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Original Article

Optimizing Handover Decisions for 5G and Legacy Networks Using the Chaotic Whale Optimization Algorithm

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Abstract - *The evolution of Fifth-Generation (5G) mobile communication technology has made seamless connectivity a critical requirement for users. Ensuring uninterrupted service while maintaining superior Quality of Service (QoS) across various network technologies is paramount. Users often seek continuous connections to nearby networks that offer optimal performance. To facilitate this, effective decision-making strategies are required to determine whether to initiate the handover process or maintain the current connection. Artificial Intelligence (AI) techniques have gained significant attention for their ability to enhance decision-making in heterogeneous networks by addressing challenges associated with large-scale frameworks. In this paper, we apply the Chaotic Whale Optimization Algorithm (CWOA), a nature-inspired meta-heuristic technique, to optimize the handover process across multiple network technologies, including Wi-Fi, WiMAX, UMTS, LTE-A, and 5G New Radio. Our results demonstrate a comparative analysis of these technologies in terms of key performance metrics, such as Received Signal Strength (RSS), Signal-to-Noise Ratio (SNR), delay, throughput, and average power consumption, all measured against distance. The findings indicate that 5G New Radio outperforms other technologies in most metrics, providing superior QoS during handover, especially when optimized using CWOA.*

Keywords - *Chaotic Whale Optimization, Fifth Generation wireless networks, Handover/Handoff, LTE-A, Nature inspired meta-heuristics.*

1. Introduction

Wireless technology has transformed the way people interact with the modern environment. It has eliminated the need for large wires and costly infrastructures associated with wired networks, providing a more affordable and adaptable alternative. The growing reliance on wireless communication has attracted public interest, making it an essential component of our daily lives. The internet has become indispensable, influencing practically every facet of modern life. Its significance has grown to a point where it is now considered as essential as electricity itself [1]. Numerous advantages have been realized through wireless communication, such as rapid response to user demands, reduced setup time for communication infrastructure, increased internet usage, and instant service delivery. Wireless technology allows dynamic adaptation to real-world conditions, ensuring stronger connections between customers and service providers. For instance, in cloud computing, two key aspects are considered: the underlying technology that establishes the wireless framework and the applications that guide the sequence of functions based on user requests. Currently, researchers are exploring new paradigms to improve information exchange over wireless networks. However, several challenges must be addressed when designing wireless communication standards, including:

Reliability: Ensuring near-error-free communication.

Speed: Achieving speeds comparable to wired networks.

Security: Protecting data from unauthorized access and attacks.

Compatibility: Supporting diverse conditions and protocols.

Environmental Impact: Minimizing harmful radiation and adhering to ecological safety standards

Several strategies and challenges exist in establishing reliable wireless communication:

Radio Frequencies: Wireless communication typically uses frequencies between 902 MHz and 928 MHz, but research is ongoing into more reliable methods, such as frequency hopping with spread spectrum techniques. There is also interest in utilizing less commonly used frequencies in the gigahertz range. However, using higher frequencies presents challenges: Higher frequencies result in shorter wavelengths, which have difficulty penetrating solid objects (as per the concept of skin depth). Frequencies above 3 GHz require licensing, which may interfere with satellite communications [2].

A significant portion of cellular technology connections is driven by corporate sectors despite the high implementation costs. The initial setup of cellular communication often relies on a hybrid system, where wired networks support wireless communication. In such systems, data is broken into little units called packets, the size determined by the device's specs and the transmission protocol. These packets are passed to the nearest network node, which then relays them to the next device, repeating the process until the data arrives at its destination.

The increasing usage of wireless communication devices, such as satellite phones, Personal Digital Assistants (PDAs), and cellular phones, has become critical to many people's daily activities. Wireless technology has become an essential component of current communication systems due to its ease of use and versatility [3].

Personal Digital Assistants (PDAs) and cellular phones operate by transmitting equal amounts of power in all directions, facilitating effective communication for multiple users within a specified area. However, microwave communication typically follows a unidirectional or end-to-end approach, allowing communication to occur in only one direction at any given time [4, 5]. A multiple-access connecting framework is essential to achieve universal coverage, ensure high-quality service, minimize hardware costs for both users and hosts, and reduce the number of necessary cell sites [6]. This framework aims to balance greater coverage with high-quality service delivery. Additionally, providing academic training through resource processing in a wireless manner enhances user capacity, reduces costs, and improves the overall service experience. Wireless information processing and sharing can address several complexities, including wider area coverage, consistency, speed, and cost-effectiveness in both establishment and utilization [7].

The emergence of mobile communication has witnessed significant advancements, evolving from simple voice-based interactions to complex interconnected systems that provide a wide range of services. These advancements have enabled faster connections for a large number of clients and devices [8].

Diverse characteristics play a crucial role in shaping the future mobile framework, driven by technical innovations and strategies that address the increasing traffic demands in mobile communication [9].

Future networks utilizing mobile technology will face numerous complexities, including higher capacity, improved functionality, reduced energy consumption, efficient bandwidth utilization, and enhanced commercial viability.

The evolution of Fifth-Generation (5G) technology aims to address the surging volume of data in mobile communications while introducing new capabilities and services. This evolution has sparked significant research interest within both academic and corporate sectors, inspired by the rapid growth in internet usage facilitated by mobile technology and the rising demand for commercial activities.

5G is expected to deliver cost-effective solutions, lower energy consumption, enhanced data security, and reliability. Communication speeds could reach 10 Gbit/s, with latency reduced to just a few milliseconds. The number of connected devices is also anticipated to increase dramatically [10].

5G technology aims to improve data transmission, overcoming existing limitations related to distance and time and facilitating seamless interactions between users and devices, thereby significantly reducing the gap between individuals and technology [11].

A key concept in managing radio resources is the handover mechanism. To enhance efficiency and reliability in modern communication systems, particularly those utilizing wireless technology, it is crucial to develop and implement effective handover strategies.

The handover process occurs when a device connected to a base station moves out of the coverage area of its current connection and into the range of an adjacent terminal. This transition involves transferring control from the original terminal to the new one.

Handover is essential, especially when the signal quality of the current connection degrades due to factors like changes in atmospheric conditions. In such cases, the system must seamlessly switch to the adjacent terminal to maintain uninterrupted connectivity.

Failure to execute a successful handover can result in a loss of connection, highlighting this mechanism's importance in ensuring continuous service.

Figure 1 illustrates the fundamental prototype of the handover mechanism. Selecting an appropriate handover mechanism is crucial for ensuring continuous service and high-quality performance in wireless communication systems.

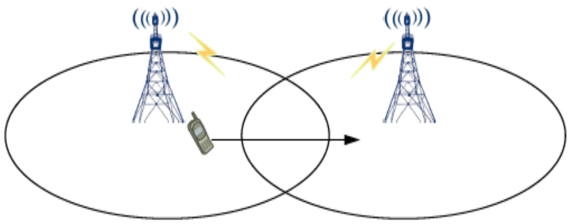

Fig. 1 Fundamental model for handover mechanism

This strategy plays a pivotal role in the overall functionality of the system, particularly within the complexities introduced by the 5G network. Due to the high speeds associated with 5G, there is an increasing demand for rapid computing capabilities.

However, this can lead to a loss of control as the number of connected terminals increases. Consequently, handover procedures will require smart devices to execute these processes effectively [12].

Challenges related to information security may arise, making clients hesitant to share their profiles. As a result, various handover mechanisms are expected to emerge to meet the demands of fifth-generation networks.

When developing new handover strategies, the following aspects must be considered:

Accurate Signal Measurement: The construction of millimeter-wave communication at higher frequencies can significantly enhance the interaction capabilities of the framework. However, these high frequencies are susceptible to severe signal degradation due to environmental factors and obstacles.

This can limit the effectiveness of frequency utilization [13]. Additionally, substantial deterioration in signal quality and various faults may lead to inefficient switching mechanisms and unnecessary handovers, impacting overall connectivity.

Frequent Handover: With the denser infrastructure of 5G networks, smaller handover radii are observed compared to existing dimensions. Consequently, if a base station maintains a connection for a minimal duration, it may trigger frequent handover processes [14].

Different Network Layers Switching: Handover mechanisms can be executed among similar network layers with analogous structures. In the framework of the fifth-generation network, handovers between various technologies, such as Long-Term Evolution (LTE), Wideband Code Division Multiple Access (WCDMA), and Wireless Local Area Networks (WLANs), are sometimes required. Horizontal handover occurs when structures are comparable, and vertical handover occurs when technologies are distinct.

2. Literature Survey

The progression of mobile communication, coupled with the investigation of internet-related data and other techniques, can significantly enhance the existing mobility framework, particularly in optimizing the handover process. In the context of Fifth-Generation (5G) technology, the utilization of big data can be instrumental. By analyzing user behavior and attributes, along with additional contextual information, it becomes possible to estimate the navigation paths chosen by clients and the conditions of the services provided. This proactive analysis allows for developing more efficient handover mechanisms tailored to user needs and service circumstances [15].

Fifth-generation mobile technologies have demonstrated a reduction in latency while imposing stricter demands for fault identification. The requirement for minimal latency presents challenges in formulation. Mukherjee (2018) [16] proposed a strategy to balance energy consumption efficiency with client delay mechanisms for future fifth-generation technologies. The study introduced various strategies to facilitate the switching process of control terminals. Specifically, in the context of Ultra-Reliable Low Latency Communication (URLLC), solutions were suggested to address issues such as Discontinuous Reception (DRX) and navigational considerations, all while ensuring that latency is not compromised during the process.

Numerous techniques leveraging wireless strategies have been proposed to meet the increasing transmission speeds required for data transfer applications, such as video streaming, in the context of next-generation networks utilizing wireless technologies. However, these techniques often face a trade-off between coverage area and data transfer rates—either offering a wider coverage area with lower transmission speeds or a limited coverage area with higher speeds. One of the most prominent demands from clients in fourth-generation networks is the ability to utilize resources anytime and anywhere. Ahmed and Rikil (2018) [17] established a vertical handover strategy between 802.11e and IEEE 802.16e, designed to meet Quality of Service (QoS) demands based on the provided traffic. This approach aims to optimize outcomes by considering factors such as received signal strength, client requirements, processing load, the speed of equipment movement, latency, and bit error rate during data transmission.

Modern fog network architectures, powered by IoT applications and 5G communication technologies, are characterized by many mobile nodes that frequently undergo handovers. This frequent mobility introduces a significant load on the network entities involved. Given these architectures' distributed and flat nature, Distributed Mobility Management (DMM) emerges as the most viable option for efficiently managing handovers in such scenarios. While existing DMM solutions facilitate smooth handovers, they often lack robustness from a security perspective. Specifically, DMM typically relies on external mechanisms for handover security and utilizes a centralized device, which raises security and performance concerns in flat architectures where hierarchical dependencies can lead to complications. To address these challenges, Sharma et al. (2018) [18] propose a novel DMM schema based on blockchain technology. This approach resolves hierarchical security issues without disrupting the network layout and meets the requirements for fully distributed security while consuming less energy.

In heterogeneous wireless networks, multi-interface terminals have access to diverse network technologies, which introduces complexity in the handoff process due to various decision-making attributes, including user preferences. Several approaches have been proposed for effective handoff decision-making to address this complexity. Singh and Singh (2014) [19] present a variety of multi-attribute decision-making algorithms, including the Analytic Hierarchy Process (AHP), Simple Additive Weighting (SAW), Total Order Preference by Similarity to the Ideal Solution (TOPSIS), and Grey Relational Analysis (GRA) methods. These algorithms are specifically designed for handoff decisions in a WiMAX-WLAN environment, aiming to enhance the quality of service for users. Among these methods, AHP is utilized to calculate the weights of the decision parameters, allowing for a systematic approach to prioritize the factors influencing handoff decisions.

Heterogeneous Network (HetNet) deployments are essential for providing ubiquitous coverage and enhancing capacity in LTE-Advanced networks. They significantly contribute to meeting the high data rate and quality of service requirements outlined for next-generation wireless networks. To optimize handover conditions for the evolved Node B (eNB), Goyal et al. (2019) [20] propose a concept that considers both User Equipment (UE) and eNB characteristics. Their approach employs the Analytic Hierarchy Process (AHP) combined with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methodology to refine the eNB selection process and prioritize UEs effectively. Additionally, the post-optimal eNB solution is managed using a Q-learning process, resulting in reduced impacts of Handover Failure (HOF) and Handover Ping-Pong (HPP) compared to traditional methods.

The deployment of small cells in heterogeneous network (HetNet) environments is anticipated to be a critical feature of 4G networks and beyond, playing a vital role in delivering higher user throughput and enhanced cell-edge coverage. To facilitate handovers, Sun et al. (2020) [21] introduced a novel technique based on user mobility-centered Coordinated Multipoint (CoMP) that incorporates dwell duration—defined as the time spent within a particular cell's coverage. This approach aims to achieve large bandwidth, predict handovers, and improve cell coverage in highly dense HetNets. The optimal cooperative set of base stations is selected by considering user speed, base station density, and stochastic geometrical features.

Palas et al. (2021) [22] presented an intelligent mobility management system that employs the Enhanced Multi-Objective Optimization Method by Ratio Analysis (E-MOORA) along with Q-learning techniques to optimize handover processes in 5G networks. Enhancing the quality of service and user experience in 5G networks will require integrating machine learning techniques and complex optimization approaches into future handover optimization algorithms. To facilitate intelligent handover decisions, developing and implementing machine learning models capable of effectively learning and predicting network conditions, user preferences, and mobility patterns is essential.

Alhabo et al. (2022) [23] developed a game-theoretical approach to reduce energy consumption in dense small cell networks by effectively managing transmission power and balancing cell load. However, this study does not address potential drawbacks or limitations associated with the multiple attribute TOPSIS technique used for cell selection during handover. Additionally, it fails to examine the trade-offs between energy efficiency and other performance metrics, such as latency and throughput.

Mbulwa et al. (2023) [24] concluded that the proper tuning of Time To Trigger (TTT) and Handover Margin (HOM) while considering various mobile speed scenarios, enhances system performance and reduces Radio Link Failure (RLF). However, the study does not address the accuracy and effectiveness of the handover optimization strategies employed. Similarly, Tashan et al. (2024) [25] proposed a self-optimizing Handover Control Parameters (HCP) approach that effectively adapts to varying conditions without the need for manual tuning, demonstrating its potential for real-world applications. Nevertheless, this approach does not focus on improving performance for serving cell-based HCP optimization, particularly for users travelling at speeds exceeding 70 km/h.

3. Problem Statement

In the context of future communication using mobile technology, the handover mechanism is critical for ensuring seamless connectivity as devices transition across different cells. This process guarantees uninterrupted communication and enhances the reliability and integrity of the overall connection framework. The design and implementation of effective handover strategies significantly influence the performance of Fifth-Generation (5G) networks, especially given the complexities associated with this new technology.

This paper aims to explore and integrate various concepts related to handover mechanisms in 5G technology, addressing the challenges presented by high user mobility and increasing demands for network performance. The analysis highlights the necessity for advanced handover decision-making strategies and the application of multiple approaches to optimize the handover process. Additionally, the requirement for rigorous cell placement and the utilization of broader frequency bands underscores the heightened expectations for efficient handover mechanisms. Therefore, this study focuses on enhancing handover decision strategies and identifying the most effective implementation approaches, ultimately striving to improve the functionality of the handover process and ensure a high-quality connection and service experience for users.

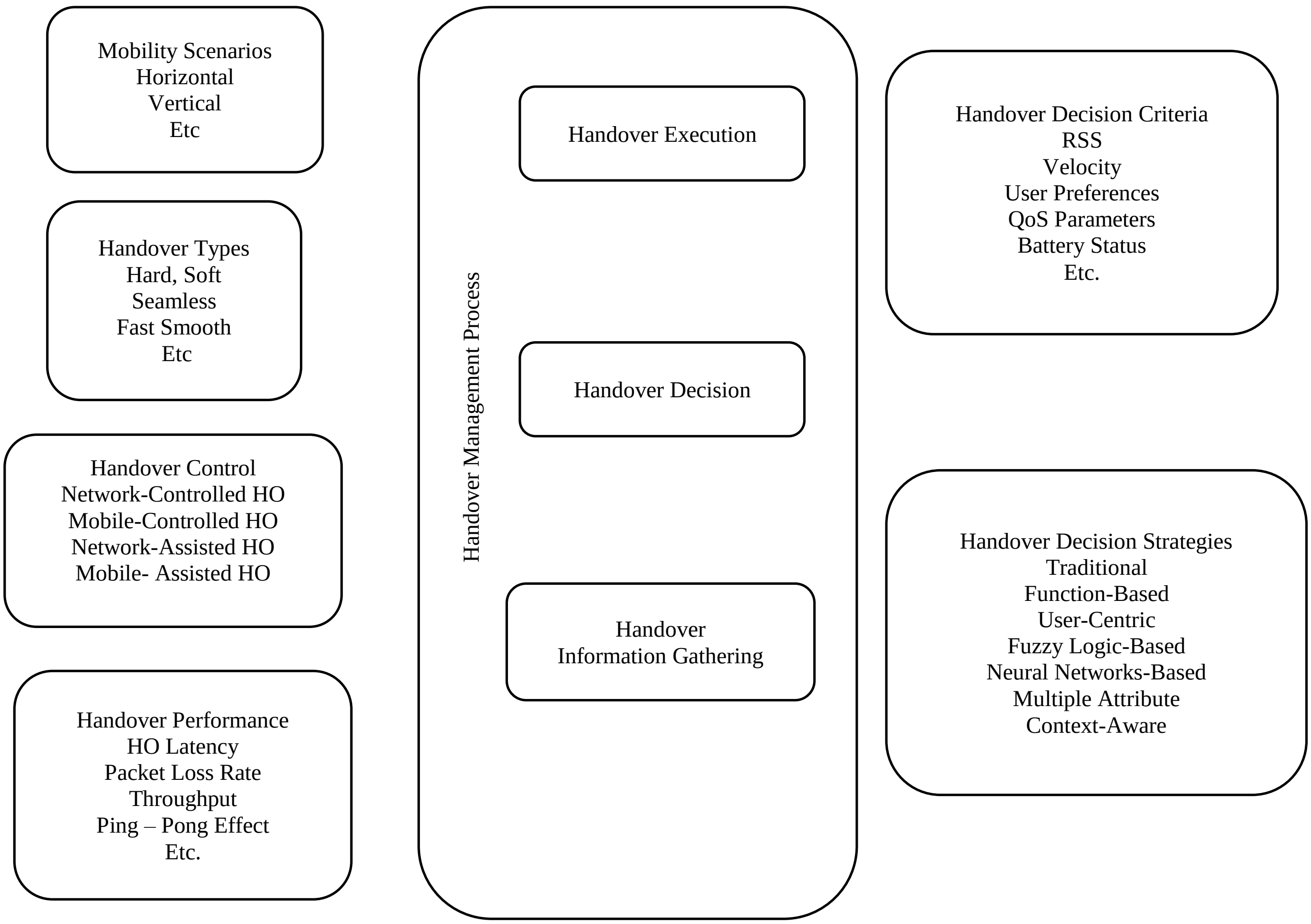

Fig. 2 Handover management

4. Proposed Methodology

In the context of 5G and heterogeneous networks, the handover decision-making strategy will be initiated during the handover commencement stage. This phase is crucial as it determines whether to proceed with or withdraw from the handover process in cellular networks. Traditionally, in horizontal handovers, the decision is triggered when the signal strength of the serving base station drops below a defined threshold, prompting the need for a handover to maintain connectivity.

In heterogeneous network environments, however, the situation is more complex. Clients can transition between diverse networks that employ different technologies, such as Wi-Fi, LTE, and 5G. This ability to navigate across multiple networks provides several benefits, including expanded coverage, faster data transmission speeds, reduced latency, and optimized energy usage. The process of making handover decisions in such diverse environments introduces a higher level of complexity compared to homogeneous networks.

The proposed methodology will focus on developing an enhanced handover decision-making strategy that accounts for these complexities. This includes optimizing the criteria for handover initiation, considering signal strength and additional factors like user mobility, network load, latency, and energy efficiency. Figure 2 illustrates the handover process and highlights the added complexity in heterogeneous networks compared to homogeneous ones.

The handover procedure can be divided into three main phases: selecting the target network, establishing a radio frequency connection, and allocating the communication medium. The handover process facilitates the decision of which network to switch to, along with establishing a link to that network. This involves setting up new connections through radio frequency with the target network and allocating the communication resources necessary for seamless data transfer [26].

Vertical handover decision strategies assist in selecting the best network framework from available options in heterogeneous environments, where devices can connect across multiple technologies. This research focuses on enhancing the efficiency of vertical handover decision-making processes. Unlike horizontal handover, which primarily considers Received Signal Strength (RSS) as the main criterion, vertical handovers in heterogeneous networks must also consider factors such as cost, energy consumption, and user requirements to meet the broader demands of users. These additional considerations are essential for optimizing handover strategies and ensuring a high-quality user experience in diverse network conditions.

Data Acquisition for Handover Process: This strategy is used to gather all the necessary data required to identify the need for a handover and subsequently initiate the process. This step is also referred to as handover initiation.

Decision-making in Handover Process: This step involves determining how the handover process will be executed by selecting the most suitable network, considering factors such as user requirements. It also provides guidance for the execution phase by issuing instructions for the handover implementation. This is also known as network selection.

Handover Execution: This phase involves switching the communication medium to meet the specific needs of the connection and completes the final steps of the handover process [32]. Various factors influencing vertical handover are illustrated in Figure 3.

Received Signal Strength (RSS) is widely used as a key factor in handover decision-making due to its simplicity in measurement and its direct correlation with the quality of service provided. The distance between the mobile device and the associated base station has a direct impact on the RSS measurement. Additionally, the duration a device stays connected to a particular network or base station influences RSS. The duration of attachment is an important factor in triggering the handover process to ensure that the quality of service is maintained within acceptable limits.

To minimize unnecessary handovers, calculating the duration of attachment to a specific base station is crucial. This helps avoid handovers when the device will likely remain connected for a very short time, reducing disruptions and maintaining service continuity. Available bandwidth refers to the resources available for data transmission, typically measured in Bits Per Second (bps). It serves as a key indicator, particularly in scenarios.

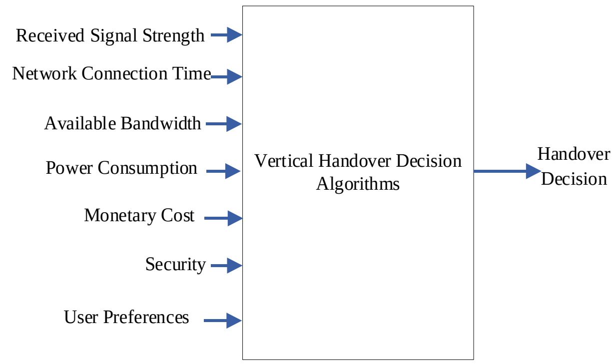

Fig. 3 Parameters deciding the vertical handover

Where traffic demand is high and access to the network is crucial. This factor becomes especially important in latency-sensitive environments where timely data transfer is critical.

Power consumption is a vital consideration, especially when a mobile device's battery is running low. In such instances, handing over to a network that minimizes energy consumption is advisable, thereby extending the device’s battery life [31].

Monetary cost is another important factor, as different networks may follow varying pricing models. The cost associated with establishing a connection should be factored into handover strategies to ensure economical usage.

Security is a critical aspect of the handover process. Ensuring the privacy of the data being transmitted is essential, and the handover strategy should prioritize networks that offer stronger data protection.

User preferences play a significant role in network selection. Users may have specific requirements for accessing a particular network, which could influence their preference for one network framework over another. Incorporating these preferences into the handover decision process ensures a more personalized and satisfactory user experience.

A quantitative analysis of vertical handover strategies will examine several performance metrics under different usage scenarios. These metrics include the average and maximum latencies involved in the handover process, the total number of handovers performed, the number of handover failures due to wrong decisions, and the overall session throughput. These measurements are essential for evaluating the efficiency of the handover mechanism, particularly in terms of minimizing delays, reducing unnecessary handovers, avoiding failures, and maintaining optimal data transfer rates [30]. The term "Handover latency" describes the amount of time that passes between starting and finishing the handover process. The latency involved in handovers can be influenced by the complexity of establishing vertical handovers, making it crucial to minimize delays, especially in latency-sensitive environments.

The frequency of handovers: Since frequent handovers can cause resource depletion and impair network performance overall, reducing the total number of handovers is generally desired. An unnecessary handover occurs when the mobile device reconnects to the original base station shortly after switching, making the handover redundant. Reducing such unnecessary handovers should be prioritized in handover strategies to conserve resources and improve efficiency [27].

Probability of handover failure: A handover failure happens when the device leaves the target base station's coverage area before the handover is completed or when the handover procedure is started, but the target base station does not have the resources to finish it. In the first scenario, the network's resource availability affects the chance of a handover failure. In the second scenario, the user's mobility patterns have an impact. [28, 29].

Throughput: represents the rate at which data is transmitted between devices within the network. During the handover process, maintaining or achieving higher throughput is typically preferred. Handover to a network that offers better throughput is usually prioritized to ensure efficient data transmission and optimal performance.

4.1. Progressing HetNets

Evolving mobile networks are characterized by being highly dynamic, diverse, large-scale, and increasingly complex. With the development of various wireless technologies, each offering different capabilities and limitations, there is a growing need to enhance their performance to support heterogeneous networks. However, the complexity arising from these different network types introduces significant challenges in managing and integrating them efficiently. To address these challenges, combining Artificial Intelligence (AI) techniques with advanced methods like Self-Organizing Networks (SON) has emerged as a promising solution for optimizing and managing network operations autonomously.

Self-Optimization: A significant focus is placed on auto-optimization strategies in heterogeneous networks. Due to the diversity of these networks, their performance must be optimized based on several factors, including load balancing, energy efficiency, and maintaining network connectivity. This involves considering aspects like radio frequency properties, traffic variations, and user requirements to ensure the delivery of the desired service. However, implementing these optimization strategies in real-world scenarios presents considerable challenges due to the complexity involved. This complexity arises from the large volume of data that must be processed, the training required to identify optimal solutions, and the difficulty of reaching decisions based on multiple interrelated factors.

Involuntary optimization of coverage and load balancing can be achieved by fine-tuning the antenna. This enhances the coverage area of the radio frequency and adjusts handover parameters by intelligently altering the cell's dimensions. Mobility optimization prevents unnecessary handovers and ensures proper timing by automatically adjusting cell selection boundaries and handover triggers.

Link quality estimation benefits from using dynamic evaluators, rather than traditional moving average methods, to improve the accuracy of connection quality assessment. This ensures better service quality [33]. Relay-based multi-hop transmission extends network coverage and strengthens resilience in heterogeneous networks by utilizing intermediary devices to facilitate multi-hop transmission. However, this approach introduces challenges related to interference and complex multi-hop route configuration [34].

4.2. Optimization Problem

To identify the best network among existing options, effectively fine-tuning the weights associated with Quality-of-Service (QoS) parameters is essential. This process begins with assessing the quality level of each network framework. A function must be formulated to grade the networks based on specified criteria. Each QoS parameter will be assigned a bias to evaluate the overall quality of the network. Client requirements and network characteristics will influence these parameters. Typically, the values assigned to these QoS factors range from 0 to 1, determined through a cost function. This function will be evaluated during the decision-making process for vertical handover. Therefore, the strategy for identifying the optimal approach involves exploring the best solutions for each framework to ensure efficient implementation.

4.3. Cost Function

The computation of costs associated with the handover strategy will be conducted for each specific network. This calculation will be applied uniformly across all networks, allowing the network selection that incurs the least cost, thereby offering the greatest advantages to the client. Different types of services necessitate various considerations, such as reliability and data rate, making the category of provided services a critical measure. Quality of Service (QoS) will also be an important factor to consider when meeting client demands. Establishing requirements related to various QoS factors based on the requested services will be necessary. Appropriate thresholds for these QoS parameters must be defined, with monitoring of their values being a significant task. These thresholds will depend on the context, such as the demands arising from the specific category of services provided [35, 36].

In the next phase, the networks will be ordered based on two types of preferences. Let the set of members be denoted as $S = \{s_1, s_2 \dots . s_N\}$ where N represents the total number of members, and let the set of parameters related to Quality of Service be represented as $Q = \{q_1, q_2, \dots q_M\}$ where M is the total number of quality-of-service parameters under consideration. Each quality-of-service parameter will have its own independent weights, reflecting the influence of that parameter on client satisfaction. The performance of each member can be calculated using Equation (1), while W_N will be derived through an experimental grading method. This method is chosen for its ability to adjust the weights of each parameter according to the specific circumstances and demands of the clients.

$$C_N = W_{Interface} * \sum_{j=1}^{M} q_j * W_j \tag{1}$$

As a result, comparative rankings between the Quality-of-Service parameters can be computed. The comparative grades between two specific parameters q_i and q_j can be calculated using Equation (2), while $R_{q_i q_j}$ represents comparative grades of the parameters q_i and q_j, and S_{qi} and S_{qj} are the corresponding grades. The expression for comparative grading is defined as

$$R_{q_i q_j} = \begin{cases} \left(1 - \frac{S_{q_i}}{S_{q_j}}\right) * 10 & j > i \\ \frac{1}{R_{q_i q_j}} & j < i \\ 1 & j = i \end{cases} \tag{2}$$

The proposed methodology for evaluating and optimizing the Quality of Service (QoS) parameters is organized into a structured approach, allowing for systematic assessments and improvements based on preference gradings. Here is a concise summary of the outlined process:

4.3.1. Matrix Construction

The preference grading matrix X of size $M \times M$ characterizes the preferences associated with each Quality-of-Service parameter. Each element X_{ij} is defined as follows:

$$X = \begin{bmatrix} 1 & R_{q_1 q_2} & R_{q_1 q_3} & R_{q_1 q_4} & R_{q_1 q_5} \\ \frac{1}{R_{q_1 q_2}} & 1 & R_{q_2 q_3} & R_{q_2 q_4} & R_{q_2 q_5} \\ \frac{1}{R_{q_1 q_3}} & \frac{1}{R_{q_2 q_3}} & 1 & R_{q_3 q_4} & R_{q_{3,} q_5} \\ \frac{1}{R_{q_1 q_5}} & \frac{1}{R_{q_2 q_5}} & \frac{1}{R_{q_3 q_5}} & \frac{1}{R_{q_4 q_5}} & 1 \end{bmatrix} \tag{3}$$

4.3.2. Standardization

Each component of X is standardized using the Equation (4).

$$X_{ij} = \frac{X_{ij}}{\sum_{i=1}^{M} X_{ij}} \tag{4}$$

This results in a normalized matrix w_{norm} expressed in Equation (5).

$$w_{norm} = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} & w_{15} \\ w_{21} & w_{22} & w_{23} & w_{24} & w_{25} \\ w_{31} & w_{32} & w_{33} & w_{34} & w_{35} \\ w_{41} & w_{42} & w_{43} & w_{44} & w_{45} \\ w_{51} & w_{52} & w_{53} & w_{54} & w_{55} \end{bmatrix} \tag{5}$$

4.3.3. Row Mean Calculation

The mean of each row is computed to prioritize each parameter, as follows:

$$\overline{w_i} = \frac{w_{i1} + w_{i2} + w_{i3} + w_{i4} + w_{i5}}{5} \tag{6}$$

This results in a vector W_N

$$W_N = \begin{bmatrix} \overline{W_1} \\ \overline{W_2} \\ W_3 \\ \overline{W_4} \\ \overline{W_5} \end{bmatrix} \tag{7}$$

4.3.4. QOS Parameters

The quality-of-service factors are defined in Equation (8).

$$Q_N = [\,S \;\; R \;\; T\, L \;\; F\,] \tag{8}$$

Where S = Signal to noise ratio (dB), R = Received signal strength (dBm), P = Average Power Consumed [Watts], L = Latency (s) T= Throughput (Bps).

4.3.5. Cost Function Optimization

To optimize the cost function, a nature-inspired meta-heuristic approach will be implemented. This approach will enhance QoS by balancing the parameters effectively, ensuring client demands are met while minimizing costs and maximizing performance.

4.4. Whale Optimization Algorithm

The Whale Optimization Algorithm (WOA), developed by S. Mirjalili in 2016 [37], is inspired by the hunting behavior of humpback whales. The algorithm specifically models their unique bubble-net hunting strategy, where the whales create a circular formation of bubbles to trap their prey. During this process, the whales dive approximately 10-15 meters deep, forming bubbles in a spiral pattern as they encircle the target.

Using alternating movements with their fins, they ensure the prey remains confined within the bubble net, preventing its escape. The scientific model of this process includes the mechanisms of target encirclement, spiral bubble-net formation, and exploration of the target, which are explained in subsequent phases.

4.4.1. Surrounding the Target

The whales move according to the number of steps from the starting point to the maximum number of repetitions, encircling the target and improving their position toward the best option for exploration. This behavior is modeled by the following equations:

$$\vec{D} = \left|\vec{C}\vec{X}^*(t) - \vec{X}(t)\right| \tag{9}$$

$$\vec{X}(t+1) = \vec{X}(t) - \overrightarrow{A}.\vec{D} \tag{10}$$

While $\vec{A}\ and\ \vec{C}$ are coefficient vectors, t specifies the present step, X^* is the location vector belonging to the greatest solution achieved so far, $\vec{X}$ is the location vector at present step, | | denotes the magnitude of vectors with component-wise multiplication. The coefficient Vectors $\vec{A}and\ \vec{C}$ computed with Equations (11) and (12),

$$\vec{A} = 2\,\vec{a}\,\vec{r} - \vec{a} \tag{11}$$

$$\vec{C} = 2.\vec{r} \tag{12}$$

In Equations (11) and (12), a decrease linearly from 2 to 0 as the number of steps increases, while r is a random vector in the range [0,1]. This mechanism allows the whales to explore and exploit the solution space effectively as they approach the optimal solution.

Bubble-Net Attacking Method

The bubble-net attacking behaviour of the modelled agents consists of two primary phases. Detailed explanations of these phases are provided in the following sections.

(a) Constricting Encircling Mechanism: The proposed approach is achieved by gradually decreasing the variable ‘a’ from 2 to 0 using expression (11), proportional to the number of steps taken. The new location of an exploration candidate is determined based on the current position of the candidate and the best solution found so far. This is done by framing arbitrary values within the interval [-1, 1]. The process ensures a balance between exploration and exploitation during the optimization process.

(b) Spiral Improving Location: The expression representing the spiral path between the target and the candidate, using a helix-based navigation approach, is given by the Equation (13)

$$\vec{X}(t+1) = \overrightarrow{D'}e^{bl}cos(2\pi l) + \overrightarrow{X^*}(t) \tag{13}$$

This dual-phase navigation combines the circular and spiral movements of the candidate around the target. To model this behaviour mathematically, there is a 50% probability of choosing between encircling the target in a circular pattern or following a spiral path for position updates. This process is represented by Equation (14)

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*} - \vec{A}.\vec{D} & \text{if p} < 0.5 \\ \overrightarrow{D'}e^{bl}cos(2\pi l) + \overrightarrow{X^*}(t) & \text{if p} \geq 0.5 \end{cases} \tag{14}$$

Here $\vec{D} = \left|\overrightarrow{X^*} - \vec{X}\right|$ denotes the distance between the candidate and the target. The variable ‘b’ is a constant that defines the shape of the logarithmic spiral, while ‘l’ is a random value in the range [-1, 1].

The probability ‘p’ is also randomly selected within the interval [0, 1] to determine the navigation approach. This combined mechanism allows the modelled candidates to dynamically adapt their positions for efficient target search and capture, enhancing the optimization process.

Search for Prey

Modifications based on the vector can be employed to explore the target more effectively. The vector takes arbitrary values greater than 1 or less than -1, enabling the exploration candidates to move further away from the reference position of the candidate animal.

This mechanism enhances the search phase by promoting exploration over exploitation, allowing candidates to survey a broader area. The mathematical prototype for this exploration stage is defined using the following expressions:

$$\vec{D} = \left|\vec{C}\overrightarrow{X_{Rand}} - \vec{X}\right| \tag{15}$$

$$\vec{X}(t+1) = -\vec{A}.\vec{D} \tag{16}$$

$\overrightarrow{X_{Rand}}$ represents a randomly selected position vector within the current group.

Chaotic Maps

The discussion on 1-D chaotic maps includes their initialization with a preliminary value 0.7, chosen to illustrate varied performance. The starting value can be selected from the interval [0,1].

However, it is noteworthy that the initial value can significantly influence the arrangement variations of certain maps [38]. Various maps have been developed based on individual behaviours [39, 40].

A significant number of these designed maps have been applied to find solutions to practical problems. Table 1 provides a comprehensive list of maps commonly used to address challenges in developing strategies for optimal solution determination.

Table 1. Chaotic maps and expressions

S. No.	Name of the Maps	Expression for the map
1	Logistic map	$x_{i+1} = a.x_i(1 - x_i)$
2	Cubic map	$x_{i+1} = a(1 - x_i^2)\ x_i \epsilon\ (0,1)$
3	Sine map	$x_i = \frac{a}{4}\sin(\pi x_i)$
4	Sinusoidal map	$x_{i+1} = a\ x_i^2 \sin(\pi x_i)$
5	Singer map	$x_{i+1} = \mu(7.86\ x_1 - 23.31x_i^2 + 28.75x_i^3 - 13.302875x_i^4$ $\mu = 1.07$
6	Circle map	$x_{i+1} = (mod)x_i + b - \frac{a}{2\pi}\sin(2\pi x_1), 1)$
7	Iterative chaotic map	$x_{i+1} = abs(\sin(\frac{a}{x_i}))\ a\ \epsilon\ (0,1)$
8	Tent map	$x_{i+1} = \begin{Bmatrix} \frac{x_i}{0.7} & x_i < 0.7 \\ \frac{10}{3}(1 - x_i) & x_i \geq 0.7 \end{Bmatrix}$
9	Piecewise map	$x_{i+1} = \begin{cases} \frac{x_i}{a} & 0 \leq x_i \leq a \\ \frac{x_i - a}{0.5 - a} & a \leq x_i \leq 0.5 \\ \frac{1 - a - x_i}{0.5 - a} & 0.5 \leq x_i \leq 1 - a \\ \frac{1 - x_k}{a} & 1 - a \leq x_i \leq 1 \end{cases}$
10	Gaussian map	$x_{i+1} = \begin{Bmatrix} 1 \\ 1 \end{Bmatrix} /mod(x_i, 1) \Big\} x_i = 0$ otherwise $\frac{1}{\mathrm{x_i}}(\mathrm{mod}(1) = \frac{1}{\mathrm{x_i}} - \left[\frac{1}{\mathrm{x_i}}\right]$

Chaotic Whale Optimization Algorithm (CWOA)

Despite possessing a convergence mechanism, the Whale Optimization Algorithm (WOA) may be inefficient in consistently establishing the globally optimal solution, reducing the strategy's convergence rate. To alleviate this shortcoming and improve the algorithm's efficacy, chaos has been introduced, resulting in the Chaotic Whale Optimization Algorithm (CWOA). Due to the properties of ergodicity and non-recurrence, chaotic behaviour functions effectively with greater rapidity and uses probabilistic exploration [41]. In the realm of optimization, it is commonly accepted that chaotic maps are dynamic and can help algorithms explore the search space more effectively and globally [43]. Most meta-heuristic algorithms with stochastic components create randomization via probability distributions. However, it can be beneficial to replace such randomness with chaotic maps. Various chaotic maps with distinct mathematical equations are employed to integrate chaos into an optimisation algorithm, as listed in Table 1. Over the past decade, chaotic maps have been highly regarded in optimization for enabling dynamic and global search space exploration. Numerous chaotic maps, designed by experts across domains such as physics, research, and mathematics, are available [44]. Among these, the ten most significant one-dimensional chaotic maps [40] have been utilized in this work to implement CWOA, with details provided in Table 1. The convergence rate of WOA has been improved by incorporating chaotic maps, as these maps introduce chaos into the feasible region, which behaves predictably only for a short initial period and becomes stochastic over time [45]. The pseudocode for the proposed CWOA algorithm is presented in Algorithm 1. The optimization process of the proposed CWOA is depicted in the flowchart shown in Figure 4.

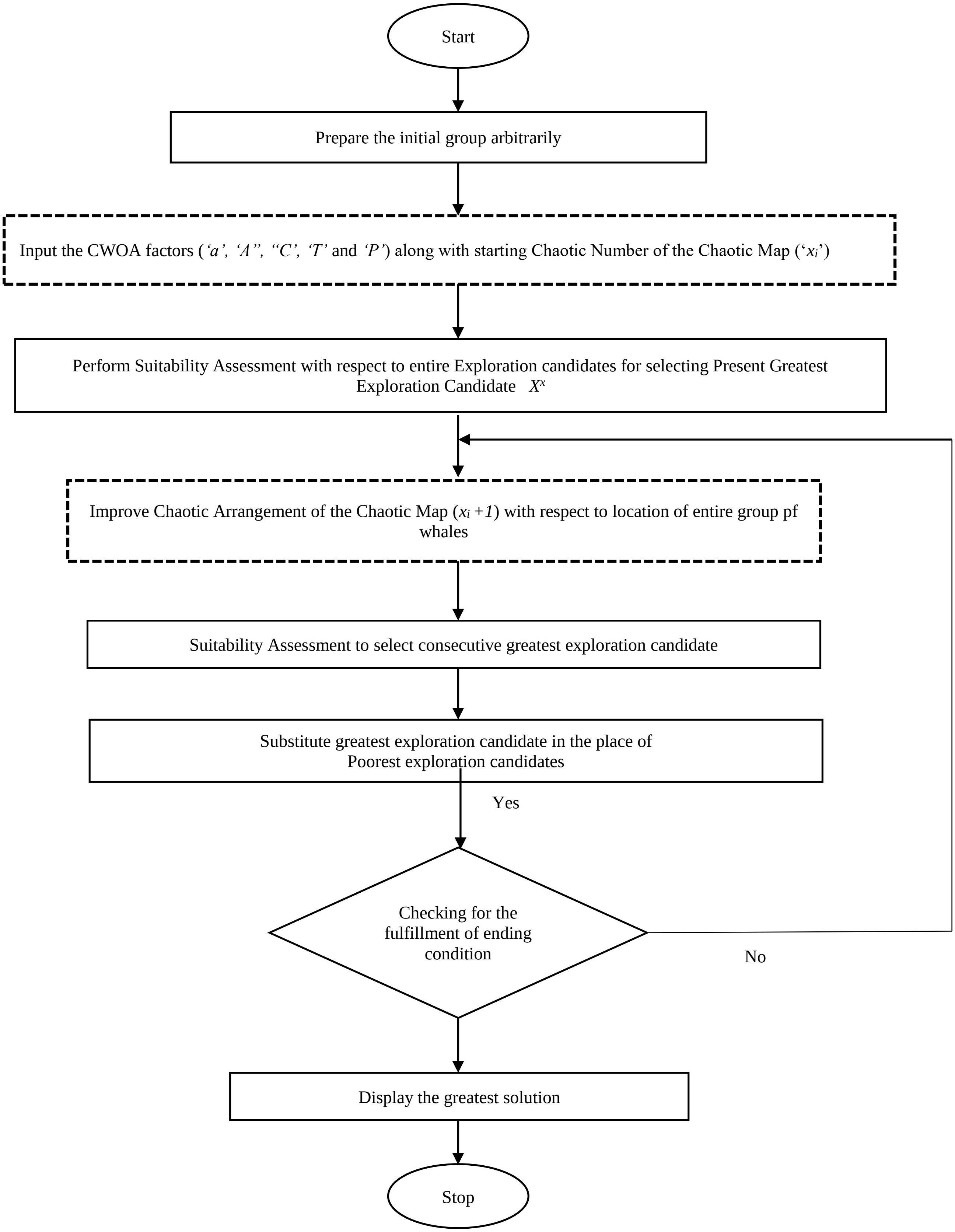

Fig. 4 Flow chart of optimization procedure using chaotic whale optimization algorithm

Algorithm 1 Pseudo Code of Chaotic Whale Optimization:
Initialize the generation counter (*t*) and randomly initialize the whale population Xi $(\mathrm{i} = 1, 2, \ldots, \mathrm{n})$
To discover the best search agent, evaluate their fitness X^*
Initialize the value of the chaotic map x_o randomly
while $(\mathrm{t} < \text{maximum number of iterations})$
Update the chaotic number with the corresponding chaotic map equation
for each search agent
Update a, A, C, l and p
if1 $(p < 0.5)$
if2$(|A| < 1)$
Update the current search agent's position using the Equation (9)
else if2 $(|A| \geq 1)$
Select a random search agent $Xrand$
Update the current search agent's position using the Equation (16)
end if2
else if1 $(p \geq 0.5)$
Update the current search agent's position using the Equation (13)
end if1
end for
Check if any search agent exceeds the search space and modify it.
Calculate the fitness of each search agent
Update X^* if there is a better solution
$t = t + 1$
end while
return X^*

The procedure begins with the stochastic initialization of the whale population. Following that, a particular chaotic map is chosen and assigned to the algorithm, along with the initialization of its first chaotic number and variable [42]. The parameters of the CWOA algorithm, including $\mathrm{a, A, C, l}$ and p those that control the exploration and exploitation mechanisms, are initialized in the same manner as in the original WOA. The chaotic number associated with the chosen chaotic map is then used to adjust the parameter of the WOA, as highlighted in Figure 4.

Next, the fitness of all whales in the search space is assessed using a variety of common benchmark functions. The whale with the most fitness is thought to be the current best search agent. When the control parameter value A<1, the current best search agent uses Equation (9) to update its location. When the control parameter is A≥1, a random whale is chosen, and the position of the current best search agent is changed using Equation (16) if a new best search agent is detected. This recurrent approach ensures that the fitter whale gradually adjusts its location, perhaps resulting in the ideal solution by the end of the process. Furthermore, the parameter is updated at each iteration using Equation (11) and (12). At the end of the final iteration, the best search agent is deemed the most optimal solution discovered by the CWOA algorithm.

5. Results and Discussions

To validate the efficiency of the proposed handover mechanism under heterogeneous networks using the Chaotic Whale Optimization Algorithm, the Network Simulator version 2.34 is employed. The initial network parameter settings are detailed in Table 2.

Table 2. Network parameter settings

Name of the Parameter	Symbol	Wifi	Wimax	UMTS	LTE-A	5G New Radio
WLAN radius	R	500 m	750 m			
Handover delay from cellular network to WLAN	τ_i	1 s	1 s	1 s	1 s	1 s
Handover delay from WLAN to cellular network	τ_0	1 s	1 s	1 s	1 s	1 s
Tolerable handover failure probability	P_f	0.005	0.004	0.003	0.002	0.001
Total unnecessary handover probability	P_u	0.005	0.004	0.003	0.002	0.001
Number of parameters	X_t	0.85	0.85	0.85	0.85	0.85
Bandwidth	B	72 Mbps	75 Mbps	2 Mbps	20 Mbps	300 Mbps
Total number of iterations for the proposed CWOA	I	100	100	100	100	100

The handover triggering mechanism is initiated using the following formula, where the summation of the received signal strength is calculated using Equation (17):

$$SUM = \sum_{T=0}^{T=S} R_T \tag{17}$$

Here, s represents the duration over which the received signal strength is compared to the activation boundary for handover R for the specified duration; $0 \leq T \leq S$

$$\begin{Bmatrix} R_n < SUM/n & No\ handoff \\ R_n \geq SUM\ /n & Intitate\ handover \end{Bmatrix}$$

Where n is the number of RSS, the following dependent conditions are also considered for effective decision-making.

$D_{Bw} = B_2 - B_1$

$D_{RSS} = R_2 - R_1$

While $B_i and\ R_i$ representing available bandwidth along with Received Signal Strength respectively.

The decision criteria for the handover are defined as:

$$\begin{Bmatrix} if\ D_{Bw} > 0 & and\ D_{RSS} > 0 & Import\ Qos\ Parameters \\ if\ D_{Bw} \leq 0 & and\ D_{RSS} \leq 0 & No\ handoff\ mechanism \end{Bmatrix}$$

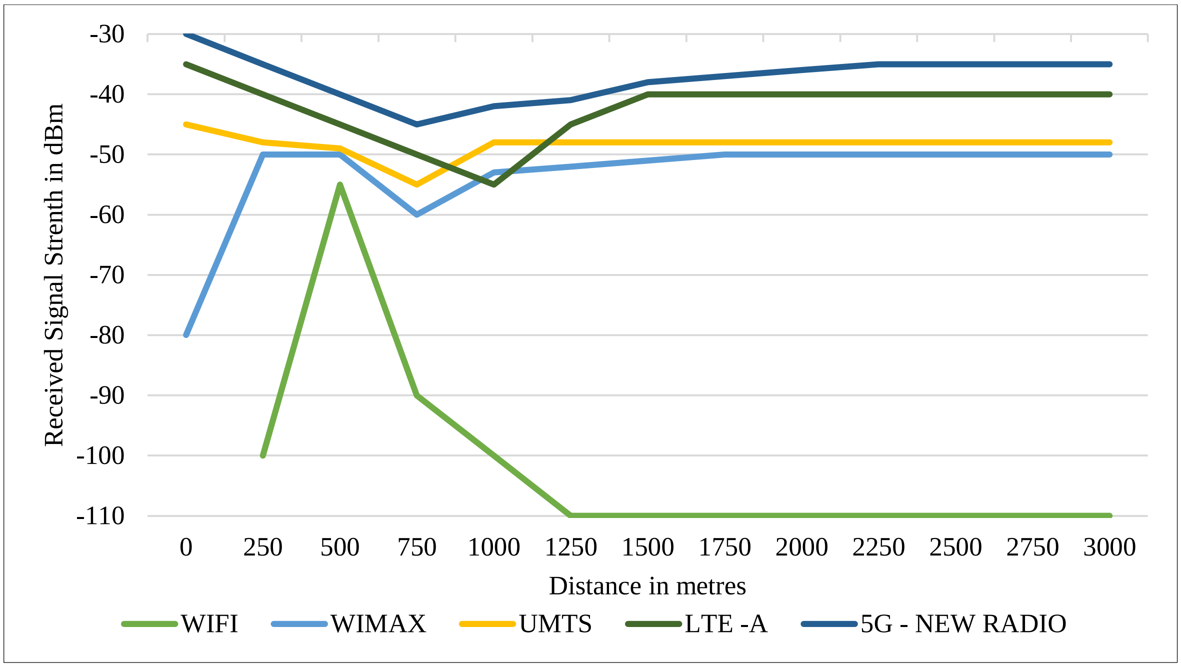

Fig. 5 Analysis of received signal strength versus distance

The next part provides a detailed comparison of several wireless communication technologies' performance, including WiFi, UMTS, LTE-A, WiMAX, and 5G New Radio (5G NR). The evaluation focuses on essential performance measures such as SNR, RSS, throughput, latency, and average power consumption, which are all shown versus distance.

Figure 5 shows the signal strength (in dBm) of various wireless technologies-WIFI, WiMAX, UMTS, LTE-A, and 5G New Radio-at different distances. As the distance increases, all technologies experience a decrease in signal strength. WIFI shows the most significant drop, starting at -80 dBm at 0 meters and reaching -110 dBm at 3000 meters. WiMAX maintains a relatively constant signal, ranging from -45 dBm to -50 dBm across the same distance. UMTS and LTE-A both exhibit steady declines, with UMTS spanning from -35 dBm to -48 dBm and LTE-A beginning at -30 dBm and falling to -40 dBm. 5G New Radio has the strongest signal, beginning at -35 dBm at 250 meters and remaining at -35 dBm even at 3000 meters.

These findings are one of the primary performance measures for assessing the success of the Chaotic Whale Optimization Algorithm (CWOA) in the decision-making process of vertical handover systems. The CWOA algorithm aids in selecting the best network depending on signal strength and distance, resulting in seamless connectivity and increased network performance across various wireless technologies.

Figure 6 shows the Signal-to-Noise Ratio (SNR) of various wireless technologies-WIFI, WiMAX, UMTS, LTE-A, and 5G New Radio-over increasing distances. As distance grows, SNR values generally decline, affecting connection quality.

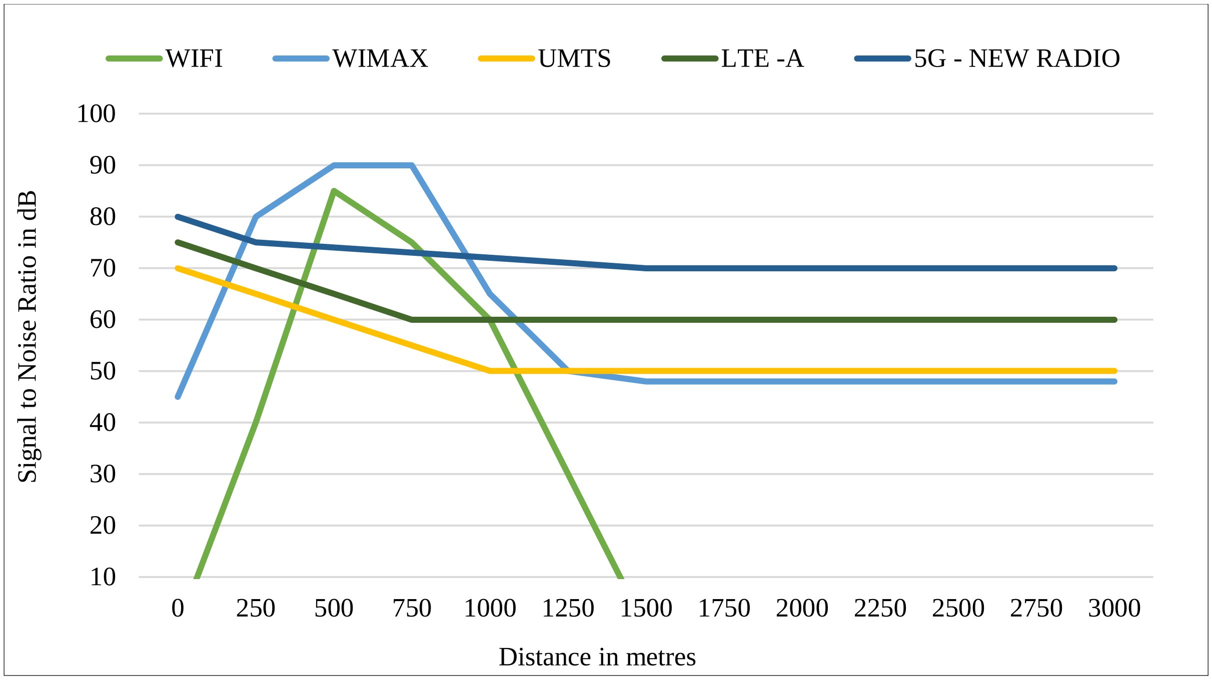

Fig. 6 Analysis of signal to noise ratio versus distance

WIFI peaks significantly at 500 meters (85 dB) but drops to 0 dB beyond 1250 meters, indicating poor long-distance performance. WiMAX maintains stable SNR values, peaking at 90 dB between 250 and 750 meters, then stabilizing at 48 dB after 1500 meters. UMTS starts at 70 dB and levels out at 50 dB after 1000 meters. LTE-A maintains a strong SNR, starting at 75 dB and stabilizing at 60 dB beyond 1000 meters.

5G New Radio demonstrates the best performance, starting at 80 dB and maintaining 70 dB beyond 1500 meters. These findings highlight the importance of using the Chaotic Whale Optimization Algorithm (CWOA) to optimize vertical handover mechanisms by selecting networks based on SNR for enhanced connectivity.

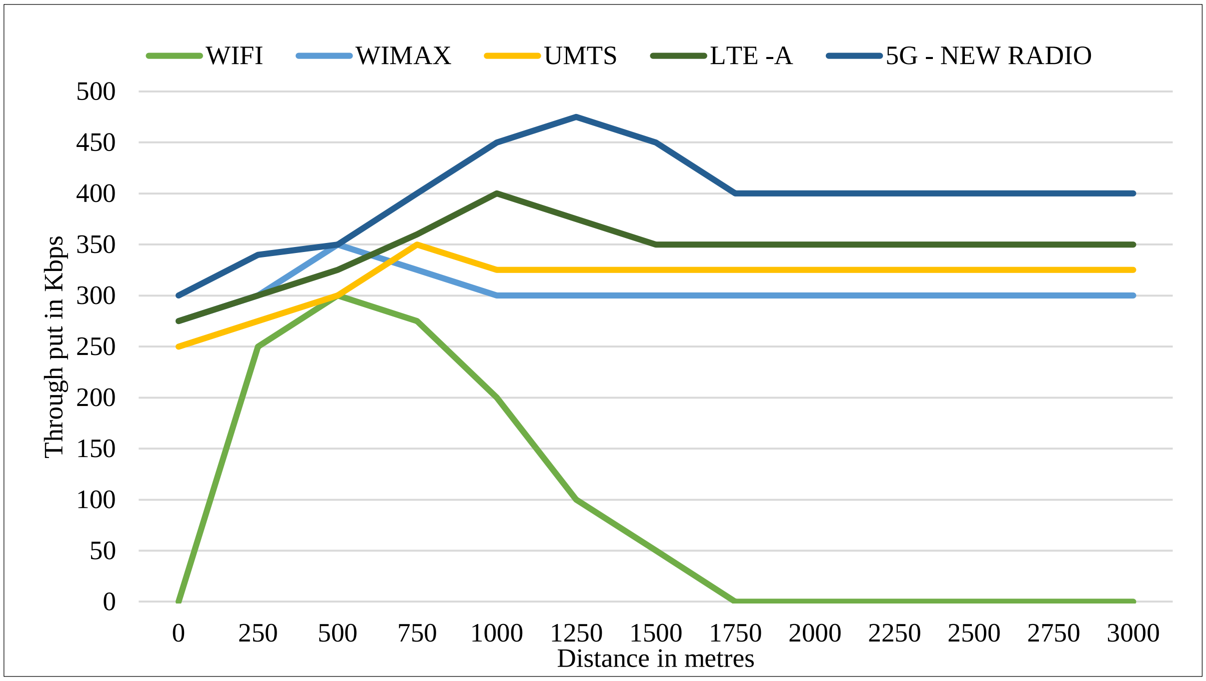

Fig. 7 Analysis of throughput versus distance

Figure 7 shows the throughput performance (in Mbps) of different wireless technologies-WIFI, WiMAX, UMTS, LTE-A, and 5G New Radio-over increasing distances. As distance increases, throughput trends vary. WIFI shows a peak at 300 Mbps at 500 meters but drops to 0 Mbps beyond 1500 meters, indicating a limited range. WiMAX maintains consistent throughput, stabilizing at 300 Mbps after 1000 meters. UMTS starts at 250 Mbps and holds steady at 325 Mbps from 1000 meters onward. LTE-A reaches a high of 400 Mbps at 1000 meters before progressively declining and stabilizing at 350 Mbps. The 5G New Radio performs best, peaking at 475 Mbps at 1250 meters and settling at 400 Mbps beyond 1750 meters. These findings illustrate the better long-distance throughput of LTE-A and 5G New Radio, demonstrating their potential for high-demand applications. In this context, the Chaotic Whale Optimization Algorithm (CWOA) optimizes vertical handover decisions by selecting networks based on throughput, ensuring improved connectivity and network performance.

Figure 8 depicts the delay performance (in milliseconds) of various wireless technologies, including WiFi, WiMAX, UMTS, LTE-A, and 5G New Radio, over varying distances. WIFI has a steady increase in latency, from 1 ms at 250 metres to 10 ms at 3000 metres, showing longer delays over extended distances. WiMAX maintains a stable low latency of up to 1000 meters and increases to 1.5 ms at 3000 meters. UMTS starts at a minimal 0.08 ms at 250 meters and rises to 1.2 ms at 3000 meters. LTE-A begins with very low latency (0.05 ms at 250 meters) and rises to 0.8 ms by 3000 meters.

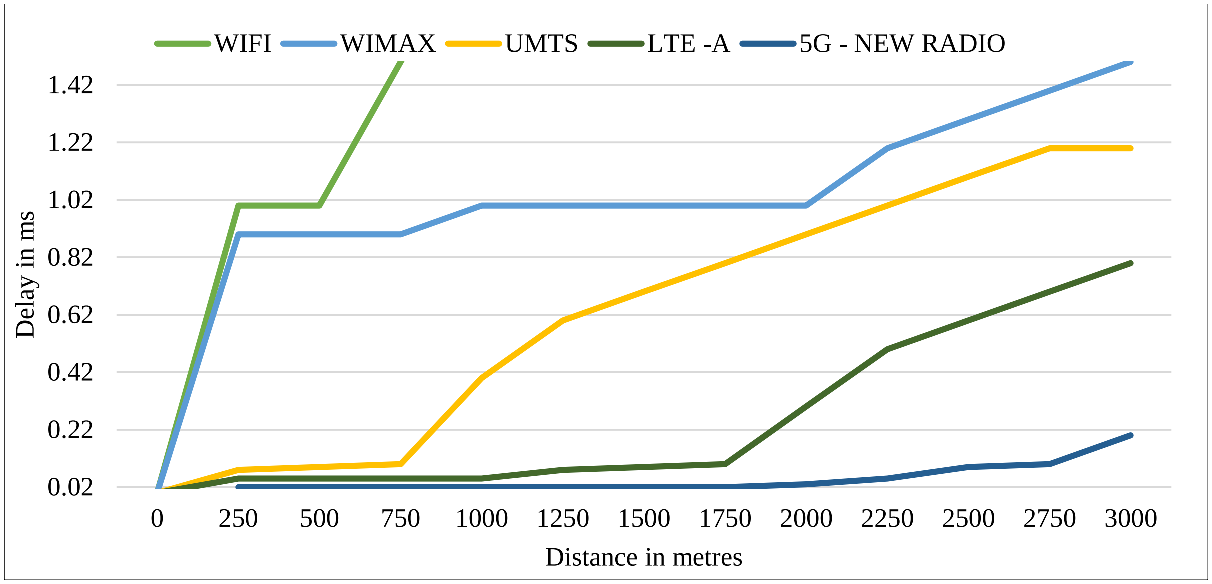

Fig. 8 Analysis of delay versus distance

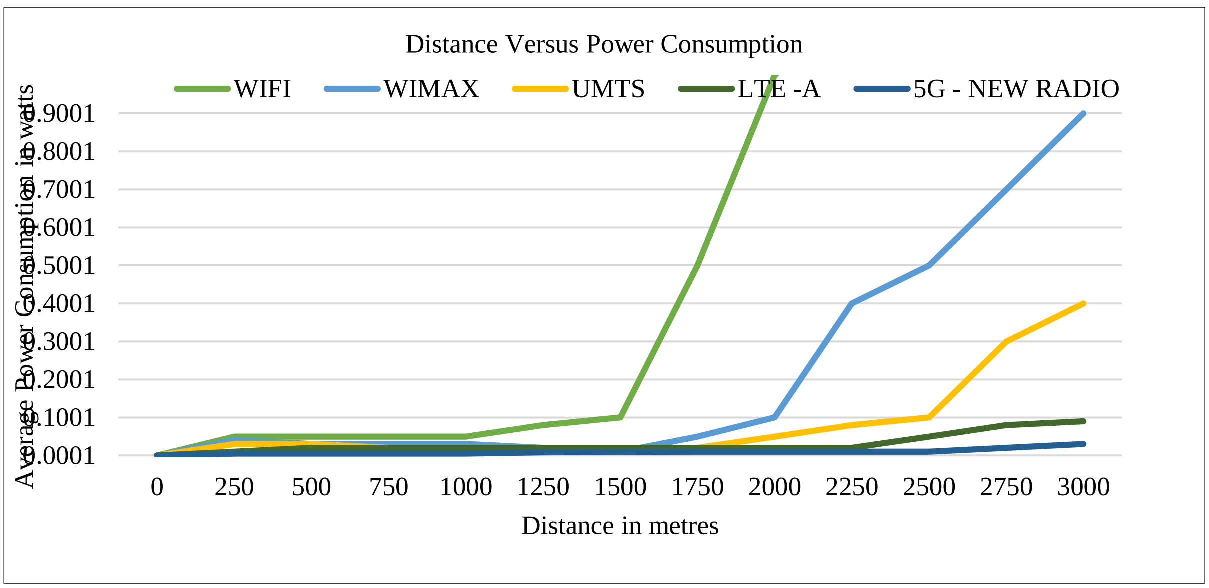

Fig. 9 Analysis of power consumption versus distance

Notably, 5G New Radio demonstrates superior performance, maintaining minimal latency (0.02 ms initially) and only increasing to 0.2 ms at 3000 meters. These findings emphasize 5G's capability for low-latency communication, which is essential for real-time applications. Figure 9 shows a comparative examination of average power usage (in watts) for various communication technologies such as WiFi, WiMAX, UMTS, LTE-A, and 5G New Radio over increasing transmission distances. At shorter distances (up to 1000 meters), power consumption remains relatively low and stable for most technologies, with 5G New Radio demonstrating the lowest consumption throughout, consistently at or below 0.005 watts. WiFi shows a sudden rise in power consumption beyond 1250 meters, peaking at 2 watts at 3000 meters, highlighting its inefficiency over long distances. Conversely, WiMAX and UMTS exhibit moderate increases, maintaining better power efficiency than WiFi but less so than LTE-A and 5G New Radio. LTE-A maintains relatively low and consistent power consumption, only slightly rising to 0.09 watts at 3000 meters. 5G New Radio stands out for its energy efficiency across all distances, indicating its suitability for energy-conscious applications over extended ranges. This study shows the substantial improvement in power consumption attained with 5G technology over past generations.

6. Conclusion

The key concepts for vertical handover mechanisms in heterogeneous wireless networks are the main emphasis of this paper's review of various handover approaches. The analysis created a unique strategy that uses the Chaotic Whale Optimization Algorithm (CWOA) to improve key performance indicators such as signal strength, Signal-To-Noise Ratio (SNR), throughput, latency, and power consumption. The data analysis highlights that 5G New Radio outperformed other technologies in maintaining stable and strong signal strength (-35 dBm across all distances), high SNR (70 dB beyond 1500 meters), superior throughput (stabilizing at 400 Mbps), minimal latency (0.2 ms at 3000 meters), and the lowest power consumption (consistently below 0.005 watts). These metrics emphasize 5G's efficiency, reliability, and suitability for high-demand and real-time applications. The CWOA was instrumental in optimizing vertical handover decisions by selecting networks based on signal strength, SNR, throughput, and latency, ensuring seamless connectivity and improved network performance. Furthermore, the algorithm enabled significant reductions in power consumption and minimized delays, demonstrating its potential to enhance energy efficiency in heterogeneous wireless environments. This study underscores the effectiveness of the CWOA in advancing handover mechanisms, positioning it as a robust tool for next-generation network optimization.

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