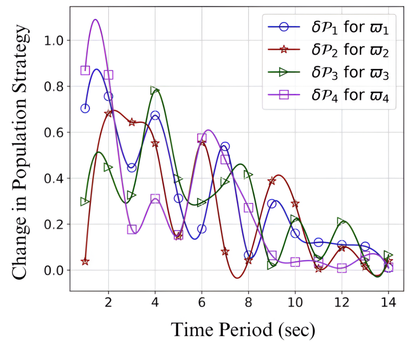

Fig. 2: Evolutionary change vs Time

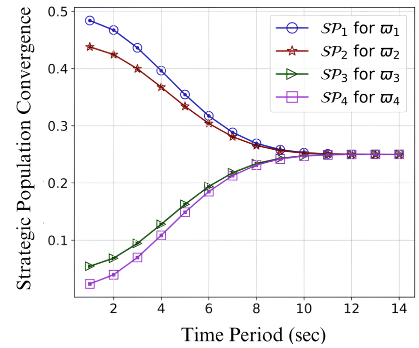

Fig. 3: Population Convergence vs Time

stability even in the face of small perturbations. In Algorithm 1, iteratively update the strategy population using RD until the change in fitness criteria $\Delta\mathcal{FC}$ is below a threshold ϵ. Compute fitness values, update populations, and check for convergence. Further, Algorithm 2 assesses stabilization by comparing the minimal fitness criteria change $\Delta\mathcal{FC}_i$ to ϵ. If the change meets the threshold, the corresponding strategy is confirmed as the ESS. Together, these algorithms identify and validate the ESS through iterative updates and stabilization checks. Furthermore, it is notable that the ϵ represents a small positive threshold determining when the fitness criteria have stabilized sufficiently to consider the population as having reached an ESS. In this instance, ϵ has been set to 0.0001, however, it can be adjusted according to the specific requirements of our analysis.

Algorithm 1 uses RD from EGT to update strategy frequencies based on relative fitness. More robust strategies increase in frequency while weaker ones decrease. The process is efficient, scalable, and converges toward equilibrium. A small threshold ϵ stops updates when fitness changes are minimal, signalling the population has likely reached an ESS. Algorithm 2 validates the ESS by comparing fitness changes to the threshold. If all changes fall below ϵ, the population is confirmed stable. This ensures the equilibrium is resistant to small perturbations, with ϵ controlling detection precision. Together, these algorithms provide an optimized approach to finding ESS, combining efficient updates with stability checks.

III. Simulation And Results

In our simulations setup, we have set the following parameters for DLR such as $\nu_u = 5$ (B/s), $\rho_u = 0.6$ (B/s), $\mathcal{V} = 1$, and $R_u = 5$kHz. From Fig. 1, we can infer that $\Delta\mathcal{FC}$ remains stable for ϖ_1, with a maximum fitness change of 13.3% throughout the simulations. In contrast, ϖ_2 and ϖ_3 strategies exhibit peak deviations. Moreover, ϖ_1 nearly reaches the point of convergence around the 11^{th} period, indicating that the strategic population distribution has stabilized, as also reflected in Fig. 3. Further, the SP_2 and SP_3 show significant irregularity, undergoing drastic changes in fitness but eventually achieving the same evolutionary stability. This suggests that ϖ_1 outperforms the other strategies. Fig. 2 provides insights into the population changes during the redistribution of base stations as strategies change. Initially, ϖ_2 and ϖ_3 experience significant fluctuations, whereas ϖ_1 maintains a consistent lower top and lower bottom, imply-

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Algorithm 1: ESS Sustainibility

Input : Payoff matrix Φ, Initial frequencies p_0, Fitness criteria $\mathcal{FC}_0$
Output: ESS
begin
  while $\Delta\mathcal{FC} > \epsilon$ **do**
    for *strategy* in *strategies* **do**
      Compute the $\mathcal{F}_0$, $\forall\varpi_i$ using Φ and the current population $\mathcal{P}_0$
      Determine $\overline{\Omega}$ based on the calculated payoffs
      Evaluate $\delta\mathcal{P}$ using RD, $\forall\varpi_i$
    end
    Update strategy population $\mathcal{P}_1 = \mathcal{P}_0 + \delta\mathcal{P}$
    Recalculate the $\mathcal{FC}_1$ based on updated population $\mathcal{P}_1$
    Compute $\Delta\mathcal{FC} = \mathcal{FC}_1 - \mathcal{FC}_0$
    if Any$(\Delta\mathcal{FC}_i) < \epsilon$ **then**
      return ϖ_i
    else
      $\mathcal{FC}_0 \leftarrow \mathcal{FC}_1$
      $\mathcal{P}_0 \leftarrow \mathcal{P}_1$
    end
  end
end

Algorithm 2: Stabilization Criteria for ESS

begin
  Let $g(x) = \min(\epsilon, \Delta\mathcal{FC}_i)$, where $i = 1, 2, 3, 4$
  for *FC* in $\Delta\mathcal{FC}_i$ **do**
    if $g(x) = \mathcal{FC}$ **then**
      $\mathcal{P}_i$ converges in *RD*
      The corresponding strategy of $\Delta\mathcal{FC}_i$ is an *ESS*
    end
  end
end

ing greater stability throughout the periods. After the 11^{th} period, unilateral switching to different strategies becomes minimal, as there is no incentive to deviate, thus attaining Nash equilibrium. The reduced fitness change observed in the 12^{th} period as shown in Fig. 1 aligns with the minimal switching in distribution seen in Fig. 2. Moreover, ϖ_2 is inconsistent due to its irregular population distribution. However, it still follows a relatively stable path with consistent upper and lower bounds, as seen in Fig. 2. Furthermore, the other strategies exhibit significant deviations but ultimately converge toward a similar path for sustainability. Lastly, Fig. 3 shows that, despite the erratic population distribution after the 10^{th} period, the overall network configuration becomes more uniform, leading to improved energy efficiency, balanced traffic loads, and enhanced network capacity ensuring the ESS.

IV. Acknowledgment

This work was supported by the Science and Engineering Research Board (SERB) under the grant EEQ/2020/000047 and the Department of Telecommunication (DoT), Ministry of Communications, Government of India under the Telecom Technology Development Fund (TTDF) scheme implemented through TCOE India under the grant TTDF/6G/48 received at Indian Institute of Technology, Dharwad, India.

V. Conclusion

Our study validates the application of ESS in allocating wireless resources within the rapidly emerging 6G network environment. By deploying a sophisticated mathematical model grounded in EGT, we have demonstrated that ESS can significantly enhance both the efficiency and fairness of resource distribution. The model's robustness in maintaining network performance amidst dynamic changes establishes ESS as a vital tool for future wireless network architectures, ensuring stability and optimized resource utilization without constant manual recalibration. The results underscore the potential of ESS to create a network ecosystem where strategies, once established, are resistant to being supplanted by alternatives. This stability is crucial, particularly in 6G networks, where the demands for high data rates and low latency are balanced with equitable resource distribution among a diverse array of devices and services. The evolutionary approach allows network strategies to adapt over time, improving the overall network resilience and response to evolving conditions and user demands. Further, the implications of this research extend beyond current network technologies to inform the design of adaptive and scalable network architectures [15]. Integrating ESS into network planning and operation can facilitate more responsive and self-optimizing networks that are better suited to meet the challenges of 6G. Furthermore, studies should explore integrating these strategies with advanced artificial intelligence and machine learning techniques to enhance their predictive capabilities and efficiency in real-time adaptations. Lastly, in conclusion, the successful application of EGT to wireless RA in 6G networks suggests a promising direction for next-generation communication research and development. In addition, it also invites a broader application of game-theoretical approaches across various network design and management aspects, potentially revolutionizing the strategies to handle complex decision-making processes in highly dynamic environments. As we move forward, the continuous refinement and empirical validation of these strategies will be essential to harness their full potential to ensure that next-generation networks can meet the expanding needs of the modern era.

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