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NABGAMES: NASH BARGAINING GAME FOR IMPROVING COVERAGE IN UNMANNED AERIAL VEHICLES (UAV)

UMA N DULHARE[1] , Dr.B.RAGHURAM[2], Dr.C.SRINIVAS[3] , S. VENKATRAMULU[4] , Dr.V.CHANDRASHEKAR RAO[5] and Dr.K.VINAYKUMAR[6]

[1]Department of Computer Science and Artificial Intelligence, Muffakham Jah College of Engineering & Technology, Hyderabad.

[2,3,4,5,6]Department of Computer Science and Engineering, Kakatiya Institute of Technology and Science, Warangal.

ABSTRACT

The deployment and positioning of unmanned aerial vehicles (UAVs) are heavily reliant on the amount of power accessible, a workable situation, and a protected connectivity. Appropriate height is required for the practical deployment of UAV modules to reach the mobile networks. Resources wastage or operation inefficiencies result from the under or overestimation of nodes' air time. The UAV coverage issue is taken into account in this research, and then a Nash bargaining game model (NaBGames) is suggested to enhance the range by utilizing UAV nodes which are controlled and managed for re - allocation and can shift positions as needed. Cellular users are permitted to flexibly alter their service cost during every round of negotiation in order to maximize their earnings. Afterwards, every user adopts "bargaining" and "warning" to create their finest reaction. Such method could function even in hostile circumstances because it is dependent on the connections between UAVs and its nearby neighbors in a distributed system. By employing the least number of UAVs required to encompass the potential specific region, the altitudes of the UAVs are modeled based on the transmitters and other installation needs. The proposed NaBGames is compared with three base line methods, whereas it achieves 18.3 ms delay, 587Mbps throughput, 16.4% of power consumption and 97.8% of Trade success probability.

Keywords: G*ame theory, Nash bargain, Unmanned Aerial Vehicles, Coverage, Power consumption***.**

1. INTRODUCTION

Unmanned aerial vehicles (UAVs) are being utilized more often in a variety of tasks, including monitoring, precision agriculture, computer vision, emergency management, civil protection, monitoring wildfires, cloud surveillance, architecture supervising, and power line assessment [1]. The unmanned aerial vehicles (UAVs) are aerial aircraft without any inside controllers. These aircraft execute automatic pre-programmed missions as well as being wirelessly and interactively controlled by a person. Smart sensors that are coupled with on-board instruments can be utilized to carry out driverless missions. Building a route for a robot to travel through each place in a given case is important for solving the Coverage Path Planning (CPP) issue, which is categorized as a trajectory planning sub - topic in robots [2]. Although this kind of aerial platform has advanced technologically in terms of autonomously flying, it is crucial to stress that due to safety precautions, the departure, mission operation, and land stages for every UAV are often accompanied by two persons. Whereas the base controller checks the satellite signal during the operation performance, such as height variations and energy depletion, the pilot monitors the operation and it may switch the fly style to manually in the event of a malfunction or a crisis during aircraft [3].

The terrain gets split into smaller regions packets called as in cellular networks. To expand the geographic region, such mobile network cells are connected to one another. Typically, a geographic coordinate tower called a Base Transceiver Station (BTS) or Base Station (BS) serves all of these cells [4]. Smaller cells are linked to large cells, that are linked to base stations, while larger cells are attached to PECO cells or microcells within those connections [5]. Further directly attached to the base stations, the specialized cells provide consumers with entry-level services. The user density in the networks is used to determine the different cell sizes. Macro, micro, and pico deployments of these cells are all possible [6]. A macrocell normally covers a wide region of circumference that is nearly 24 km based upon the quantity of users. The pico cell lines are employed to cover tiny locations like workplaces, shops, and houses while the micro cells typically have such network coverage of up to 3 kilometers [7].

The necessity for a reduced cell size is influenced by user capacity as well as the transmission range. The cells can be divided up into smaller levels, which greatly improve the channel's capacity to be reused. Online resource services are offered via the fixed BS. However, the BS only functions properly in conditions like adequate tower support area, practical construction, and unobstructed locations. While BS services provide numerous benefits, there are often burdened with greater initial investment, management concerns, as well as other lengthy procedures. Furthermore, swift rehabilitation and restoration of uninterrupted connection services really aren't feasible in areas where infrastructural construction is challenging or when there are increased odds of natural catastrophes, such as floods and tremors [8].

Additional obstacles include problems with the BS's source of electricity, the price of generators, problems with the land, and problems with accessibility, throughput, and road coverage. Unmanned Aerial Vehicles (UAVs) relying on microcellular technologies were exploited to provide interim ground-based solutions to these problems [9]. These options have also been investigated for fifth-generation (5G) cell service expansion. In order to improve the Quality of Service (QoS) for phone devices on the surface, similar aerial BSs are distributed utilizing drones, including such Drone Base Stations (DBSs) [10]. Game theory method is employed for multi-level and multi-dimensional UAV aided systems based on a critical game to devise a strategy with maximum cellular coverage by creating optimum quantities of BSs in the telecom core network. The objective of this game is to maximize range while using little transmits power.

2. RELATED WORKS

In the absence of a leader or a reference trajectory, R. Bardhan's (2018) article tackles a finite-time rendezvous problem for a fleet of UAVs [11]. Due to the assumption of Nash equilibrium, it is believed that the UAVs will use such strategies in the absence of cooperation (NES). But when UAVs are able to exchange data with one another, they can use cooperative game theoretic tactics to their advantage. When the UAVs minimize a team cost functional together, as defined by a convex combination of their individual cost functionals, a Pareto-optimal solution (POS) is achieved in a convex linear quadratic differential game (LQDG). In this paper, the authors suggest an algorithm to find the convex combination of weights that corresponds to the Pareto-optimal Nash Bargaining Solution (NBS), which provides each UAV with a lower cost than that incurred from the NES.

The convergence of the suggested algorithm to the NBS is guaranteed under certain conditions on the cost functions. A UAV may decide to switch to NES if it determines that doing so will be more beneficial than continuing with a cooperative strategy it previously agreed upon with the other UAVs, based on cost-to-go estimates for the remainder of the game duration. In these cases, a renegotiation strategy is suggested, which employs the proposed algorithm to determine the NBS that is appropriate for the game state at the aforementioned intermediate time. UAVs can work together and avoid disruptive behavior thanks to this revision technique. The effectiveness of the guidance law obtained from the suggested algorithm is demonstrated through simulations. In this context, the conditions of time consistency of a cooperative solution have been derived in relation to LQDG.

Target search is one of the most pressing concerns in the area of unmanned aerial vehicle (UAV) research because of the UAV's widespread use. When compared to using a single UAV, a multi-UAV system has greater competence, execution efficiency, and robustness when tackling more complex jobs. While multi-UAV cooperative search has many potential benefits, it also faces some novel obstacles, such as collaborative control and search area covering issues. In this article, Ni, Jianjun et al. (2020) model the cooperative search problem as a potential game and suggest a modified binary log linear learning (BLLL) method to solve the covering problem using multiple UAVs [12]. Additionally, a novel action selection strategy for UAVs is suggested to enhance the cooperative control performance based on potential game theory. By sharing this data with nearby residents, this plan can prevent a Drone from straying into a no-power zone. The process concludes with a number of trials. Experimental results demonstrate that the proposed method outperforms the original BLLL algorithm and is successful at completing cooperative search tasks.

In recent years, ad hoc networks for unmanned aerial vehicles (UAVs) have attracted a great deal of attention from academics because they offer a promising new market. UAVs have a lot of

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potential in the area of wireless communications, where they could be used as a sort of flying base station to improve and expand network access. Here, Garmani H et al. (2021) construct and analyze the correlations between UAVs with respect to price, beaconing time, and service quality [13]. The equilibrium price, the equilibrium quality of service, and the equilibrium beaconing duration are all analyzed in detail to provide a comprehensive view of the game's result. The authors then examine the circumstances under which the Nash equilibrium point is both present and unique. In addition, they supply a learning method that guarantees the rapid and decentralized convergence of the considered UAV to its individual Nash equilibrium operating point. In conclusion, numerical studies provide encouraging insights into how the game parameters should be selected for effective management.

Connectivity and coverage in cellular networks can benefit from the use of unmanned aerial vehicles (UAVs) distributed as wireless relays or aerial base stations. Unmanned aerial vehicles (UAVs) can also be used to greatly improve the efficiency of wireless sensing networks and mobile ad-hoc networks. In the not-too-distant future, UAVs will play a crucial role in the development of 5G wireless networks and the upcoming huge Internet of Things. Nonetheless, there are many difficult problems still to be solved in the planning of structures and the implementation of networks based on UAVs. Game theory, which is useful for modeling and analyzing issues in UAV-aided networks, has lately been adopted as a means of addressing the underlying issues.

Mkiramweni et al. (2019) provide a comprehensive review of how game theory can be used to address a wide range of issues in UAV-assisted networks [14]. The writers begin with a primer on wireless communications with UAVs before moving on to an overview of the fundamentals of game theory and how they apply to wireless networks. In addition, they provide a categorization of games used in UAV-aided networks and a short overview of how these games can be used to address specific challenges. The authors then present a systematic literature survey of game-theoretic methods for addressing difficulties in UAV-based wireless networks. In the end, they present cutting-edge distributed methods for managing interference in massive UAV-assisted communication networks. The purpose of this paper is to familiarize the reader with the architecture, benefits, challenges, and different game-theoretic solutions applied to UAV-aided communications networks.

Applications for unmanned aerial vehicles (UAVs) in the field of wireless communications have lately proliferated. Particularly, UAV-mounted base stations (UAV-BSs) can be used to expand coverage in wireless cellular networks while also providing high-quality network connectivity. Although UAVs have the potential to serve as aerial base stations, the issue of optimizing their energy economy must first be resolved. High availability, acceptable performance, and a financially viable UAV-USs deployment all depend on optimizing energy usage. Modeling and analyzing difficulties in UAV-aided wireless networks have lately adopted game theory as an effective tool. So as to optimize energy efficiency in UAV-assisted networks, Mbazingwa E. (2018) proposes a Nash bargaining game (NBG) theory method [15]. Nash bargaining solution (NBS) is used to handle the problem of adaptive beaconing period scheduling for UAV-USs, which provides the optimal beaconing period duration to minimize power consumption. In order to prove that our technique actually works, we run extensive simulations.

The significant benefit derived from the cooperative mechanism of UAVs when deployed as a flying base station has made UAV-assisted sensor networks a key area of research. Since both coverage and transmission performance indexes are correlated with the distance between UAVs, deployment of UAVs often faces a predicament in coverage situations due to the need to strike a balance between the two. In this article, Ruan L et al., (2018) analyze the mechanism of UAV coverage and data transmission, and then suggest a model for efficient multi-UAV cooperative deployment [16]. A game model of coalition building is used to examine the issue (CFG). It is demonstrated that the division of the CFG with Pareto order is stable. Then, a method is developed that combines coverage deployment and coalition selection so that Drones can make strategic decisions about coverage operations in concert. Coverage deployment and coalition selection are best carried out by utilizing a hybrid method that combines game-theoretic analysis, coalition selection, and a Pareto-ordered position deployment algorithm (CSPDA-PO). Finally, simulation findings are presented to verify the effectiveness of the proposed method based on a cooperative deployment model for multiple UAVs.

Swarms of autonomous unmanned aerial vehicles (UAVs) can be deployed in harsh

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environments where cyber electromagnetic activities necessitate frequent and immediate changes to swarm strategy. In such deployments, the use of centralized controllers, UAV synchronization mechanisms, or pre-planned sets of actions to control a swarm would reduce the swarm's ability to provide the anticipated services. In order for each autonomous UAV to make decisions about its next move in near real-time using only local spatial, temporal, and electromagnetic (EM) data, Kusyk J et al. (2021) present AI and game theory-based flight control methods. Our flight management algorithms ensure that each UAV in the swarm always stays in a position where the mobile ad-hoc network (MANET) remains active and the assets are spread out evenly across the target region [17].

Swarms powered by our algorithms can perform common jobs such as locating and following moving EM transmitters. Authors provide formal analysis demonstrating how our algorithms can steer a swarm to keep a MANET connected, encourage uniform network spread, and prevent swarm members from crowding each other out. We also show that they can guide a flock of autonomous UAVs to either pursue or avoid an EM transmitter while keeping a MANET connected. Through formal analysis, we have established that our algorithms can successfully cover a large enough area over a moving EM source while keeping the MANET connected. This has been confirmed through simulation tests in OPNET modeler. These algorithms are well suited for civilian and military applications that need to identify, localize, and track mobile EM transmitters in dynamic environments.

The term "edge computing" refers to a type of distributed computing architecture that places data processing and storage capabilities closer to the ends of a network's nodes. Edge computing with the help of UAVs allows for adaptable setups of mobile ground stations (MGN). Before edge computing systems can be used widely, however, they need improved energy management and better guarantees of reliability for completing computational tasks. Kim SY, et al. (2021) suggests a UAV-based edge computing system with energy harvesting to address these issues. In this setup, the MGN sends out queries for computing services to a fleet of UAVs, with the proximity of those UAVs determining whether or not the processing of the data is done centrally or in a decentralized fashion [18]. The authors suggest a stochastic game model with constraints to minimize UAVs' energy consumption while keeping a guaranteed level of reliability for task completion. To achieve a multi-policy constrained Nash equilibrium, we use a best response method. Our system outperforms the individual computing scheme in terms of lifetime while still keeping a high probability of a successful final result.

As one of the earliest sectors to embrace new technologies, aviation has benefited greatly from the contributions made by the military flight sector. Unmanned Aerial Vehicles (UAVs) have been used by the military for quite some time, but their civilian applications are only recently emerging and growing quickly. Due to their versatility and portability, they have been put to use in a wide range of activities, including monitoring, surveillance, remote sensing, and delivery.

Despite advancements in their propulsion systems and electronics, Drones continue to face significant difficulties in the areas of dependability, safety, and upkeep. The civil aviation business is subject to a wide range of regulations and standards, making quality and safety management practices indispensable. These ideas are still developing for UAVs, and neither the rules nor the standards have been finalized. The author, Ozlem Senvar (2022), set out to create a comprehensive look at UAVs from the vantage point of aircraft quality and safety management [19]. Moreover, emerging topics, methods, and technologies are addressed as well.

Resources wastage or operation inefficiencies result from the under or overestimation of nodes' air time. The UAV coverage issue is taken into account in this research, and then a Nash bargaining game model (NaBGames) is suggested to enhance the range by utilizing UAV nodes which are controlled and managed for re - allocation and can shift positions as needed. Cellular users are permitted to flexibly alter their service cost during every round of negotiation in order to maximize their earnings. Afterwards, every user adopts "bargaining" and "warning" to create their finest reaction. Such method could function even in hostile circumstances because it is dependent on the connections between UAVs and its nearby neighbors in a distributed system. By employing the least number of UAVs required to encompass the potential specific region, the altitudes of the UAVs are modeled based on the transmitters and other installation needs

3. SYSTEM MODEL

Due to overloaded connections and a rising user trend, wireless network coverage is a

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constant concern. Cellular networks' use of unmanned aerial vehicles (UAVs) has provided a receive the data to the coverage problem. UAVs are utilized by these networks as base stations (BS) to increase mobile network coverage. The UAVs are maintained and monitored to reallocate and shift positions as needed. For surface internet users to provide the services and range, which meet the system requirement, the UAVs-BS provides a more practical alternative.

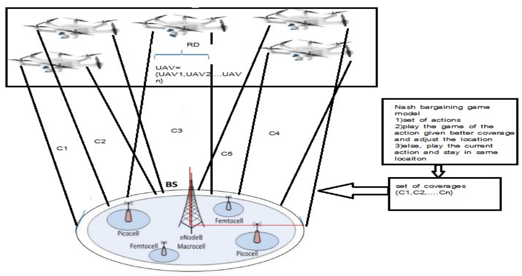

Figure 1 : Architecture of Nash bargaining game based coverage in UAV

Diagram 1 depicts an illustration of a UAV-BS coverage area where the UAV-BS covers cellular network cells. The difficult task for UAVs is determining the ideal location within the microcell. One of the adaptable and affordable options to increase grounded network access and offer high-speed data capabilities is the UAVs-BS. Providing of the coverage area remains difficult, particularly in crowded networks. A UAVs-BS coverage area concept for mobile networks is presented in this subsection. The following subsections contain a full presentation of the recommended model's stages of design and development.

3.1. Preliminaries forgame

The participants would be portrayed as decision-making entities to determine the most appropriate action that could result in increased coverage effectiveness. In order for UAVs to operate and communicate effectively, employing the finest tactics possible. Any game typically has three components:

- A group of individuals in which the vehicles (Veh) represent the participants: $\mathrm{veh} = \mathrm{veh1}, \mathrm{veh2}, \ldots \mathrm{vehm}$.
- A series of tactics or moves for every player (vehicle), where every other move or tactic symbolizes the UAV's upcoming mobility in three-dimensional (3D) spaces. As a result, every player has 28 activities within every recursion: $\mathrm{A}^{3d}_{\mathrm{veh1},\ldots,\mathrm{m}} = \{\mathrm{a}_1, \mathrm{a}_2, \ldots \mathrm{a}_{27}\}$.; these can be performed in any of the following directions: up, down, east, west, south, north, or diagonally. However, in the two-dimensional (2D) area, each player has only Nine moves available towards each player: whether one remains in the corresponding position or travels to a new enclosure (in the east, west, south, north, and four diagonal orientations): $\mathrm{A}^{2d}_{\mathrm{veh1},\ldots,\mathrm{m}} = \{\mathrm{a}_1, \mathrm{a}_2, \ldots \mathrm{a}_9\}$. Understanding that the present UAVs' motions and orientations were unrelated to their past activities and rely heavily on the utility function every UAV has attained. Every UAV in this games has 28 potential options in 3D, and it can choose to remain inside one spot or migrate into any of the following 28 according to which choice has the most utility function.
- A list of rewards ratings for every participant dependent just on chosen action is given by the formula $\mathrm{val}_{\mathrm{veh1},\ldots,\mathrm{m}} = \{\mathrm{val}_1, \mathrm{val}_2, \ldots \mathrm{val}_{27}\}$.. The functional form in this scenario depicts the player-covered area in relation to the coverage probability value.

3.2 Nash bargaining game for coverage improvement

Throughout this part, researchers presume that before cellular user j chooses to provide access to some other unregulated cellular user k, this should fully satisfy the second unregulated cellular user k's requirement for the best possible range. An unregulated cellular customer, nevertheless, seems to have the authority to reject any cellular user j in an unproductive area, such as

$$\sum_{i=1}^{M} x_{ij} = 0 \qquad (1)$$

Instead of two parties, Player 1 or Player 2 identify two separate user groups. In other terms, all approved cellular users i must play the dilemma play simultaneously with all unregistered cellular users j. If $u(i)$ authorized users are present, u dilemma play will be played concurrently. Technically, this article presents this procedure using a single dilemma game for clarity. ho_prop (keep the earlier suggestions) can only be obtained if all players in player 1 opt to do so; otherwise, cha_{prop}((change the proposals) is the option.Similar to that, Adh_for (adhere to former x) would succeed only if every unregistered mobile users stick with their previous decisions (that is, x

remains unchanged). Secondly, these study allows cellular users i to know cellular users j's decision (A or R (respond, modify the x)) as well as the "bargain" and "warn" of cellular users j in a scenario of adequate knowledge where cellular users j understand the propositions of cellular users i instead of producing a reaction. If $a_{ij} = 0$, "deal" refers to the price reduction that cellular user i must make in order for cellular user j to select cellular user i. Inform the cellular user i the coverage rate that it will abandon the customer j with the word "Warning," seeking for $a_{ij} = 0$. Understanding such deals and warnings, and providing access to every mobile phone user's "bargaining coverage range," i can determine the best range. Designers made some adjustments to the game model, established several fresh claims, and provided the supporting evidence.

Proposal 1. Every suggestion which ensures that the utility of Players 1 and 2 is "not below zero" for one round of the negotiation could be defended as a Steady state.

Proof. Players 1 and 2 are assumed to have utility values of α and β, respectively. Player 2 will adopt the approach of "I approve any proposition producing ho_prop 0 and refuse any proposition producing cha prop, 0" regardless of Player 1's choice of ho_prop or cha_{prop}. Every tactic for Player 1 which results in 0 will be used. Consequently, 0 and 0 are the mutually optimal answers, and the hypothesis has just been established.

Multiple users in Player 1 are not required or ability to attain a global optimum, despite the fact that Player 1 would approve the certain plan that results in 0, regardless whether there is one which enables Player 1 to earn the highest benefit underneath the assumption of 0 without collaboration. The personal best of one user, however, is more significant.

The Conditional probability cannot be reached in a single negotiation round. As a result, the negotiation will continue until the Nash balance is reached. In actuality, bargaining will continue until the Nash balance is reached. Relying on the extrinsic constraints, an indefinite game is impossible in real-world applications. Finite numerous games of negotiating could answer the coverage area challenge with a finite number of rounds, as demonstrated by eqns 2 and 3:

$$argmax \prod i\,(x), for\ \forall i \epsilon \{1,2,\dots X\} \quad (2)$$

$$such\ that\ \sum_{j=1}^{n}(G_i, a_{ij}) \le X_i, i = 1,2,\dots X\} \quad (3)$$

$$a_{ij} \epsilon \{a_{ij}, argmax\ \pi_i\,(p), for\ all\ i = \{1,2,\dots X\}\}, j = 1,2,\dots N$$

Every cellular user I would transform its coverage price to achieve its own optimum value. Every time a user chooses a course of action, it is based on the opponent's most recent move. To put it another way, every player in Player 1 modifies the approach in response to previous coverage requests by Player 2, whereas each player in Player 2 takes the decision on the cost of Player 1. Until an agreement is formed, a procedure in which all individuals can constantly discover the best tactics would remain. The relative distance (RD) $dis_{i,j}$ here between UAV_i and UAV_j are deconstructed together into shortest path $dis_{i,j}$ inside the x-axis position and a distance vector $dis_{i,j}$ in the y-axis direction following consensus building, and the RD expressions in between UAVs is as depicted in formula after this process.

$$dis_{ij\_x} = x_i - x_j \quad (4)$$

$$dis_{ij\_y} = y_i - y_j \quad (5)$$

$$dis_{i,j} = \sqrt{{dis_{i,j\_x}}^2 + {dis_{i,j\_y}}^2} \quad (6)$$

The UAV would relocate underneath the RD whenever the spacing between UAVs is below the cutoff point, and also the new location is

$$\begin{cases} x_{new\_dis} = x_{old\_dis} + \frac{dis_{ij\_x}}{dis_{i,j}} \times maxi\_UAV \times e^x \\ y_{new\_dis} - y_{old\_dis} + \frac{dis_{ij\_y}}{dis_{i,j}} \times maxi\_UAV \times e^y \end{cases} \quad (7)$$

In which $maxi\_UAV$ is the largest scale parameter the UAV can take while moving underneath the RD, $(x_{old\_dis}, y_{old\_dis})$ have become the positioning coordinates of the UAV well before iteration, $(x_{new\_dis} y_{new\_dis})$, are the updated position parameters of the UAV.

4. PERFORMANCE ANALYSES

This section will examine the success of the suggested NaBGames based on the ideal coverage value attained, flexibility to variations in the challenging environment, and connectivity durability in the event of a failure. Following an overview of the system, we present the outcomes of

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our game-based methodology. The beginning locations of the 15 UAVs, which are scattered at random in a square area of R = 10K, still had no bearing on the distribution problem's outcomes. To determine the occupied squares per each UAV at every time, the territory is made up of 100 100 cells. As a preliminary step, researchers also have prior knowledge about target region.

4.1 Comparative results

The performance of our proposed Nash bargaining game model (NaBGames) is carried out using parameters such as. These parameters are compared with three state-of-art methods cooperative graphical game (CGG), network potential game theory (NPG), evolutionary game theory (EGT)

Table1 Analysis of delay and throughput

Number of iterations	Delay (ms)				Throughput (Mbps)			
	CGG	NPG	EGT	NaBGames	CGG	NPG	EGT	NaBGames
0	45.6	51	60.1	20.1	789	879	678	567
10	43	52.4	62.1	18.7	783	854	657	533
20	47.3	56	65.3	19	778	832	698	587
30	48	54.3	67.3	16.5	721	842	672	531
40	48.7	58	65	17	763	875	653	521
50	46	58.4	66.4	17.9	758	871	643	589
60	43	58	68	18	795	882	623	567
70	43.2	54	69	16.9	765	884	632	593

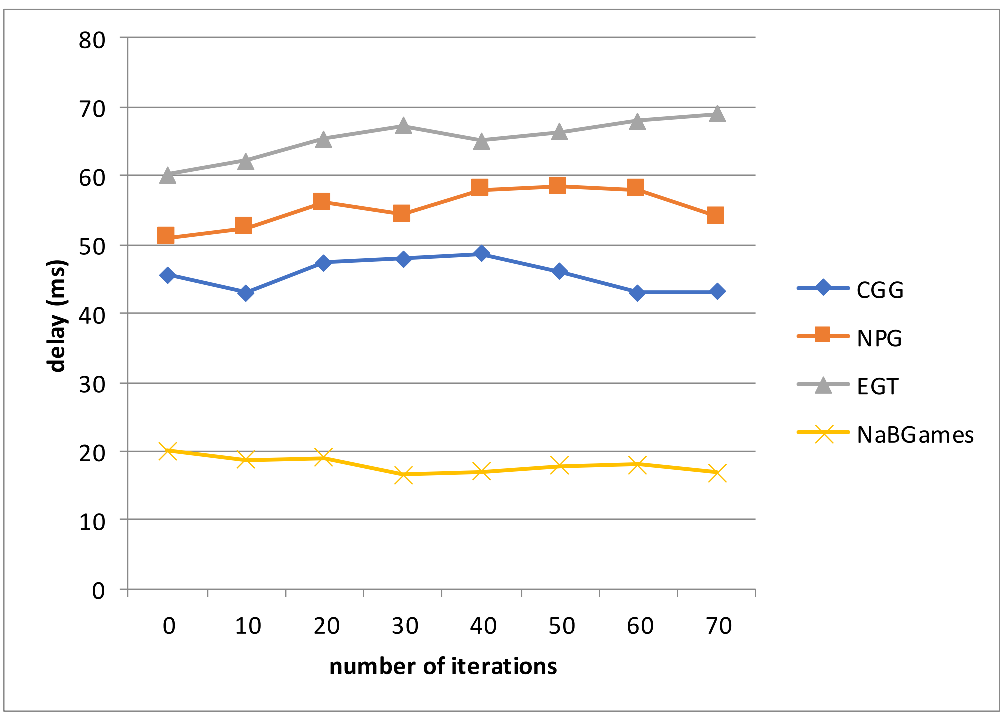

Figure2: Comparison of delay

Figure 2 and 3 depicts the shows delay and throughput comparison of existing CGG, NPG, EGT and proposed NaBGames. X axis and Y axis shows that number of iteration and the values obtained in milliseconds and Mbps, respectively. When compared, existing CGG, NPG, EGT

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methods achieve 44.3ms, 56.7ms and67.4ms of delay while the proposed NaBGames method achieves 18.3ms of end delay which is 26ms,38.4ms,49.1ms better than above mentioned existing methods. Moreover, existing methods achieves 768Mbps, 854 Mbps, 689Mbps of throughput which is 199Mbps, 267Mbps and 102Mbps better than NaBGames method

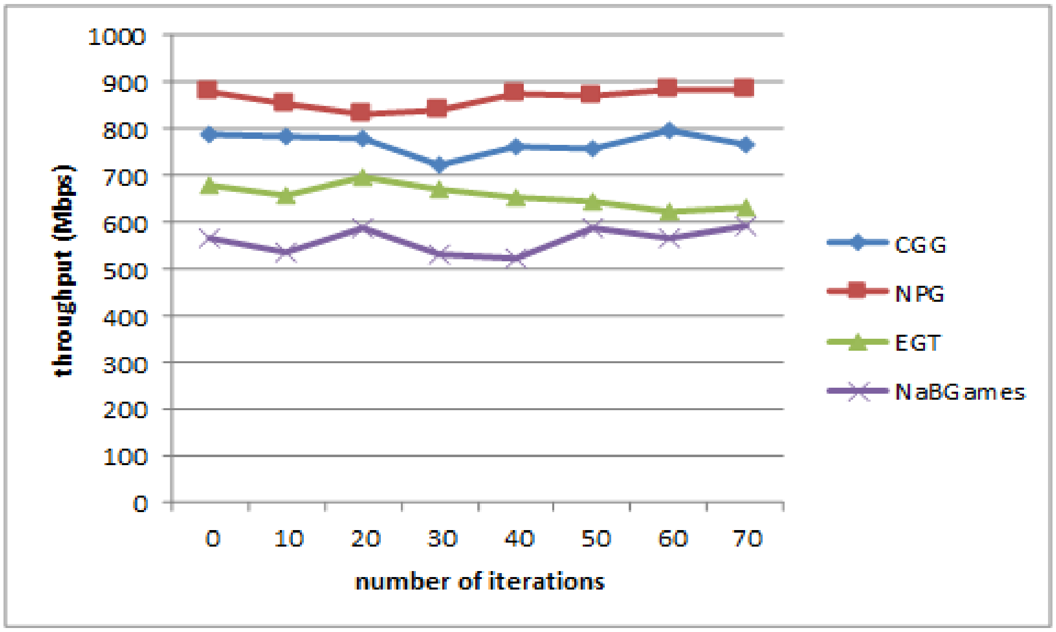

Figure 3: Comparison of throughput

Table 2: Analysis of power consumption and trade success probability

Number of iterations	Power consumption (%)				Trade success probability (%)			
	CGG	NPG	EGT	NaBGames	CGG	NPG	EGT	NaBGames
0	78.8	81.4	35.7	12.5	65.4	71.9	85.3	98.6
10	76.4	84.3	36.7	14.6	67.9	71.7	82.3	95.7
20	78.9	84.3	38.2	13.6	65.4	74.5	81.5	93.8
30	73.5	86.5	39.4	14.6	64.9	76.9	86.7	94.7
40	77.3	85.3	38.5	14.9	63.8	78.9	89.5	97.4
50	76.2	87.3	32.1	14.4	67.9	79.8	85.6	92.5
60	79.3	89.1	31.8	14.8	62.9	77.6	84.6	95.6
70	76	87	35.2	15.4	65.7	75.4	83.5	97.3

Figure 4 and 5 depicts the shows power consumption and trade success probability comparison of existing CGG, NPG, EGT and proposed NaBGames. X axis and Y axis shows that number of iteration and the values obtained in percentage, respectively. When compared, existing CGG, NPG, EGT methods achieve 78.5%,87.5%,39.7% of power consumption while the proposed NaBGames method achieves 16.4% which is 62.1%,71.1%,23.3% better than above

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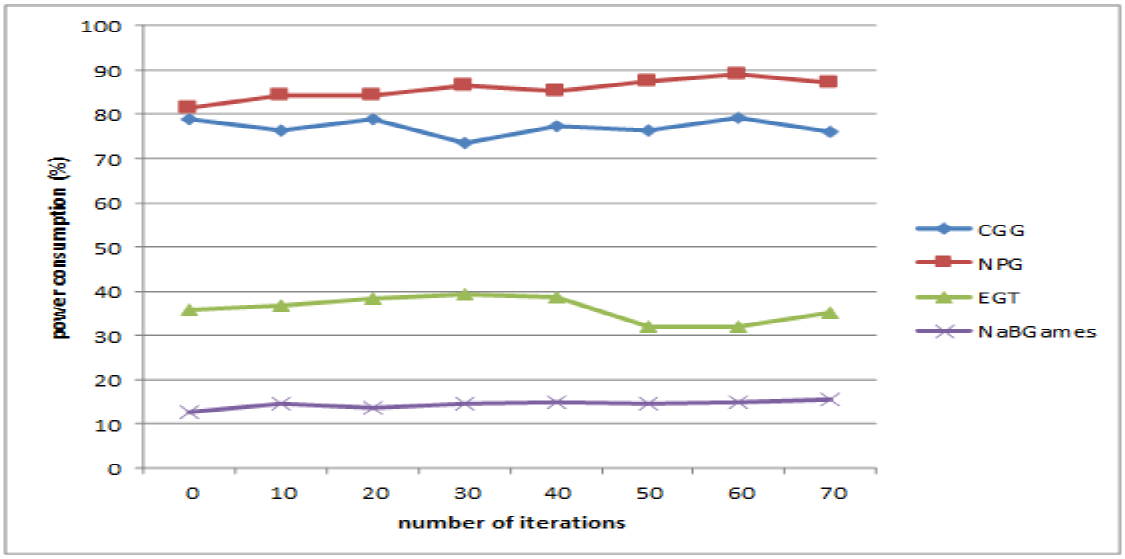

Figure 4: Comparison of power consumption

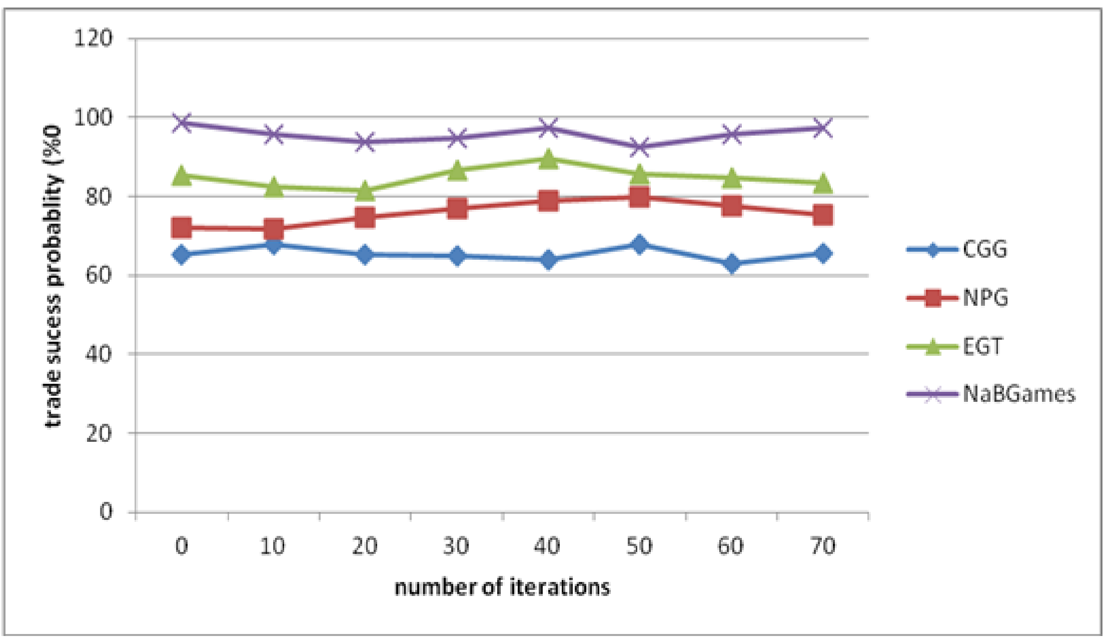

Figure 5: Comparison of trade success probability

mentioned existing methods. Moreover, existing methods achieves 69.2%,78.9%88% of trade success probability which is 28.6%,18.9,9.8% better than NaBGames method.

Table3: Performance Metrics

parameters	CGG	NPG	EGT	NaBGames
Delay (ms)	44.3	56.7	67.4	18.3
Throughput (Mbps)	768	854	689	587
Power consumption(%)	78.5	87.5	39.7	16.4
Trade success probability (%)	69.2	78.9	88	97.8

5. CONCLUSION

In this research, we proposed an autonomous game-theoretical decision-making method for a successful implementation utilizing relatively high concentrations and multi-dimensionally dispersed UAVs. Researchers looked somewhere at variance in coverage probability for every UAV dependent on its subsequent motion while employing the least amount of transmission capacity. In order to raise the coverage value and boost the reward for the UAV, researchers built its motions as a multi-

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player game. Whenever the accomplished payoff is smaller than the existing value, the UAV may shift locations or remain in the same place. In the future, we choose to incorporate a game model based on reinforced operations to improve the results.

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