BER and power consumption minimization through optimization in wireless cellular network

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ABSTRACT

Quality of service (QoS) of wireless cellular networks affect due to more power consumption, maximum bit error rate (BER), minimum throughput and improper resource allocation. Improvement in QoS can be done by reducing power consumption, BER and enhancing throughput. Hence there is a need to address the approaches for reduction in power consumption, BER, enhancement in throughput and proper resource allocation through different schemes. In this paper grey wolf optimization (GWO) technique is investigated with different database functions and Its outcome is contrasted with alternative methods like particle swarm optimization (PSO) and genetic algorithm (GA), It is evident that the GWO algorithm performs exceptionally well in terms of BER and power consumption minimization than the other techniques. Hence the QoS of the wireless cellular network will not affect due to minimization of the BER and power consumption through our proposed scheme.

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1. INTRODUCTION

Quality of service (QoS) depends upon many factors or parameters in wireless cellular networks. Most of the researchers work on many parameters in their research to improve the QoS. Different optimization algorithms used to optimize the services in wireless cellular networks to enhance the wireless cellular networks' performance and providing the better QoS. Due to more power consumption, maximum bit error rate (BER), minimum throughput and improper resource allocation the QoS of wireless cellular networks degrades and the performance of the wireless cellular networks affected. So as a good service provider or wireless cellular networks must have the good QoS. Hence QoS can be improved or enhace by reducing the minimal BER and low power usage, by enhancing the maximum throughput and using the proper resourse allocation in the network. In this work we use the grey wolf optimization (GWO) technique as estimated method for fitness function optimization for minimum BER and minimum power consumption so that the BER and power consumption must be minimum to enhance the QoS. GWO algorithm resembles grey wolves' hunting strategy and management hierarchy inwireless cellular network environment. Alpha, beta, delta, and omega are the four varieties of grey wolves that are used to resemble the management hierarchy. Furthermore, hunting consists of three primary steps, finding prey, surrounding prey, and attacking prey are taken into consideration while implemting the methodology [1].

For designing system framework, each cellular network must be capable of to adapt the transmission settings to the information about the surroundings. Therefore, it is necessary to establish the essential parameters, such as the transmission and environment parameters. In order to compute the fitness functions and assist cellular networks in making decisions, the environment characteristics need be known ahead of time. In optimization process of the bandwidth allocation, the fitness function should be defined to guide the searching direction. There are two fitness functions in this paper, and they are BER minimization, and power consumption minimization.

Power consumption minimization's fitness function is described as [2]:

$$f_{min-power} = 1 - \frac{P}{P_{max}} \quad (1)$$

where P_max is the maximum available transmit power and P is the average transmit power of all the subcarriers.

BER minimization fitness function is provided as (2).

$$f_{min-BER} = 1 - \frac{\log_{10}(0.5)}{\log_{10}(P_{be})} \quad (2)$$

There is a tension between the two signal-objective fitness functions; for instance, minimizing power usage often raises the BER. As a result, the actual optimization results should balance these signal-objective fitness functions in order to satisfy the system's communication needs while maximizing other performance. Consequently, the multiple-objective fitness function of the whole network may be defined as:

$$f = \omega_1 \times f_{min-power} + \omega_2 \times f_{min-BER} \quad (3)$$

where the three control objectives', relative significance is determined by the weight vector W, which must satisfy the $\omega_1 + \omega_2 = 1$ [2].

Section 2 presents a literature review to support and help the proposed work. In section 3 outlines the proposed research methodology using GWO algorithm and hierarchy of the same and its complete working algorithm. The obtained results in terms of minimum BER and minimum power consumption and their comparision with the PSO and genetic algorithm (GA) is discuused in section 4. Finally, section 5 concludes presented work and it offers some ideas for future research areas.

2. RELATED WORK

Koutsorodi *et al.* [3], introduced a mobile terminal structural design tailored for devices operating in heterogeneous environments. They proposed a strategy that independently identified the optimal attachment point and local interface while accounting for factors such as user preferences, network conditions, service requirements, and resource availability. To address the multi-criteria access network selection (ANS) problem, [4] utilized fuzzy logic (FL) and GAs. This approach incorporated a multi-metric software assistant (SA) to support both users and network operators in delivering the required QoS while ensuring flexibility, scalability, and simplicity. Results demonstrated that the SA and the proposed scheme were more robust and delivered better performance compared to random-based selection methods.

The fuzzy neural framework presented in [5] employed a multi-criteria decision-making approach that considered subjective criteria and operator policies. For example, certain radio access technologies (RATs) could be prioritized over others, or traffic could be balanced across multiple RATs. Kha*n et al.* [6], a user-centric network selection mechanism based on an auction system was proposed. This approach involved negotiations between users and network operators, taking into account service quality metrics such as truthful network behavior, user consumption patterns, and the pricing offered by network operators. FL was utilized to reduce the frequency of handovers, enhancing network efficiency.

The autonomic interface selection architecture (AISA), introduced in [7], employed fuzzy control to dynamically and automatically select the most suitable interface from multiple available options. AISA used diverse autonomic evaluation rules to adapt to changing network conditions and user demands. The system was designed to sense and interpret relational changes within the network, ensuring adaptability to dynamic environments. By applying fuzzy set theory, AISA leveraged human-like reasoning to autonomously identify the optimal interface for specific applications.

A user preference-oriented network selection (UPNS) algorithm was developed in [7] by integrating the fuzzy analytic hierarchy process (FAHP) with entropy theory. This approach enhanced efficiency by aligning with individual user preferences, thereby improving user satisfaction. Singhrova and Prakash [8], a neuro-fuzzy multi-factor vertical handoff decision algorithm (VHDA) was proposed. This method evaluated six metrics and employed a rule-based framework to make vertical handoff decisions. Simulation results showed that the algorithm significantly reduced the number of vertical handoffs while offering superior QoS compared to existing techniques, as reflected in its handoff quality indicator.

The algorithm in [8] also incorporated GAs, particle swarm optimization (PSO), and FL controllers for decision-making based on inputs such as user velocity, service cost, QoS parameters, service type, and customer requirements. Radhika and Reddy [9], FL with multi-criteria decision-making attributes was introduced to optimize network selection. The network selection function (NSF) evaluated the capability of available radio resources individually, with the network attaining the highest NSF value being chosen as the target network for handover.

A radio network selection (RNS) solution was proposed in [10], combining parallel FL control and multi-criteria decision-making (MCDM) systems. This adaptive approach demonstrated higher robustness and better performance than previously explored methods. Sangwan *et al.* [11], a user-specific intelligent vertical handoff (UIVH) algorithm was introduced, utilizing the adaptive neuro-fuzzy inference system (ANFIS) for network selection. UIVH effectively identified the most suitable network while considering specific user requirements. Results indicated a gradual increase in relinquishing completion time alongside a rise in the number of handovers.

A QoS-aware VHO mechanism leveraging fuzzy rules and multi-criteria decision-making was presented in [12]. It efficiently met the diverse needs of applications across various environments. Additionally, a valuation model employing a non-birth-death Markov chain demonstrated improved performance for different traffic scenarios compared to conventional algorithms. Kaleem *et al.* [13], a multi-criteria VHO algorithm addressed user preferences, traffic types, and system metrics, maintaining QoS standards through modules like the target network option and VHO necessity estimation (VHONE). A fuzzy linguistic weighting scheme was also proposed to enhance decision reliability.

Rios *et al.* [14] and Lahby *et al.* [15], the integration of FLwith grey relational analysis (GRA) and analytic hierarchy process (AHP) decision-making methods was suggested. These methods proved useful in prioritizing alternative network options, with artificial intelligence techniques further refining the accuracy of results. A ranking algorithm combining mahalanobis distance and multi-attribute decision-making (MADM) techniques was introduced in [15], [16]. This algorithm categorized criteria into consistent classes, determined intra-class and inter-class weights using MADM and fuzzy AHP methods, and applied Mahalanobis distance for ranking. The approach effectively reduced ranking irregularities and optimized network selection.

Thumthawatworn *et al.* [16] and Goel *et al.* [17], a handover decision system (HDS) was proposed using FL to address network selection challenges. The system demonstrated significant improvements in execution time and network selection accuracy. Further network selection mechanisms were discussed in [17]-[20] for seamless vertical handoff in heterogeneous wireless networks. These approaches facilitated mobility across technologies such as WiMax, Wi-Fi hotspots, and cellular networks. Traditional methods relying on general metric evaluations often fail to deliver efficient network selection decisions. To overcome these limitations, we propose a novel algorithm based on GWO, which offers a more robust and efficient solution for network selection in heterogeneous environments.

3. PROPOSED RESEARCH METHOD

The alpha wolf serves as the leader of the pack and can be either male or female. This wolf is responsible for making key decisions regarding hunting, selecting sleeping locations, and determining wake-up times. All other wolves in the pack are required to adhere to the alpha's commands, making this role the highest position in the hierarchy. Below the alpha is the beta wolf, which assists in decision-making and ensures the alpha's directives are followed by the rest of the pack. The beta wolf, also male or female, plays a crucial role in maintaining discipline within the group. In the event of the alpha's absence or death, the beta is the most likely successor to take on the leadership role [21].

At the bottom of the hierarchy is the omega wolf, which is subordinate to all other wolves. Omega wolves often yield to the dominant members of the pack and are the last to eat after others have finished. Although they appear to have a less significant role, omega wolves are essential for reducing tensions within the pack by acting as scapegoats or outlets for aggression. The delta wolves rank below the alpha and beta but are superior to the omega. This group includes scouts, hunters, caretakers, and elders, each with specific responsibilities like safeguarding the pack and ensuring its well-being by managing food and health-related tasks. Delta wolves must submit to the authority of the alpha and beta while maintaining dominance over the omega wolves. Figure 1 illustrates the hierarchical structure of grey wolf packs, highlighting the distinct roles and responsibilities of each group.

In the GWO, the alpha (α) wolf represents the best solution, serving as the leader in the social hierarchy. The beta (β) and delta (δ) wolves signify the second and third best solutions, respectively. Decision-making regarding the hunting process is primarily led by α\alphaα, β\betaβ, and δ\deltaδ. The remaining wolves, referred to as omega (ω), follow the directions of the top three wolves. Figure 2 illustrates the potential hunting positions and the encircling behavior of the wolves. The process of wolves encircling their prey can be described using (4) and (5).

$$\vec{D} = \left|\vec{C}.\vec{X}_P t - \vec{X}(t)\right| \tag{4}$$

$$(X)\vec{}(t+1) = X\vec{}\_P\, t - A\vec{}.D\vec{} \tag{5}$$

where, X is position vector of wolf. A and C are coefficient vectors and t is current iteration.

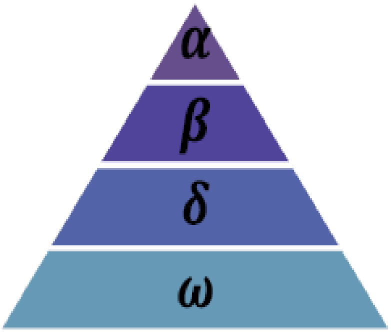

Figure 1. Hierarchyofgrey wolf [22]

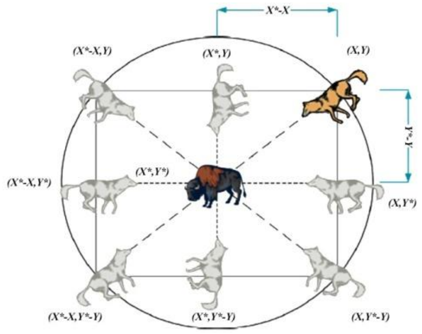

Figure 2. Possible hunting locations and encircling behaviour of wolves [22]

3.1. Grey wolf optimizer algorithm

1) Grey wolves exhibit a strategic hunting behavior that revolves around the positions of the alpha, beta, and delta wolves. During the search phase, they disperse (divergence) to explore the environment for potential prey. Once the prey is located, the wolves regroup (convergence) to coordinate their attack effectively [23].

$$A\vec{} = 2.a\vec{}.r\vec{}\_1 - a\vec{} \tag{6}$$

$$C\vec{} = 2.r\vec{}\_2 \tag{7}$$

   Where, r ⃗_1 and r ⃗_2 are random vectors:
2) The initialization of GWO population is given by at counter iteration t=0:

$$X\_i = (1,2,3 \ldots \ldots \ldots \ldots n) \tag{8}$$

3) Further A, C and a are also initialized
4) Now the fitness function for each searching agent is evaluated and is represented as:
   X_α denotes best searching agent
   X_β denotes 2nd best searching agent
   X_δ denotes 3rd best searching agent
5) If the total no. of iterations is given as t=n, then
   For (t=1; t≤n)
   Using above equations update the position of searching agents
   End for
6) Update A and C coefficients
7) Evaluate fitness function for each searching agent
8) Update X_α, X_β, X_δ
9) Set t=t+1 (iteration counter increasing)
10) Return best solution X_α

3.2. Working principle of grey wolf optimizer

The following steps outline the functioning of the GWO [24], [25]:

1. Problem solving through iterations: GWO tackles optimization problems by iteratively refining potential solutions to identify the most optimal one.
2. Encircling behavior: algorithm simulates wolves encircling their prey, representing a search space neighborhood. This behavior can be conceptually extended to a spherical region, as illustrated in Figure 3.
3. Role of coefficient vectors (AAA and CCC): AAA and CCC coefficient vectors enable the algorithm to create random hyperspheres of varying radii around potential solutions, enhancing the exploration process.
4. Hunting mechanism: hunting strategy allows the algorithm to approximate the prey's (optimal solution's) exact location through coordinated movements influenced by the top-performing wolves.
5. Exploitation and exploration control: values of parameters aaa and AAA play a critical role in balancing exploration (global search) and exploitation (local refinement) of the solution space.
6. Iteration dynamics based on AAA: As AAA decreases over the course of iterations, the algorithm dynamically transitions from exploration to exploitation, allocating equal iterations for both phases to ensure effective optimization.

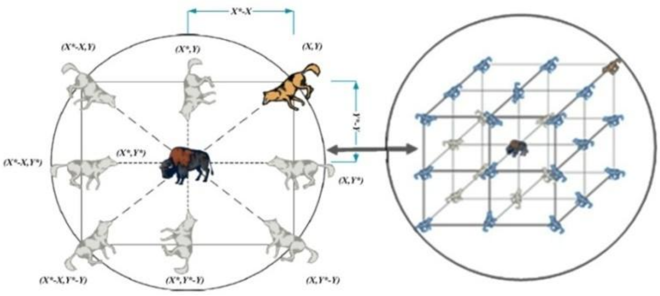

Figure 3. Expansion of surrounding form into a sphere

4. RESULTS AND DISCUSSION

Here we have taken the tabular appearance for comparison of the obtained results through our proposed method with another existing methods so that we can easily make comparative analysis of the results and able to comment on effectiveness of the proposed method for research work. Each cellular network should be able to modify thetransmission parameters in an adaptive manner in response to environmentaldata. Therefore, it is important to define the crucial parameters, such as theenvironment and transmission parameters. In order to achieve optimal QoS, GWO based approach is proposed. In this work GWO technique is examined with different database functions to find the best suitable fitness function for minimum BER and minimum power consumption and its outcome is contrasted with alternative methods like PSO and GA as listed below.

A comparative result in balanced model, multimedia mode, emergency mode, and low power model at various subcarrier index in Tables 1 to 4 shows that the BER and power consumption is minimized by GWO algorithm as compared to the PSO algorithm and GA. Hence from these obtained results we can say that the proposed GWO algorithm works very effectively for achieving minimum BER and also reduce the power consumption as compared to the GA and PSO. Therefore, we affirm that improvement in QoS can be achieved through this obtained minimum BER and reduced power consumption in wireless cellular networks.

Table 1. Comparative result in low power mode at various subcarrier indexes

Subcarrier index	BER			Power consumption		
	PSO	GA	GWO	PSO	GA	GWO
1	0.00195	0.00180	0.00071	0.03500	0.03000	0.02500
2	0.00515	0.00457	0.00215	0.03500	0.03000	0.02500
3	0.00189	0.00017	0.00098	0.02000	0.01500	0.02000
4	0.00025	0.00015	0.00010	0.03000	0.02500	0.01000
5	0.00057	0.00077	0.00012	0.01500	0.01000	0.01500
6	0.00249	0.00182	0.00182	0.02500	0.02000	0.02000
7	0.00607	0.00051	0.00045	0.03000	0.02000	0.01000
8	0.00793	0.00651	0.00207	0.04500	0.03000	0.02000
9	0.00586	0.00330	0.00330	0.04500	0.04000	0.02000
10	0.00349	0.00146	0.00044	0.03000	0.02500	0.02000

Table 2. Comparative results for emergency mode at various subcarrier index

Subcarrier index	BER			Power consumption		
	PSO	GA	GWO	PSO	GA	GWO
1	0.00204	0.00178	0.00065	0.02000	0.02000	0.02500
2	0.00454	0.00463	0.00200	0.03000	0.04000	0.02500
3	0.00245	0.00022	0.00087	0.03500	0.03000	0.01000
4	0.00074	0.00019	0.00016	0.01500	0.01000	0.01000
5	0.00094	0.00075	0.00011	0.02500	0.02500	0.02000
6	0.00268	0.00179	0.00174	0.04500	0.02500	0.01500
7	0.00621	0.00067	0.00048	0.03000	0.03000	0.01000
8	0.00807	0.00664	0.00191	0.03000	0.02000	0.02000
9	0.00579	0.00345	0.00329	0.03000	0.02500	0.02000
10	0.00356	0.00155	0.00038	0.03500	0.03000	0.02500

Table 3. Comparative results in multimedia mode at various subcarrier indexes

Subcarrier index	BER			Power consumption		
	PSO	GA	GWO	PSO	GA	GWO
1	0.00187	0.00175	0.00067	0.03000	0.02500	0.01000
2	0.00509	0.00478	0.00207	0.030000	0.02500	0.01000
3	0.00181	0.00167	0.00099	0.03500	0.03000	0.02000
4	0.00056	0.00044	0.00022	0.02500	0.02500	0.02000
5	0.00081	0.00075	0.00010	0.03000	0.03500	0.01000
6	0.00197	0.00186	0.00169	0.03500	0.02500	0.02000
7	0.00156	0.00110	0.00041	0.04000	0.02500	0.01500
8	0.00887	0.00784	0.00199	0.02500	0.04500	0.02000
9	0.00497	0.00387	0.00270	0.03000	0.03000	0.02000
10	0.00446	0.00361	0.00043	0.03500	0.03000	0.01500

Table 4. Comparative results in balanced mode at various subcarrier indexes

Subcarrier index	BER			Power consumption		
	PSO	GA	GWO	PSO	GA	GWO
1	0.00271	0.00224	0.00105	0.03500	0.03000	0.02500
2	0.00679	0.00653	0.00348	0.04500	0.04000	0.03000
3	0.00239	0.00197	0.00145	0.04000	0.03500	0.02000
4	0.00047	0.00022	0.00014	0.04500	0.04000	0.03500
5	0.00077	0.00083	0.00063	0.04000	0.03500	0.02500
6	0.00263	0.00249	0.00178	0.03500	0.03000	0.02000
7	0.00744	0.00501	0.00379	0.04000	0.03500	0.02000
8	0.00839	0.00679	0.00307	0.04500	0.04000	0.03000
9	0.00671	0.00487	0.00190	0.04500	0.04000	0.03000
10	0.00365	0.00293	0.00092	0.04500	0.03500	0.02000

5. CONCLUSION

This research work focused on QoS in wireless networks. Power and error rate is controlled optimally to claim for better QoS in proposed system model. GWO algorithm has been tested with various database functions and its performance has been compared to other techniques like PSO as well as GA. Output show that GWO surpasses the alternative methods with regard to minimizing BER as well as power consumption. Specifically, the average BER values achieved using GWO are 0.0012185, 0.0011646, 0.0011312, and 0.0018249 in different modes (low power, emergency, multimedia, and balanced mode). Similarly, the average power consumpstion values achieved using GWO are 0.0185, 0.018, 0.016, and 0.0255 in the same modes. Overall, the results indicate that GWO is a highly effective algorithm for minimizing BER and power consumption in low power, emergency, multimedia, and balanced mode as compared to PSO and GA. For the future study or work, the enhancement of the throughput and proper resourse allocation must be taken into account to support the better QoS in wireless cellular network thorugh different schemes or techniques for guaranting the good QoS.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Tushar Hrishikesh Jaware		✓	✓	✓	✓	✓		✓		✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

There are no conflicts of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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