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Article

Energy-aware power and rate control in MANETs using adaptive game theory and grey wolf optimization

Chandrashekhar Goswami[1,2]*, Chin-Shiuh Shieh[2], Prasun Chakrabarti[1]

[1]Sir Padampat Singhania University, Udaipur, Rajasthan, India
[2]Research Institute of IoT Cybersecurity, Department of Electronic Engineering, National Kaohsiung University of Science and Technology, Taiwan

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*Corresponding author
Email address:
shekhar.goswami358@gmail.com

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ABSTRACT

Inherent resource constraints within Mobile Ad Hoc Networks (MANETs) necessitate resource optimization, specifically power and rate control, as a critical focus for enhancing network performance in terms of energy, throughput, and delay. Although traditional power and rate control mechanisms have successfully improved throughput or energy efficiency, they fail to address the complex trade-offs between delay, energy consumption, and network stability, particularly in highly dynamic or unpredictable networks. Motivated by this, this study introduces a new Dynamic Power-Rate Optimization Grey Wolf Algorithm (DPRO-GWA) mechanism derived from a game-theoretic framework that balances outage probability and residual energy demands to achieve energy efficiency and quality of service (QoS) in mobile ad hoc networks (MANETs). The proposed approach formulates power and rate allocation as a super-modular game, which ensures both the existence and uniqueness of a Nash Equilibrium (NE) as the optimal solution for distributed non-cooperative nodes. We subsequently introduce an Adaptive Grey Wolf Optimizer (AGWO), which enhances the Grey Wolf Optimizer (GWO) by increasing convergence speed through adaptive tuning of the exploration-exploitation trade-off. Extensive simulation results demonstrate that DPRO-GWA significantly outperforms existing algorithms, including the Dynamic Rate and Power Allocation Algorithm (DRPAA), Energy Conserving Power and Rate Control (ECPRC), and Rate-Effective Network Utility Maximization (RENUM) in terms of energy consumption, throughput, and delay. Additionally, the proposed method maximizes the energy-delay trade-off, leading to considerable improvements in the network lifetime and performance, particularly in time-variant and fading channel environments. Thus, this study creates a promising avenue for refining power and rate control protocols for next-generation MANETs.

1. Introduction

Mobile Ad Hoc Networks (MANETs) are a type of ad hoc network formed by mobile devices that dynamically interconnect and communicate with one another without relying on a pre-existing infrastructure (such as cellular networks). These networks are important to note as they are highly flexible and dynamic in nature, as the nodes (such as mobile phones, laptops, and sensors) can join and leave at will, and the movement of nodes frequently causes changes in network topologies. Because of their capacity to function in settings where classic infrastructure-based networks are impractical or inaccessible, MANETs are utilised in a wide range of applications, such as disaster recovery, military communication, vehicular networks, and remote sensing [1]. Despite the numerous advantages of MANETs, resource management issues, such as power consumption, bandwidth allocation, and data transmission rate optimisation, remain challenging. The limited energy of the nodes, which are often battery-powered, and the unreliable and erratic characteristics of wireless channels are two sources of challenges that affect the longevity and performance of WSNs. Hence, optimal power and rate control remain challenges to enhance network performance, lifetime, and quality of service (QoS) [2].

Abbreviations

ACO	Ant Colony Optimization
AGWO	Adaptive Grey Wolf Optimizer
DPC	Dynamic Power Control
DPRO-GWA	Dynamic Power-Rate Optimization Grey Wolf Algorithm
DRPAA	Dynamic Rate and Power Allocation Algorithm
ECPRC	Energy Conserving Power and Rate Control
GAs	Genetic Algorithms
GWO	Grey Wolf Optimizer
JRPC	Joint Rate and Power Control
MAC	Medium Access Control
MANETs	Mobile Ad Hoc Networks
NE	Nash Equilibrium
PSO	Particle Swarm optimization
QoS	Quality of service
RENUM	Rate-Effective Network Utility Maximization
RWM	Random Waypoint Model
SAGWO	Self-Adaptive Grey Wolf Optimizer
SINR	Signal-to-Interference-plus-Noise Ratio
WSNs	Wireless Sensor Networks

Power and rate management are major challenges in MANETs. Because nodes in MANETs are usually battery-driven and have limited communication resources, we must ensure that any transmission is energy efficient and of good quality [3]. Meanwhile, the network must be capable of adjusting to changing channel states, network congestion, and traffic loads. Dynamic power and rate-control strategies are essential for achieving this goal. They are designed to drive the network to optimal performance, maximise throughput, minimise energy consumption and average delay, and maintain system stability in the presence of nonlinearities [4]. In MANETs, an explicit conventional method for designing a power and rate control system to maximise throughput and profit is beneficial. Although such methods are potentially feasible for deployment in learning-based systems, they largely overlook the relationships between delay, energy consumption, and throughput. This oversight results in numerous practical cases that lead to unsatisfactory performance [5].

Specifically, the available power and rate control schemes are primarily designed to restore the throughput or energy efficiency separately. Throughput-maximising approaches overlook energy consumption, whereas energy-efficient approaches do not adequately address delays. Therefore, delay constraints must be integrated into the optimisation process for time-sensitive applications, such as voice communications or real-time video streaming, where delays can severely degrade the quality of service [6]. This is due to the fact that previous work on power and rate control in MANETs focuses on maximizing throughput or minimizing energy consumption, but never both simultaneously. However, the literature does not consider the various trade-offs arising from different solutions concerning energy efficiency, throughput, and end-to-end delay in highly dynamic and uncertain environments. Such constraints are especially evident in applications requiring low latency, such as real-time communication or disaster recovery, for which delay-sensitive services require fast and effective power and rate tuning [1]. In addition, the vast majority of conventional methods depend on centralised control or heuristic-based algorithms, which do not scale well in large networks and typically incur high arithmetic complexity. Although generic power control solutions exposed in game theory-based approaches exist under non-cooperative conditions, these solutions usually ignore delay constraints or do not account for outage probability in the sensitive and lossy wireless environments of MANETs. Furthermore, there is a lack of proper integration of residual energy considerations, which can cause the batteries of mobile nodes to become exhausted early and lead to network fragmentation [7].

Another challenge is the stochastic and time-varying features of wireless channels in MANETs. The network performance is highly volatile owing to the highly dynamic channel conditions, loss, interference, and noise encountered by the transmitted signals. Therefore, static power and rate allocation solutions may not be suitable for the dynamic nature of MANETs. Many traditional algorithms, including those based on optimisation techniques such as Lagrangian multipliers and convex programming, involve high computational complexity and lead to power consumption and excessive communication overhead, which are particularly problematic in resource-constrained environments [8].

1.1 Game theory: a promising approach to joint power and rate control

In particular, game theory, which models the interaction between a number of players (i.e. nodes) attempting to optimise their own objectives, has recently been shown to be a promising approach to joint power and rate control in MANETs. Game-theoretic models treat each node as an independent player in a non-cooperative game and seek a Nash equilibrium (NE), in which no player can benefit by changing their strategy unilaterally [9]. Different game-theoretic techniques for joint power and rate control in MANETs have been proposed. For instance, a node optimisation problem would typically be formulated as a noncooperative game, where nodes try to maximise their utility (throughput) while minimising their energy consumption. However, most of these developments do not consider important performance metrics, including delay constraints, channel outage probability, and residual energy constraints. One clear reason is the lack of delay handling, which affects the performance of delay-sensitive applications, and ignoring the residual energy of nodes may cause an early disconnection of the network [10]. In addition, conventional game-theoretic methods are mainly based on centralized solutions or algorithms with high computational complexity, which are unsuitable for the distributed and resource-limited environments of MANETs. Thus, more flexible, scalable, and energy-efficient solutions that can accommodate varying channel conditions over time and the diverse QoS needs of various applications are required [11].

These issues highlight the necessity of an adaptive mechanism that can appropriately manage the trade-offs between power consumption, data rate requirements, and delay in a stable, decentralised, and scalable manner. This study introduces a new dynamic power-rate optimisation grey wolf algorithm (DPRO-GWA) mechanism tailored for MANETs, employing a game-theoretic approach to optimise power and rate allocation in the context of the critical trade-offs among throughput, energy consumption, and end-to-end delay [12]. Traditional approaches formulate an individual node's local knowledge in terms of utility, where the factors affecting the utility are either static, such as the energy required by the node to serve other nodes, or based on unreliable, stale information. This would make the problem of power and rate allocation a super-modular non-cooperative game model, and the Nash Equilibrium (NE) ensures that the optimal solution exists for the case of distributed self-interested nodes [13]. We also improve the solution strategy by presenting Adaptive Grey Wolf Optimizer (AGWO), a modified form of traditional Grey Wolf Optimizer (GWO). This acceleration enhances the convergence rate of the optimisation algorithm, providing an inherent reduction in time complexity at the expense of solution accuracy [14]. The primary objectives of this study are:

- To propose a novel Dynamic Power-Rate Optimization Grey Wolf Algorithm (DPRO-GWA) for Mobile Ad Hoc Networks (MANETs) that effectively balances the trade-offs between energy consumption, throughput, and delay.
- To integrate a game-theoretic approach to model power and rate control as a non-cooperative game, ensuring the existence and uniqueness of the Nash Equilibrium (NE) for optimal distributed solutions.
- To introduce the Adaptive Grey Wolf Optimizer (AGWO) to improve the convergence speed and efficiency of the optimization process, addressing the challenges of dynamic and resource-constrained environments.
- To evaluate the performance of the proposed method through extensive simulations, demonstrating its advantages over existing algorithms such as DRPAA, ECPRC, and RENUM in terms of energy consumption, throughput, delay, and outage probability.

The remainder of this paper is structured as follows: Section 2 provides a review of related work in the area of joint power and rate control in MANETs and highlights some of their limitations. Section 3 presents the proposed methodology. In this section, we introduce the system model along with the problem formulation, highlighting the relevant variables and constraints related to the power and rate control problems. In Section 4, we present the DPRO-GWA approach and the AGWO algorithm, along with details about each component of the optimisation solution. Section 5 presents the performance evaluation, demonstrating the effectiveness of the proposed approach through extensive simulations. Section 6 summarises the study and outlines future work.

2. Related work

The Grey Wolf Optimizer (GWO), developed by Mirjalili et al. [15], is a population-based optimisation algorithm based on the social hierarchy and hunting mechanism of grey wolves. Since the algorithm's introduction, various variants and enhancements have been proposed to overcome its shortcomings, resulting in broader applications in various fields, including engineering, machine learning, and complex system design. In recent years, GWO has undergone several enhancements, including the incorporation of adaptive strategies that improve its convergence properties and mitigate premature convergence to local optima. Alattas K. [16] compared their modified GWO with the unmodified one and presented their results, indicating that the modified GWO has better exploratory and exploitative faithfulness by presenting an adaptive search framework of this approach. By adjusting the spread of the wolves, this modification helps the GWO maintain a rich balance between exploration and exploitation, which is often a challenge in multimodal optimisation problems. Advanced customisations have resulted in the introduction of customised GWO variants in the literature. For instance, Wario F, et al. [17] proposed a self-adaptive grey wolf optimiser (SAGWO) in which parameters are adapted based on the dynamics of the optimisation problem. Because existing methods apply a fixed parameter setting while searching for the global optimum, SAGWO utilises a self-adaptive approach to adaptively update the search parameters to further enhance its performance in solving highly dimensional optimisation problems. Similarly, Liu H, et al. [18] proposed an enhancement of GWO employing a hybrid method merging machine learning techniques to optimise the search. These developments illustrate the versatility of the algorithm for several theoretical and practical problems, including structural design optimisation and environmental control. However, conventional GWO has certain limitations. A frequent criticism is its premature convergence, especially when dealing with highly complex, nonconvex issues [19]. To address these challenges, researchers have sought to hybridise GWO with alternatives such as Particle Swarm optimisation (PSO) and Genetic Algorithms (GAs) to leverage their strengths. However, these hybrid models introduce additional complexity, which complicates optimal parameter tuning [20].

The GWO algorithm version examines its convergence speed and fails to process dynamic environments. It has difficulty adapting to real-time systems, where problem landscapes evolve over time. Tumula S, et al. [21] have addressed this issue by introducing a dynamic version of the Grey Wolf Optimizer, the Volitive Grey Wolf Optimizer, which adapts its search process during optimization in response to variations in the optimization problem. Despite this progress, these adjustments should only be optimised without extensive retraining and may not be applicable to the broader scope of dynamic systems, such as robotics or adaptive models of network routing. These studies demonstrate the applicability of the GWO algorithm in a wide range of fields, such as multi-objective optimisation, engineering design, and machine learning. However, as mentioned, challenges persist, particularly with respect to convergence speed and the need for more robust adaptations in dynamic scenarios. Future work in this area will likely develop a better balance between exploration and exploitation, improve adaptation during run time, and ease the hybridisation of the GWO model to lead to more easily applicable versions for real-world problems [22].

Mobile Ad Hoc Networks (MANETs) rely on power and rate control as key features of the Medium Access Control (MAC) and network layers. These mechanisms aim to maximise the transmission power and data rate to ensure optimal performance in terms of energy consumption, throughput, and delay [23]. Power control in classical methods seeks to constrain the transmission power of nodes to ensure minimum energy use if the Signal-to-Interference-plus-Noise Ratio (SINR) of the receiver is above the threshold. In MANETs, power control is a significant concern because nodes have limited battery capacity; thus, many power control strategies have been developed to mitigate this problem. Centralised power control schemes generally involve a central entity that determines the power levels of all nodes [24]. Although this method can produce energy-efficient solutions, it is non-scalable and does not accommodate mobile nodes, which is a prominent feature of MANETs. The idea behind Decentralised approaches enables nodes to make local decisions to adjust their power levels according to their immediate surroundings, such as the received power or interference levels. These systems provide better scalability and resiliency but usually at the cost of inefficiencies owing to a lack of global coordination [25]. Rate control in mobile ad-hoc networking is concerned with adjusting the transmission rate in a way that satisfies throughput, application-specific, and/or QoS (Quality of

Service) requirements. Many rate control mechanisms use a channel-dependent approach by choosing an appropriate combination of modulation schemes and error correction codes [26]. Various techniques have been proposed, such as feedback-based methods and dynamic rate-adjustment algorithms. Feedback-based approaches require continuous communication between nodes to share information regarding channel conditions, whereas dynamic rate control methods modify the transmission rate in real time based on the detected channel quality. However, the trade-off between throughput and energy consumption, which exists in distributed systems and is not limited to centralised methods, is frequently neglected, even in high-mobility environments, where channel conditions vary rapidly [27]. Dynamic Power Control (DPC) and Joint Rate and Power Control (JRPC) are among the most commonly used power and rate control methods in MANETs. DPC adjusts the transmission power of the source node based on the SINR received by the receiver to prevent interference or packet loss, whereas JRPC can combine adjustments to both power and data rate simultaneously to maximise throughput and minimise packet loss [5]. Other energy-aware rate control strategies that consider transmission energy and QoS have also been proposed. However, these schemes incur high delays and energy consumption and do not address these issues simultaneously, particularly in rare case scenarios with regular mobility of nodes or the dynamic nature of the network model [28].

Recently, game theory has emerged as an analytical tool for the interactions among different nodes of wireless networks (such as MANETs). Game theory is used to form a mathematical framework for our case of non-cooperative nodes regarding power and rate control, where the nodes choose their power and rate levels independently to maximise their utility. This means that each node of the network is a "player" in the "game", and the action of one player impacts the payoff of others because of the shared wireless medium [29]. The initial application of game theory in the context of MANETs was the use of noncooperative games to address power control, where nodes adjust their power levels to minimise interference and energy consumption while maintaining communication quality. This falls within the realm of potential game theory, in which each node chooses a strategy to maximise its utility. The game reaches a state known as the Nash Equilibrium (NE), where no node can further improve its utility by changing its power level without influence from any other node [30].

The second proposal, network utility maximisation (NUM), formulates the power and rate control problem as a utility maximisation problem, where the users have utility functions that express either satisfaction or performance [31]. Several game-theoretic approaches have been designed based on pricing, allowing every node to adjust its transmission power via the pricing mechanism to minimise its transmission costs while satisfying the network's overall demand [32]. Despite the success of game-theoretic solutions, there exist computational complexity, scalability, and usage limitations in time-varying network scenarios for existing proposals. In addition, in time-varying dynamic applications, such as video conferencing and emergency communication in MANETs, such models often ignore delay requirements and outage probabilities, which are important parameters [1]. Metaheuristic algorithms have been considered in the literature to solve difficult optimisation problems in MANETs, such as power and rate control. They developed algorithms that can provide flexible, adaptive, and efficient solutions to dynamic large-scale optimisation problems for which traditional approaches may become prohibitively expensive. As an example of a metaheuristic-based algorithm, we can list the Grey Wolf Optimiser (GWO), which is inspired by grey wolves hunting. The role of GWO as an optimiser in wireless networks (e.g. for power control and rate allocation) is significant. The merit of GWO is that it has mixed exploration and exploitation in the searching process, which can effectively search in the high-dimensional searching space and converge to the global solution. However, the convergence rate of GWO is slow when dealing with large and complex networks. To address this limitation, some extensions have been proposed, such as the Adaptive Grey Wolf Optimiser (AGWO). Based on the classical GWO, the trade-off between the exploration and exploitation of the AGWO is tuned using a logarithmic function. This change leads to a faster convergence rate of the algorithm, which can contribute to excellent speed and solution quality [33].

Other filtering methods based on metaheuristic algorithms are also presented, such as Particle Swarm Optimisation (PSO), Genetic Algorithm (GA), and Ant Colony Optimisation (ACO). These techniques have been applied to joint power and rate control problems for energy efficiency, throughput, and network lifetime maximisation. For example, we have a PSO approach for joint power and rate allocation for a MANET, where the transmit power and rates are jointly optimized towards the optimal network performance [26]. Despite their success, the scalability and complexity of the majority of these algorithms are still open issues. The overhead of metaheuristic algorithms, especially in large-scale networks, is a drawback. More importantly, while these algorithms provide near-optimal solutions, they do not capture important performance measures, such as the outage probability and delay, which are needed for most real-time applications. Although much improvement has been made in the research on power and rate control in MANETs, some gaps remain. Recent approaches either target low-energy designs or maximise throughput and do not effectively address the trade-off among delay, energy, and throughput in real-time and delay-sensitive application systems. Many solutions only partially or simply ignore the change in topology and the unreliable characteristics of the links.

This study bridges the above gap by proposing a novel game-theoretic approach for integrating the delay-dependent energy outage probability and residual energy constraints for the power and rate control framework. Using the adaptive grey wolf optimiser (AGWO), we also enhance the speed of convergence of the solution via low-complexity and scalable optimisation for high-mobility large-scale networks. These improvements make the DPRO-GWA scheme more robust and practical for MANET deployments.

3. System model and problem formulation

In this section, we provide a formal system model for joint power and rate control in Mobile Ad Hoc Networks (MANETs), which constitutes the basis for the energy-efficient scheme proposed in this study. In this study, we combined and optimised both power and traffic control to achieve their performance metrics regarding throughput, delay, and energy consumption. We aim for a distributed adaptive scheme that runs well in dynamic and resource-limited MANET environments. The system model specifies the network components, utility functions, constraints, and optimization problem to be solved.

3.1 Network model

In MANETs, nodes are mobile devices that exchange messages with each other without using fixed infrastructure. Every node can tune its transmission power, and the network topology is subject to change because of the mobility of the nodes. A MANET is generally applied in places such as emergency relief, military use, and vehicular networks without a traditional infrastructure. The network may include any number of nodes, where each node may be a transmitter or receiver.

The simulations were performed using NS-3 (Network Simulator-3), an open-source discrete-event simulator designed to support realistic models of wireless and mobile networks. The simulation environment accurately replicates real-world conditions, including variations in mobility patterns, changes in network topology, and fluctuations in traffic load.

A. Simulation Parameters:

- Traffic Model: We used the Constant Bit Rate (CBR) traffic model, which is widely employed in MANET simulations to model real-time data traffic, such as voice and video streaming. Each source node generates a fixed-rate data stream for the duration of the simulation.
- Mobility Model: We utilized the Random Waypoint Model (RWM) for node mobility. This model is commonly used in MANET studies to simulate the random movement of nodes within the simulation area. The nodes choose random destinations and speeds, and the mobility parameters include a maximum speed of 10 m/s, a pause time of 100 seconds.
- Number of Simulation Runs: To ensure the robustness of the results, we conducted 20 independent simulation runs for each scenario, averaging the results to minimize statistical bias.

B. Key Parameters:

- α (Utility Function Weighting): The weight factor for throughput in the utility function is set to 0.4, indicating that throughput is a significant but not dominant factor in the optimization.
- β (Utility Function Weighting): The weight factor for energy consumption is set to 0.3, reflecting the importance of minimizing energy usage in the optimization process.
- γ (Utility Function Weighting): The weight factor for delay is set to 0.3, indicating the need to balance delay sensitivity, particularly in real-time applications.
- p_min/p_max (Transmission Power Range): The minimum and maximum transmission power values are set to 0.1 mW and 100 mW, respectively, to ensure that the nodes adaptively adjust their transmission power within a reasonable range.
- ζ_max (Maximum Tolerable Outage Probability): The maximum outage probability is set to 0.1, ensuring that the system prioritizes reliability while avoiding excessive packet loss due to poor channel conditions.

For simplicity, we consider here that the MANET is working in a square area of 100×100 meters. The nodes uniformly populated this area. Nodes move based on the Random Waypoint Model (RWM), a well-known mobility model in MANETs. In RWM, each node chooses a random destination within the area and advances rapidly towards the selected destination. Upon arrival at a destination, the node halts for a predetermined interval, selects a new destination and speed, and continues the process. Nodes are mobile, which leads to frequent changes in the network topology, presenting a huge problem for achieving stable communication.

The wireless channel model typically governs the channel conditions in a MANET. Owing to the dynamic nature of MANETs, channels are subject to frequent fading (for example, Rayleigh fading), interference, and path loss. The received signal strength at a node depends on the distance to the transmitter and the environmental factors. The channel between any pair of nodes i and j is characterized by a path gain G_{ij} and a fading factor F_{ij}, which accounts for the randomness in the signal strength due to obstacles and mobility.

The signal-to-interference-plus-noise ratio (SINR) is a critical factor in determining communication quality. The SINR is influenced by both the transmission power of the nodes and interference caused by other nodes. The SINR at the receiver of the node i is given by:

$$\mathrm{SINR}_i = \frac{G_{ii}F_{ii}p_i}{\sum_{j\neq i} G_{ij}F_{ij}p_j+\sigma^2}) \tag{1}$$

where:

- p_i is the transmission power of the node i,
- G_{ii} and F_{ii} are the path gain and fading factor for the link from the node i to itself (i.e., the signal strength),
- G_{ij} and F_{ij} are the path gain and fading factor for the interference between nodes i and j,
- σ^2 denotes the noise power at the receiver.

The nodes in the network are also subject to battery limitations. Because MANETs operate in energy-constrained environments, managing energy consumption is critical. The energy of each node is limited by the residual energy, which decreases as it transmits and receives data. Thus, nodes must adapt their transmission power and data rate to prolong their operational lifetime while maintaining efficient communication.

The SINR defines the link quality between two nodes and is crucial for determining the transmission rate of the link. The instantaneous capacity C_i of a link can be computed using Shannon's capacity formula:

$$C_i(p_i) = B\log_2\left(1+\mathrm{SINR}_i(p_i)\right) \tag{2}$$

where:

B denotes the bandwidth of the channel.

The transmission rate r_i for node i is determined by the available capacity $C_i(p_i)$, subject to the constraints of the channel conditions, the interference, and the power level.

Additionally, in MANETs, the channel is often lossy owing to the nature of wireless communication, and nodes must adapt to the varying quality of the channel. This variability is accounted for by considering the outage probability rate, which models the likelihood that the incoming rate exceeds the channel capacity as follows:

$$Pr\left(r_i > C_i(p_i)\right) = \zeta_{\max} \tag{3}$$

where ζ_max is the maximum tolerable outage probability for node *i*. This constraint helps maintain communication reliability by preventing data loss owing to channel congestion or poor quality.

The main purpose of this study is to optimize power and rate control in a MANET by considering the trade-offs between energy consumption, throughput, delay, and stability of the network. We can treat this problem as an optimization problem, the objectives of which are as follows:

1. Maximizing network throughput: To obtain a high rate, we must switch the nodes' transmissions on and off.
2. Minimizing energy consumption: Power consumption should be minimized at the nodes so that they last a long time

before their batteries drain and they are no longer effective in communicating.

3. Minimize Delay: Satisfy the delays of delay-sensitive applications (e.g. real-time communications).

3.2 Optimization objectives and constraints

Let N represent the number of nodes in the network. Each node $i \in \{1,2,\dots,N\}$ has a transmission power $p_i \in [p_{min}, p_{max}]$ and a transmission rate $r_i \in [r_{min}, r_{max}]$. The optimization problem can then be formulated as:

$$\text{Maximize: } \sum_{i=1}^{N} U_i\,(r_i, p_i) \tag{4}$$

where $U_i(r_i, p_i)$ is the utility function for the node i, reflecting its throughput and energy consumption, subject to the following constraints:

Power constraint: The transmission power of each node must lie within the allowable range

$$p_{min} \le p_i \le p_{max} \quad \forall i \tag{5}$$

Rate constraint: The transmission rate of each node must be between the minimum and maximum limits.

$$r_{min} \le r_i \le r_{max} \quad \forall i \tag{6}$$

SINR constraint: The SINR at the receiver must exceed a minimum threshold for reliable communication.

$$\text{SINR}_i \ge \gamma_{\min} \quad \forall i \tag{7}$$

where $\gamma_{\min}$ is the minimum required SINR for successful transmission.

Delay constraint: The total average delay must be within acceptable limits for delay-sensitive applications:

$$D_i \le D_{\max} \quad \forall i \tag{8}$$

where D_i is the average delay for the node i, and $D_{\max}$ is the maximum acceptable delay.

Energy constraint: The residual energy of each node must be above a certain threshold to prevent early node failure.

$$E_{\text{residual},i} \ge E_{\min} \quad \forall i \tag{9}$$

3.3 Game theory framework

The problem of joint power and rate control is modelled as a noncooperative game, where each node is a player. The players (nodes) independently decide on their transmission power and rate to maximize utility. In this context, the utility function of each node i is defined as:

$$U_i(r_i, p_i) = \text{throughput} - \alpha \cdot \text{energy consumption} - \beta \cdot \text{delay} \tag{10}$$

where α and β are weights determining the trade-off between throughput, energy consumption, and delay.

Each node aims to select its optimal power p_i^* and rate r_i^* that maximizes its utility while considering the actions of other nodes in the network. The system reaches Nash Equilibrium (NE) when no node can improve its utility by changing its strategy, given the strategies of the other nodes. The existence and uniqueness of the NE in this game are guaranteed under certain conditions, such as the supermodularity of the utility function and the convexity of the power and rate constraints.

3.4 Supermodular game and Nash Equilibrium (NE)

A game is considered supermodular if a player's utility increases when other players adopt higher strategies. In the context of power and rate control, increasing the transmission power or rate of one node may increase the utility of neighboring nodes owing to improved signal quality or reduced interference. The utility function $U_i(r_i, p_i)$ exhibits increasing differences and is therefore supermodular. In the context of game theory, supermodularity refers to a condition where the utility function of a player exhibits increasing differences with respect to the strategies of other players. This property plays a crucial role in ensuring the existence of a Nash equilibrium, particularly in games where players' decisions are interdependent, such as in wireless networks and resource allocation scenarios [36]. In our proposed game, players (nodes) engage in strategic interactions that affect their utilities, which are influenced by the decisions of other players.

To formally prove supermodularity in our game, we aim to demonstrate that an increase in one player's strategy (e.g., power or rate) leads to a positive change in the utility of other players, thus reinforcing the cooperative or competitive dynamics in the system. This interaction implies that the game satisfies the conditions for supermodularity, which, in turn, guarantees the existence of at least one pure strategy Nash equilibrium [37]. Furthermore, we establish that the supermodularity of the game is key to ensuring the existence of a Nash equilibrium. A Nash equilibrium occurs when no player can unilaterally improve their utility by changing their strategy, given the strategies of the other players. The supermodularity property ensures that the game has a structure that supports such equilibria, facilitating the analysis and prediction of player behaviour in the network. A Nash Equilibrium (NE) exists when each node, i selects a power p_i^* and rate r_i^* such that:

$$U_i(r_i^*, p_i^*, r_{-i}, p_{-i}) \ge U_i(r_i, p_i^*, r_{-i}, p_{-i}) \quad \forall i \tag{11}$$

where r_{-i} and p_{-i} represent the rates and powers of all other nodes except the node i. No node can improve its utility at NE by unilaterally changing its power or rate.

3.5 Outage probability and residual energy

The concept of outage probability was introduced to handle unpredictable channel conditions. In a wireless channel, fading and interference can cause the signal strength to drop below an acceptable threshold, leading to packet loss. The outage probability at the link m is defined as:

$$Pr\big(r_m > c_m(p_m)\big) \le \zeta_{\max} \tag{12}$$

where $c_m(p_m)$ is the channel capacity at node m, and $\zeta_{\max}$ is the maximum tolerable outage probability. By exploiting the outage probability in the utility function, the model guarantees that the power and rate control decisions will minimise the risk of communication failure owing to fading or interference.

The compensation of residual energy is also an important issue. The utility function punishes the node with lower residual energy by incorporating the residual energy ratio RE_i into the decision-making procedure. Nodes with low residual energy are not allowed to transmit at high power levels that preserve the energy of the network.

4. The Proposed DPRO-GWA Approach

The Dynamic Power-Rate optimisation Grey Wolf algorithm (DPRO-GWA) is a new technique for optimising power and rate in a mobile ad hoc network (MANETs) environment, where the mobile nodes are highly dynamic and power consumption is a significant problem. DPRO-GWA is intended to balance the trade-off between energy consumption, throughput, and delay, and to keep the switch active under such conditions. The method is game-theoretic, and nodes selfishly optimise the trade-off between power overhead and rate obfuscation while considering the global network performance. In the following sections, we discuss the DPRO-GWA methodology in detail, including the game-theoretical model, outage probability derivation, utility function definition, Nash equilibrium analysis, and use of the AGWO for an efficient optimisation solution.

4.1 Game-theoretic framework

The DPRO-GWA approach leverages a game-theoretic framework to model the power and rate control problems in a decentralized and noncooperative environment. In this framework, each node in the network is considered a player seeking to maximize its utility. Because nodes are independent, non-cooperative entities, they make decisions based on local information, such as residual energy, current Signal-to-Interference-plus-Noise Ratio (SINR), and the rate at which data can be transmitted. In this context, the strategy space of each node i consists of its transmission power p_i and transmission rate r_i. Each node independently selects its strategy to maximize its utility, which is a function of the node's throughput, energy consumption, and delay. The utility function for the node i, denoted by $U_i(r_i, p_i)$, reflects its trade-off between these factors. Nodes are considered in a non-cooperative game, where the payoff for each node depends on its strategy and the strategies chosen by other nodes. We formulate the problem as a supermodular game, where increasing one player's strategy (e.g. power or rate) benefits the other players (nodes) owing to positive externalities. Specifically, if we can increase a node's transmission power, it might experience improved signal quality, allowing neighbouring nodes to also increase their rates or reduce co-channel interference.

The game equilibrium is such that, at equilibrium, no node would benefit from unilaterally changing its strategy, regardless of the strategies of the other nodes. In the context of DPRO-GWA, this optimality is modelled as a Nash Equilibrium (NE), meaning that no node is incentivised to deviate from its strategy to improve its utility. Through the DPRO-GWA approach, the NE is achieved by accounting for the energy, throughput, and delay requirements, resulting in a proper and fair solution for all the nodes in the network. The DPRO-GWA treats power and rate control as a game. Its decentralised nature allows each node to independently make transmission-setting decisions using local network information, which is scalable with respect to the network size, unlike its centralised counterparts.

4.2 Outage probability

In wireless networks, the outage probability is an important measure that captures the reliability of transmission under dynamic channel variation. The signal quality degrades because of the packet loss phenomenon introduced by attenuation and interference in MANETs. The DPRO-GWA method includes the outage probability in the game-theoretic model to reduce the risk of communication failure.

Let $Pr_{\text{out}}(p_i)$ represent the outage probability for the node i when transmitting with power p_i. The SINR determines this probability at the receiver, where if the SINR falls below a threshold, the transmission fails and an outage occurs. The outage probability is given by

$$Pr_{\text{out}}(p_i) = P(\text{SINR}_i < \gamma_{\min}) \tag{13}$$

where $\gamma_{\min}$ is the minimum SINR threshold required for successful transmission. By incorporating the outage probability into each node's utility function, the ECAPRC ensures that the nodes adjust their transmission power and rate to minimize the likelihood of communication failures owing to fading or interference. This leads to a more reliable network and improves the overall system stability.

Incorporating the outage probability also helps avoid over-allocating power, which could lead to interference with neighboring nodes. This ensures that the power and rate control processes maintain a balance between achieving a high throughput and avoiding communication failure.

4.3 Utility function

The utility function for the node i, denoted as $U_i(r_i, p_i)$ reflects the trade-offs between energy consumption, throughput, and delay. This function is carefully designed to ensure that nodes make power and rate decisions that optimize their performance and contribute to the overall efficiency of the network. Let us define the utility function as follows:

$$U_i(r_i, p_i) = \alpha_i \cdot \text{Throughput}_i - \beta_i \cdot \text{Energy}_i - \gamma_i \cdot \text{Delay}_i \tag{14}$$

where:

- $\alpha_i, \beta_i, \gamma_i$ are the weights represent the relative importance of throughput, energy consumption, and delay for a node i.
- $\text{Throughput}_i = r_i$, the transmission rate of the node i, which contributes positively to the utility.
- $\text{Energy}_i = p_i \cdot T_{\text{transmit}}$, the energy consumption of the node i, which is proportional to the transmission power and the time for which the node transmits.
- Delay_i represents the delay associated with data transmission, which is typically inversely related to the rate but is directly affected by power control decisions and network congestion.

The objective is to maximize the throughput while simultaneously minimizing the energy consumption and delay. In this formulation, the throughput contributes positively, whereas the energy and delay introduce negative penalties. The relative importance of these factors can be adjusted using the weights. $\alpha_i, \beta_i, \gamma_i$, which may vary based on the type of application or the network conditions (e.g., real-time applications prioritize delay minimization). By appropriately balancing these conflicting goals, the DPRO-GWA method ensures that each node works toward achieving optimal performance for both individual utility and network efficiency. The DPRO-GWA algorithm is presented in Table 1.

4.4 Nash equilibrium and proof

The systems are ensured to converge to the Nash Equilibrium (NE), a set of settings for the DPRO parameters, where none of the devices can achieve a utility increment through independent deviations from the chosen settings. Such equilibrium is important because each node's strategy is the best response based on the strategies of all other nodes. We first define the payoff function for each node as its utility function:

$$U_i(r_i, p_i) = \alpha_i \cdot r_i - \beta_i \cdot (p_i \cdot T_{\text{transmit}}) - \gamma_i \cdot D_i \tag{15}$$

Given that the utility function is supermodular, meaning that the utility increases when the other players' (nodes) strategies are higher, it follows that the game satisfies the conditions for a Nash Equilibrium. A supermodular game guarantees that players (nodes) will converge to an optimal strategy profile in which no player can improve their payoff by unilaterally changing their strategy (i.e. power or rate).

4.5 Algorithm 1: Pseudo code for proposed DPRO-GWA

```
// Initialize the system parameters:
    x = [(p1, r1), (p2, r2), ..., (pN, rN)]  // List of nodes with their initial power (p) and rate (r)
    utility(x)  // Calculate the utility of each node based on initial conditions
  Repeat until convergence (or until a stopping condition is met):
 // Step 1: Sense the Channel Conditions
    for each node i in the network:
      Sense the current channel conditions (e.g., SINR, residual energy, etc.)
      If a change is detected in the conditions:
        Broadcast new power and rate (p_i, r_i) to neighbors
 // Step 2: Notify Neighbors and Call AGWO Algorithm
    for each node i that detects a change:
      Notify neighbors about the change
      Call AGWO algorithm with the updated states (power, rate, and channel conditions)
      Store the updated output in x_new
 // Step 3: Update Power and Rate
    for each node i in the network:
      // Update power and rate for the node and its neighbors
      Update power and rate for node i based on the new values from x_new
      Broadcast the updated values to neighbors
 // Step 4: Evaluate Utility Comparison
    for each node i in the network:
      Calculate the utility for the old state (x_old) and the new state (x_new)
      If utility(x_old) < utility(x_new):
        // Accept the new values as the best solution
        x[i] = x_new[i]  // Update power and rate for node i
    // If convergence criteria are met, exit loop
    If convergence_condition_met():
      Break
  Return the final power and rate values for each node: x = [(p1, r1), (p2, r2), ..., (pN, rN)]
```

To prove the existence and uniqueness of the Nash Equilibrium, we can apply the fixed-point theorem and the fact that the utility function is continuous and quasi-concave. This ensures a unique solution for the strategies of each node at equilibrium and that the solution is efficient and stable in the context of the network.

At the NE, each node chooses its optimal power and rate such that any unilateral deviation results in a lower utility for the node. Therefore, the system reaches a stable configuration in which the overall network performance is maximized and the nodes achieve a balance between throughput, energy, and delay.

4.6 Adaptive Grey Wolf Optimizer (AGWO)

The proposed technique is named the Dynamic Power-Rate optimisation grey wolf algorithm (DPRO-GWA), which is used to optimise power and rate allocation in a mobile ad hoc network (MANET), considering energy, network throughput, and delay. It assumes a game-theoretic model to describe the behaviour of nodes that minimises energy usage but maximises throughput. The AGWO is a fast-converging and energy-efficient optimisation algorithm that fulfils the desired throughput and operates at the required QoS levels.

The DPRO-GWA uses AGWO, which is an upgrade of another popular optimisation algorithm, the Grey Wolf Optimiser (GWO). GWO is an optimisation algorithm based on the grey wolf social hierarchy and their manner of hunting for food. However, the classical GWO cannot find an optimal balance between exploration and exploitation in the search space. The AGWO further improves it by using a logarithmic decrease formula of the parameter which controls the trade-off between exploitation and exploration.

The Adaptive Grey Wolf Optimizer (AGWO) is used to provide a clearer understanding of the improvements made to the standard Grey Wolf Optimizer (GWO). Specifically, the following enhancements are discussed in detail:

- Adaptive Tuning Mechanism: A key enhancement lies in the logarithmic decay of the coefficient α, which governs the trade-off between exploration and exploitation during the optimization process. Initially, the algorithm emphasizes a broader exploration of the solution space, allowing for a more comprehensive search. As the iterations progress, the algorithm gradually shifts focus towards refining the solutions, thereby enhancing exploitation. The logarithmic decay function ensures a balanced transition between these two phases, preventing premature convergence to local optima while accelerating convergence towards the optimal solution over time.
- Mathematical Formulation: At each iteration, the value of α is progressively reduced using a logarithmic function, enabling AGWO to efficiently explore the global solution space. This adjustment allows the algorithm to focus more on exploitation as the search progresses, ensuring that the best solutions found thus far are further refined.
- In order to validate the choice of GWO as the optimization engine, we have included a comparative analysis with other popular metaheuristics, such as Particle Swarm Optimization (PSO), Differential Evolution (DE), and Genetic Algorithms (GA).
- Performance Comparison: The benefits of GWO compared to various algorithms, especially regarding convergence velocity, capacity to evade local optima, and appropriateness for extensive and intricate optimisation challenges. The efficacy of AGWO compared to PSO, DE, and GA across several benchmark optimisation issues illustrates that AGWO surpasses these algorithms for solution quality and computing efficiency in the realm of MANET optimisation.
- Qualitative and Quantitative Analysis: Qualitative talks and quantitative data from simulations comparing AGWO's performance with PSO, DE, and GA regarding convergence rate, accuracy, and stability. This comparison substantiates the assertion that GWO, especially with its adaptive improvements in AGWO, is more appropriate for the optimisation tasks necessitated in MANETs, considering the problem's dynamic characteristics.

4.7 GWO: Grey Wolf Optimizer

Grey Wolf Optimizer (GWO) is a bio-inspired optimization algorithm based on the grey wolves' hunting and social behaviour. Nature Grey wolves have a social ranking order that follows alpha wolves, then beta wolves, delta wolves, and omega wolves. The decisions made by the alpha wolves and the pack were followed. This behaviour is used to guide the search for the optimal solution in the optimisation problem. In GWO, the best solution is the alpha wolf, the second best is the beta wolf, and the third best is the delta wolf. Finally, the wolves search for and share information

based on the best solutions. Thus, wolves can search the solution space efficiently and attain the global optimum.
The key update equations for the GWO are as follows:
1. Distance Calculation:

$$D_\alpha = | C_1 \circ X_\alpha - X |, \quad D_\beta = | C_2 \circ X_\beta - X |, \quad D_\delta = | C_3 \circ X_\delta - X | \tag{16}$$

where C_1 is a coefficient vector, and X represents the current position of a wolf.
2. Position Update:

$$X_1 = X_\alpha - A_1.(D_\alpha), \quad X_2 = X_\beta - A_2.(D_\beta), \quad X_3 = X_\delta - A_3.(D_\delta) \tag{17}$$

Here, A_1 is a coefficient that controls the step size, and D_α is the distance vector.
3. Convergence:

$$X(t+1) = \frac{X_1+X_2+X_3}{3} \tag{18}$$

This equation combines the positions of the three best solutions to update all wolves' positions.

4.8 AGWO: Adaptive Grey Wolf Optimizer

The AGWO adopts a logarithmic decay for the coefficient a associated with exploration and exploitation, which is better than the GWO. This enables the algorithm to adapt effectively by balancing the discovered, but previously exposed, high-quality solutions and exploring unexplored search space regions. Logarithmic decay also prevents local optimal convergence, so the search can still be steady towards the global optimum. The adjustment of a is done as follows:

$$a(t) = 2 - \left| \log\left(\frac{ab+dc\cdot i}{T_{\max}}\right) \right| \tag{19}$$

Where:
- ab and dc are constants that determine the scale of adjustment.
- i is the current iteration, and $T_{\max}$ is the maximum number of iterations.

The logarithmic updating mechanism contributes to a more satisfactory exploration and faster convergence than the linear updating in the conventional GWO, resulting in better energy preservation and resource allocation performance.

Algorithm 2: AGWO (Adapted Grey Wolf Optimization)
Input:
- Network, Population Size

Output:
- α (Optimized Solution)

1. Initialize:
2. Set Population ← ∅;
3. Set Xα ← ∅;
4. Set Xβ ← ∅;
5. Set Xδ ← ∅;
6. Initialise the iteration counter t = 0.
7. For i = 1 to PopulationSize do:
8. Set Xi ← RandomPosition;
9. Set Pi ← RandomPower;
10. Set Ri ← RandomRate;
11. Set xp_best ← Xi;
12. Calculate Fitness(i) using Eq. (14);
13. End For
14. While ¬TerminationCondition do:
15. Increment t = t + 1;
16. Adaptively adjust coefficient α using Eq. (28);
17. For i = 1 to PopulationSize do:
18. Update Position Xi using Eq. (26);
19. Update Power Pi using Eq. (27);
20. Update Rate Ri using Eq. (29);
21. Calculate Fitness(i) using Eq. (14);
22. Update α, β, and δ;
23. End For
24. End While
25. Return the optimal solution α.

4.9 Complexity Analysis of AGWO

The complexity of the AGWO algorithm is analyzed based on the number of wolves N. The dimension of the search space H, and the number of iterations $T_{\max}$. The computational cost of traditional GWO is $O(H \cdot N^2 \cdot T_{\max})$, which can become expensive as the number of nodes increases. However, the AGWO algorithm introduces a logarithmic reduction in the exploration-exploitation ratio, which reduces computational overhead. The time complexity of AGWO is $O(H \cdot N \cdot \log(N) \cdot T_{\max})$, which is more efficient compared to traditional GWO. This reduction in complexity allows the AGWO to handle larger networks with faster convergence and minimal overhead.

5. Simulation setup and performance evaluation

In this section, the performance evaluation of the proposed DPRO-GWA is presented, which is obtained through comprehensive simulations. We compared DPRO-GWA with DRPAA [34] and RENUM [35] for power and rate control algorithms included in the literature. The simulation scenario, performance metrics, and comparison with other algorithms are described. Furthermore, the convergence behaviour of DPRO-GWA, its outage performance, and the energy-delay trade-off are analysed. The network topology was generated using the random waypoint mobility model to model the nodes in the network with a speed of up to 10 m/s and a fixed pause time of 100 s. The packet inter-arrival times are based on the Constant Bit Rate (CBR) application; the traffic is generated by three traffic classes to simulate traffic in the Mobile Ad-Hoc Network (MANET). Each test comprised 20, 10-minute-long, randomly selected source-destination pairs. A specific situation of an ad-hoc network layout with lossy links and flows is depicted in Figure 1 with source nodes S1 and S2 and destination nodes D1 and D2. The packets are transferred from the source to the destination over the path defined by the power allocation and transmission rate.

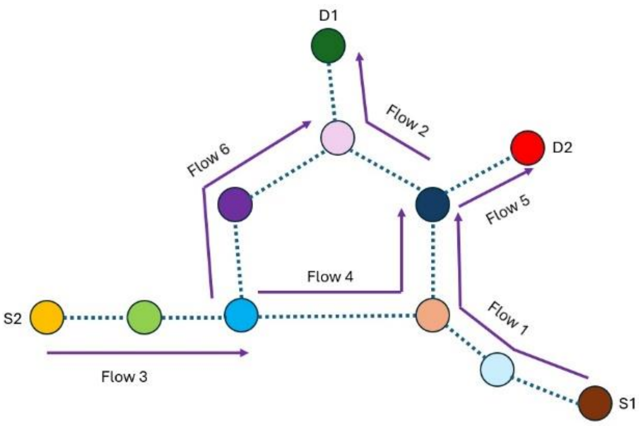

Figure 1. An example of a wireless ad hoc network with lossy links

5.1 Simulation environment

These were simulated using NS-3 (Network Simulator-3), an open-source discrete-event network simulator for the research and education community to simulate wired and wireless IP networks. One of the reasons why we chose NS-3 for the simulation in this study is that it provides a complete set of wireless communication models (Wi-Fi, LTE, and MANETs); hence, we can model the complex dynamics of MANETS. The simulation parameters were defined to closely resemble realistic mobile ad hoc network (MANET) environments, including mobility patterns, topologies, and traffic loads. In the Random Waypoint Mobility Model (RWM), each node chooses a destination and speed randomly from a range in [0, 10] m/s, before it pauses for a random amount of time before proceeding. This model reflects the dynamic and random behaviour of the node mobility scenario in MANETs.
In the communication model, every node works in half-duplex mode and sets the transmission power and rate range between. It uses a Rayleigh fading model to simulate the channel conditions, which models the effects of scattering, reflection, and diffraction on signal propagation. We used User Datagram Protocol (UDP) traffic between the nodes, in which the size of the packets was fixed to 1024 bytes. We set the average packet arrival rate of each node to 10 packets per second.

The key simulation parameters are as follows:

- Number of nodes: 50.
- Transmission power range: [10,50] mW.
- Transmission rate range: [1,10] Mbps.
- Mobility model: Random Waypoint with speeds ranging from [1,10] m/s.
- Simulation time: 1000 seconds.
- Traffic pattern: Constant Bit Rate (CBR) traffic.

Simulations were conducted for various scenarios with different mobility speeds and traffic patterns to evaluate the robustness of the DPRO-GWA under varying network conditions.

5.2 Performance metrics

The performance of the DPRO-GWA was assessed and compared using the following metrics:
1. Throughput: The data successfully sent to the device over the network in bits per second (bps). Greater throughput means more availability of the network, which can be valuable in facilitating communication requirements. The throughput of such a channel can be measured by:

$$\text{Throughput} = \frac{\text{Total Transmitted Data}}{\text{Simulation Time}} \tag{20}$$

2. Energy consumption: Total consumed energy of the entire network during the simulation, which also includes the transmission and reception of the energy consumed by data packets. In an energy-constrained environment, the objective is to minimise energy consumption to extend the life of the nodes. Consuming energy can be recognized by

$$\text{Energy Consumption} = \sum_{i=1}^{N} (p_i \cdot T_{\text{transmit}}) \tag{21}$$

where p_i is the transmission power and T_{transmit} is the time spent transmitting by the node i.
3. Delay: The average end-to-end delay is the time taken by a packet to reach the destination node from the source node. A lower delay is required for real-time applications, such as voice and video. The average end-to-end delay is then given by:

$$\text{Delay} = \frac{\sum_{i=1}^{N} \text{End-to-End Delay}_i}{N} \tag{22}$$

where End-to-End Delay_i is the delay for the packet i.
4. Outage Probability: This quantifies the likelihood of transmission degradation owing to an insufficient SINR, which typically results in packet loss. This provides a measure of communication reliability.

$$\text{Outage Probability} = \frac{\text{Failed Transmissions}}{\text{Total Transmissions}} \tag{23}$$

These metrics have an instantaneous impact on the performance of the DPRO-GWA, and trade-offs among throughput, energy efficiency, and delay under all possible situations while ensuring a balanced network uptime.

We evaluated the proposed DPRO-GWA algorithm and compared it with three existing schemes: DRPAA, ECPRC, and RENUM. Although both approaches are intended for optimising power or rate control, the DRPAA and RENUM are not designed to quantify multi-perspective trade-offs (energy, delay, and throughput) for dynamic environments.
DRPAA varies as the simulation evolves and does not fix the power level depending on the network configurations, such as congestion and node movement. However, it ignores the effect of outage probability or residual energy, which are vital to the stability and reliability of the network. The DRPAA also presents a redundant coordinator, which is not desirable for large networks. Although RENUM aims at joint rate and energy optimisation, it is not designed for delay constraints and outage probability, which are the most important parameters in real-time applications. The RENUM static power and rate adaptation algorithm may not be optimal because of node mobility and the dynamic topology in a wireless mesh network environment.

In contrast, DPRO-GWA has the following advantages.
1. Adaptive Power and Rate Control: This approach relies on game theory. It allows an individual node to adapt its power and rates while separating the rate and power adaptation based on the local information. This has decentralised, scalable, and efficient implications for the industry.
2. Integration of Outage Probability: DPRO-GWA incorporates the outage probability into the utility function.
3. Trade-offs in Energy and Delay: DPRO-GWA is a protocol that balances energy savings with minimal delay and functions optimally under varying traffic loads and mobility scenarios.

Simulation results show that DPRO-GWA achieves better throughput, energy consumption, and delay than DRPAA and RENUM under node mobility and disproportionate, abrupt traffic patterns. However, DPRO-GWA has a higher outage probability, indicating improved reliability for communication while in motion.

5.3 Results and analysis

We chose throughput, total energy consumption in communication, and end-to-end delay for the transmission timespan of packets as metrics to describe the DPRO-GWA performance. In this study, we modified the rate outage probability to minimise fluctuations and maintain a balance between the power level and data rate, reflecting changes in the network topology during mobility. Delays in packet transmission, queuing time, retransmission time, route discovery time, and propagation delay help maintain network connectivity at the optimal power level during packet transmission. The performance measure of nodes 1-6 is measured to view the power of the nodes and the assigned rate to the nodes. The convergence behaviour of the developed method for power and rate allocation is illustrated in Figure 3 and Figure 4. Without loss of generality, it is assumed that all nodes in the network utilise the same method to determine the rate and power levels. As shown in Figure 2, if all users possess high power (milliwatts) from the start of the alumni process setting, nodes are initially unfamiliar with the network, requiring more energy for packet transmission. After adjusting the mapping, the process becomes iterative with additional cycles, converging towards fairness for each user measurement, as shown in Figure 3. This convergence reduces the per-user transmission power utilisation to a low level, thus improving the performance-to-outage probability.

Similarly, the rate (kbps) of the links illustrates the rapid changes in Figure 4, where the user's entropy becomes uniform after a few iterations. The user rates were determined by their respective maximum utilities. Because each user's utility at NE differs, their power and rate also vary. The AGWO helps users achieve optimal power and rate quickly; however, lossy and unreliable wireless links cause significant topological changes. The solution to this problem lies in the use of the rate outage probability, which is another concern of the DPRO-GWA approach.

Figure 4 illustrates how the outage probability is used to determine the rate for all users, whereas synchronisation is maintained at the nodes to handle unexpected variations in the channel.

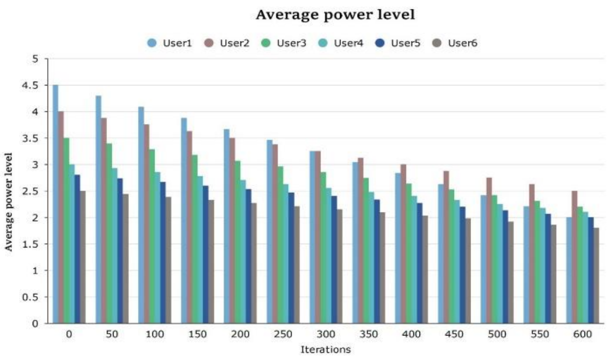

Figure 2. Average power levels

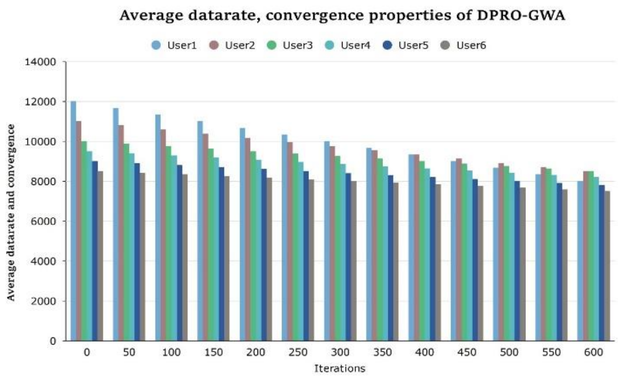

Figure 3. Average data rate, convergence properties of DPRO-GWA

The energy consumption of individual nodes is controlled to a limit based on the imbalance of energy consumption among different nodes and selfish behaviour of the nodes. Initially, all users had zero energy consumption, but this increased over time. The utility of each node differed, as was the case for the NE point. Consequently, the energy consumption varies as the nodes transmit at different power levels. Therefore, energy consumption also increases over time because of the number of packets transmitted during transactions between nodes. The nodes transmit packets with a power level determined using the DPRO-GWA. The system nodes must be utilised to their maximum capacity to gain the greatest benefits while preventing other nodes from enhancing their benefits by altering resource consumption. The convergence point of the proposed algorithm for the supermodular game in terms of AGWO is illustrated in Figure 4. The proposed method then utilised the dynamic behaviour of the DPRO-GWA to minimise energy consumption. Figure 5 compares the total system energy consumption between the ECPRC (using GWO only) and DPRO-GWA. This indicates that the AGWO achieves an effective convergence point with very low complexity and energy consumption compared with the GWO.

Owing to its efficiency, the proposed approach outperforms existing power and rate control methods. To illustrate this behaviour, we compared the proposed algorithm with the Lagrangian multiplier-based algorithm RENUM and the particle swarm intelligence-based algorithm DRPAA in terms of the aggregated throughput achieved, as shown in Figure 6. The results indicate that the variations in the end-to-end throughput at time T s increase with an increase in the number of hops per flow.

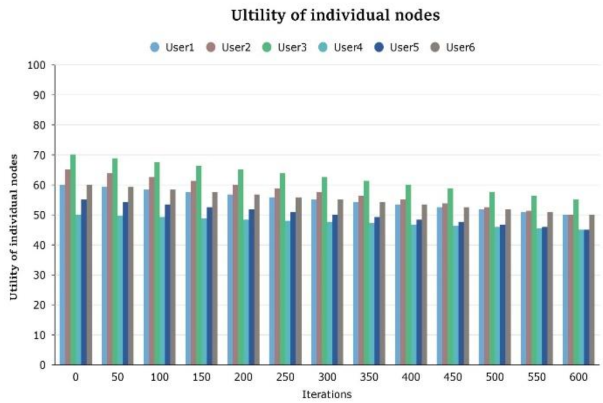

Figure 4. Utility of individual nodes

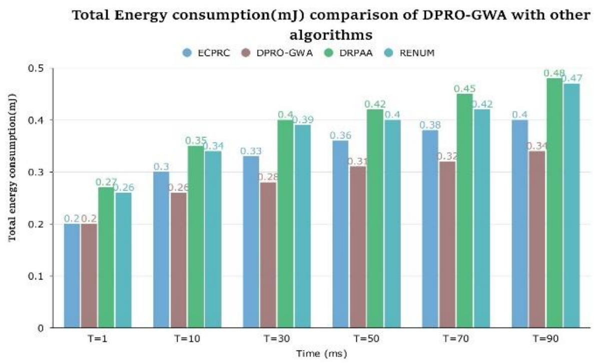

Figure 5. Total energy consumption (mJ) comparison of DPRO-GWA with other algorithms

Figure 7 shows the average power consumption, data rate, and delay of the ECPRC, DPRO-GWA, DRPAA, and RENUM algorithms. The average power consumption of the proposed approach is better than that of the DRPAA and RENUM, whereas the data rate achieved in DPRO-GWA is almost equal to that of the RENUM-based algorithm. Additionally, DPRO-GWA reduces the end-to-end delay.

Figures 5 and 8 present the same information for all algorithms concerning the total energy consumption and average delay, respectively. From Figure 5, it is evident that DRPAA and RENUM consume more energy than DPRO-GWA. As shown in Figure 8, the average delay for all algorithms is initially considerable; however, after a few iterations, the decision-making time decreases. This is because the convergence and delay become static. From Figure 8, it can be noted that the delay for DPRO-GWA is less than that of the other heuristic algorithms. The convergence rate of the proposed approach is illustrated in Figure 9, and the convergence order is clearly outlined in Figure 9, indicating that the convergence rate improved in the DPRO-GWA.

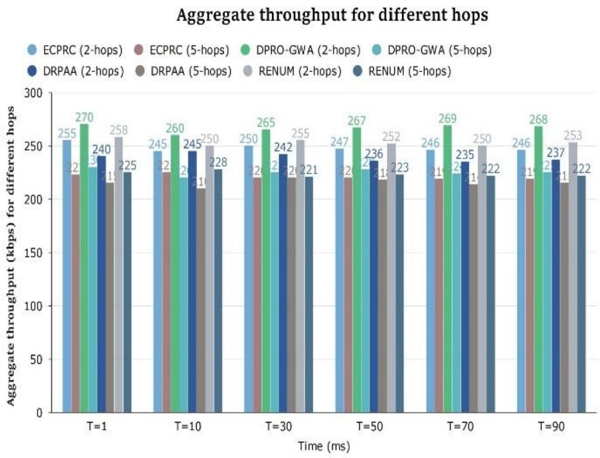

Figure 6. Aggregate throughput for different hops

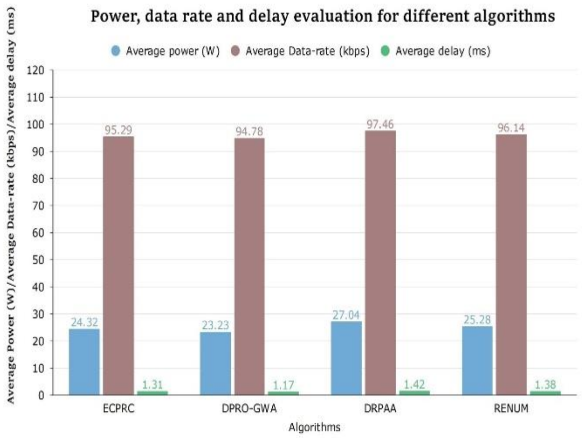

Figure 7. Power, datarate and delay evaluation for different algorithms

One of the key strengths of the DPRO-GWA is its efficient convergence to the optimal solution. The adaptive gray wolf optimizer (AGWO), which is used to solve the power and rate control problems, improves the convergence speed compared to traditional optimization algorithms. In DPRO-GWA, the parameter a. In the AGWO, a logarithmic reduction is used, allowing the algorithm to balance exploration and exploitation more effectively during optimization.

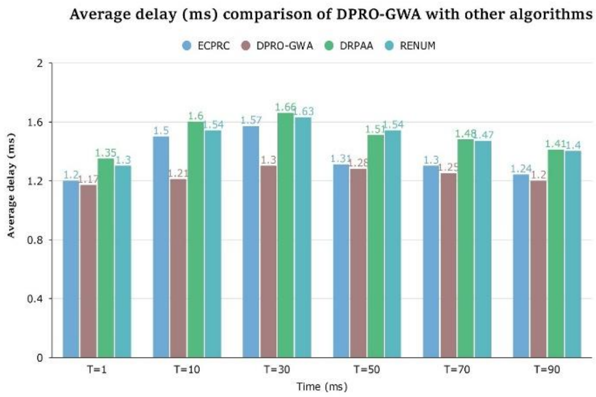

Figure 8. Average delay (ms) comparison of DPRO-GWA with other algorithms

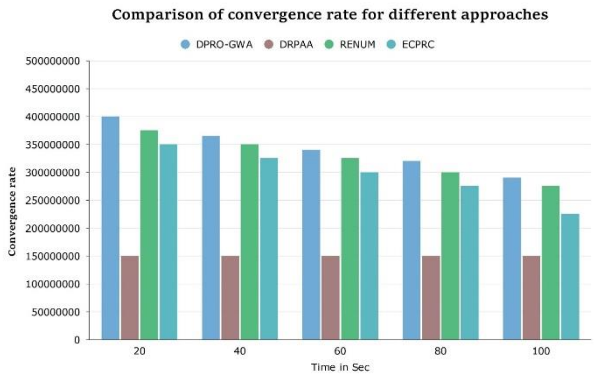

Figure 9. Comparison of convergence rate for different approaches

The simulation results show that DPRO-GWA converges faster than other optimization-based algorithms, including DRPAA and RENUM, particularly in networks with many nodes. The convergence rate of the DPRO-GWA is measured by the number of iterations required to reach a stable state, where the nodes' power and rate decisions no longer change significantly. DRPAA and RENUM take significantly longer to converge, particularly under high mobility and dynamic conditions.

The DPRO-GWA significantly enhances the network reliability through the built-in outage probability. Therefore, DPRO-GWA considers the probability of transmission failure arising from inadequate SINR values while executing power and rate control to minimise such outages, leading to a lower packet loss rate. The simulation results indicate that DPRO-GWA has a lower outage probability than DRPAA and RENUM, particularly in high-interference environments or under rapidly varying channel conditions. This results in better communication reliability, making it well-suited for delay-sensitive applications in which seamless connectivity is important.

We focus on delay and energy-efficient designs and believe that DPRO-GWA strikes a fine balance between these two factors. The utility function of DPRO-GWA was designed to penalise throughput loss and time overhead, resulting in power and rate settings that jointly optimise both objectives. The simulation results show that DPRO-GWA achieves lower energy consumption for the same delay as DRPAA and RENUM, which optimise their systems only for throughput or energy. This is especially relevant for real-time applications, where reducing latency is as important as lowering the energy consumption.

Moreover, through DPRO-GWA, the energy-delay trade-off ensures that when focusing on energy efficiency, the system experiences only a limited loss in communication quality, as reflected in the average delay and total throughput across varying network configurations. This combination makes DPRO-GWA highly versatile for energy-constrained real-time applications in MANET.

6. Discussion

Simulation results indicate that DPRO-GWA outperforms other algorithms in dynamic rate and power adjustment and the rate- and energy utility-based network optimisation algorithm (DRPAA-RENUM). Based on these results, we can conclude that DPRO-GWA will likely provide the best performance in terms of throughput, energy, and delay, irrespective of changing environments and high mobility. In addition, the DPRO-GWA consumes more energy and has a higher throughput. This process is game-theoretic, involving nodes that become powerful and act independently, achieving a trade-off between energy and throughput. Another advantage is that the optimal solution can operate with both DRPAA and RENUM. It has a lower outage probability than the DRPAA and RENUM because the DPRO-GWA uses the outage probability as an optimisation criterion. Because wireless channels are typically affected by interference and fading, the improvement is particularly notable; under these conditions, DPRO-GWA can adaptively adjust the transmission power and rate to reduce the number of lost data packets, ensuring reliable communication.

The same cannot be said for the delay on DPRO-GWA, which shows a significant improvement in quality over the conventional algorithms. This is particularly important in applications that require real-time feedback, in which minimising delays is essential. DPRO-GWA depends on a utility function to dynamically evaluate the transmission configuration that could enhance network performance, although it compromises energy conservation with minimal impact on reliability in terms of energy savings. We have defined the evaluation metrics used to assess the performance of DPRO-GWA. The following metrics were included in our analysis:

Energy Consumption per Node: This metric represents the average energy consumed by each node during the simulation. It was computed by summing the transmission and reception energy at each node over the simulation period.

Throughput: The total amount of successfully delivered data to the destination nodes, measured in bits per second (bps).

End-to-End Delay: The average delay for a packet to travel from the source node to the destination, including all delays due to transmission, propagation, queuing, and retransmissions.

Packet Delivery Ratio (PDR): The ratio of the number of successfully delivered packets to the total number of packets sent by the source nodes, which reflects the reliability of the network.

Outage Probability: The likelihood that the transmission between nodes fails due to insufficient SINR (Signal-to-Interference-plus-Noise Ratio).

We have included performance graphs to visually illustrate the comparisons between DPRO-GWA and the other algorithms in the results and analysis section. These graphs allow for an intuitive understanding of the performance differences and help highlight the advantages of DPRO-GWA across the different metrics. Overall, DPRO-GWA is an effective power and rate control algorithm in MANET. It addresses several key factors, such as energy efficiency, delay, and reliability, which are especially crucial in constrained and real-time applications.

6.1 Challenges and limitations

Although the DPRO-GWA approach works well, it has some constraints and limitations. As AGWO is applied to solve the power and rate control problems, its computational complexity is a major concern. Although the proposed AGWO accelerates convergence compared with other optimisation algorithms, the optimal solution may not be found reasonably, particularly for large networks (on the order of thousands of nodes). Consequently, this may create a significant overhead for implementing the DPRO-GWA protocol in large MANETs, as the nodes must adapt to the variable mobility models and traffic distribution in the scenario. A major challenge is that MANETS are dynamic networks with constantly changing topologies owing to node mobility. The game-theoretic task assumes that nodes must independently make effective decisions regarding their states in non-static environments based on local information. Rapidly changing network topologies often result in delays or errors in real-time decision-making. For instance, nodes may lack the most up-to-date data on channel conditions and the power settings of surrounding nodes, leading to inefficient performance.

It also accounts for external interference and inter-node communication delays, which can lead to performance degradation, particularly in high-density networks and those with significant external interference. Additionally, in cooperative networks, it is a common assumption that different nodes will not collaborate to optimise network performance but will operate independently of each other.

Finally, although the outage probability term is useful for tuning reliability, it may not be sufficient in extreme fading scenarios or very dense interference situations, where even with optimal power control, the SINR could still be too low for successful communication. DPRO-GWA is a viable scheme for resource-deprived wireless networks, such as MANETS, vehicular networks, and disaster recovery applications. It is especially suited for scalable and dynamic environments with impractical, centralised control. However, all these benefits come with their own set of challenges when implementing DPRO-GWAs in real-world scenarios. Resource management is essential for implementing and deploying AGWO in an aerial network, minimising computational overhead, and achieving fast convergence. Furthermore, real-time channel conditions and node mobility are critical requirements for an effective algorithm design. Inferring the outage probability from real-world systems also requires real-time monitoring of network conditions.

Nevertheless, DPRO-GWA can strike a balance between throughput, energy consumption, and delay, making it a strong candidate for next-generation wireless networks, where energy efficiency and low-latency communications are vital to the success of applications such as autonomous vehicles and Internet of Things (IoT) deployments.

7. Future work

The Dynamic Power-Rate Optimisation Grey Wolf Algorithm (DPRO-GWA) mechanism shows considerable achievements in power optimisation and efficient rate control on MANET as a powerful feature; therefore, we still highlight some topics for future work.

Cross-layer optimisation (CLO): This is one of the prime extensions, where cross-layer optimisation strategies are utilised to tune parameters between different layers, including application, network, and MAC layers. DPRO-GWA operates independently on the Physical and Data Link layers;

however, in practical networks, the joint optimisation of these layer decisions can enhance the overall efficiency of real-time applications, such as video conferencing or autonomous vehicle communication. In future work, the DPRO-GWA framework can be extended to include decisions related to packet size, routing, and channel access policies to achieve end-to-end optimisation.

Integration of 5G: The transition to 5G networks presents enhanced challenges and opportunities for the DPRO-GWA. 5G is equipped with high-end technologies to utilise and improve power exploitation and rate control for dense networks (such as massive Multiple Input, Multiple Output (MIMO), beamforming, and network slicing) [7]. Integrating the DPRO-GWA with these 5G features enables real-time power allocation and flexibility in rate adjustments, depending on spectrum availability and the physical channel state. Furthermore, the ability to allocate dedicated resources through network slicing in 5G introduces another promising aspect for improving DPRO-GWA performance by providing differentiated services for IoT and critical communication domains.

Realistic Large-Scale Deployments: As an evolutionary methodology, DPRO-GWA requires testing its real-world performance through simulations, particularly using test beds or field trials. There are Ansible tools capable of simulating complex scenarios, such as environmental factors, node heterogeneity, and node mobility, which are difficult to incorporate into a simulation model. Additionally, enhanced scalability and performance can be realised by introducing real-time traffic patterns with the DPRO-GWA and shifting some computational tasks to the edge via edge computing.

8. Conclusion

This paper presents a mechanism, the Dynamic Power-Rate Optimisation Grey Wolf Algorithm, for a novel approach to modify power and rate allocation to boost Mobile Ad Hoc Networks (MANETs) performance. DPRO-GWA is the first study to apply a game-based model to a network where an AGWO ensures that nodes in the network make the best decisions to achieve a trade-off among energy, delay, and throughput while maintaining the stability of the network. The key gaps addressed by our approach are as follows:

1. Handling the Trade-off Between Energy, Throughput, and Delay:
   Unlike DRPAA and RENUM, which primarily focus on either optimizing throughput or energy efficiency, our proposed approach (DPRO-GWA) integrates both energy conservation and throughput maximization while explicitly incorporating delay constraints. This makes our method uniquely suited for real-time applications in MANETs where low-latency communication is critical (e.g., voice and video streaming). ECPRC, while energy-efficient, fails to adequately account for delay and network stability under dynamic conditions. DPRO-GWA specifically targets the energy-delay trade-off, offering a more balanced solution for practical MANET applications.
2. Outage Probability Consideration:
   A significant limitation of DRPAA and RENUM is their neglect of the outage probability (the likelihood of transmission failure due to poor channel conditions). Our approach explicitly integrates outage probability into the optimization process, which improves communication reliability, especially in highly dynamic and lossy networks. By considering the risk of packet loss due to fading or interference, DPRO-GWA enhances the robustness of the network, which is critical for mission-critical applications in MANETs.
3. Incorporation of Adaptive Grey Wolf Optimization (AGWO):
   While both DRPAA and RENUM rely on fixed optimization techniques, our work introduces an adaptive version of the Grey Wolf Optimizer (AGWO), which significantly accelerates convergence without compromising solution quality. This adaptation allows for faster and more efficient optimization in dynamic network environments where network conditions can change rapidly. Traditional metaheuristic algorithms like GWO suffer from slow convergence, especially in large or complex networks. AGWO overcomes this by balancing exploration and exploitation more effectively, thus offering improved performance with lower computational complexity compared to standard GWO and other optimization algorithms.
4. Game-Theoretic Framework with Distributed Power and Rate Control: While game-theoretic approaches like those used in DRPAA provide a decentralized framework, they often do not fully address critical aspects such as the interplay between residual energy and real-time communication requirements. Our work leverages a supermodular game-theoretic model, which guarantees the existence and uniqueness of the Nash Equilibrium (NE), ensuring a robust, distributed, and self-stabilizing power-rate control mechanism. This game-theoretic foundation distinguishes our approach from others by providing a formalized mechanism that adapts to the needs of individual nodes while ensuring that the system as a whole remains stable and efficient.

The DPRO-GWA outperforms various state-of-the-art algorithms, such as the DRPAA and RENUM, in terms of average throughput, energy consumption, and delay. This performance is exacerbated in dynamic and high mobility environments, as supported by the simulation results. This is particularly important for real-time microphones, which require low packet loss; therefore, the outage probability is included in the optimisation to ensure better results and reliability.

The main contributions of this work can be summarised as follows:

(1) a game-theoretical model to optimise both the system power and rate control,

(2) inclusion of outage probability to allow for increased reliability of the communication link,

(3) Application of AGWO to provide a possible faster convergence to the optimal solution, and

(4) a comprehensive evaluation of the approach through simulation results demonstrating an improvement over typical method.

Future work will focus on extending the DPRO-GWA to cross-layer optimizations, 5G integration, and real-world testbed implementations to ensure its practical viability and further enhance its performance in real-world networks.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement
The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest
The authors declare no potential conflict of interest.

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