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MULTI-OBJECTIVE RESOURCE ALLOCATION OPTIMIZATION IN OVERLAPPING WI-FI AND LTE NETWORKS USING HYBRID METAHEURISTIC ALGORITHMS

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ABSTRACT:

As one of the key solutions for managing the increasing growth of data traffic, Wi-Fi/LTE overlap networks require advanced resource allocation methods that can simultaneously improve throughput, energy efficiency, and traffic offloading efficiency. The resource allocation problem in these networks is nonlinear, constrained, and multi-objective in nature, and due to user competition and interaction of two heterogeneous technologies, the use of classical optimization methods does not meet practical needs. In this paper, a hybrid meta-heuristic method based on Aquila Optimization Algorithm (AO) and Fosa Optimization Algorithm (FOA) is presented to solve the resource allocation and uplink traffic offloading problem in Wi-Fi/LTE overlap networks. The main idea of the proposed method is to combine the global search power of AO with the local exploitation capability of FOA in order to create an effective balance between exploration and exploitation in the search space. The problem is formulated as a multi-objective optimization model including throughput, energy efficiency, and unloading indices, and time and logical constraints of the system are also considered. Simulation results show that the proposed hybrid method reduces the value of the objective function by about 0.028 and provides better performance compared to independent methods. Also, the system throughput using this method has increased to about 22.4 and the energy efficiency has improved to approximately 20.8. Statistical analysis of the results using the Friedman test also shows that the superiority of the proposed method is statistically significant and is not due to random fluctuations. Overall, the results of this research show that the AO–FOA hybrid method can be used as an efficient, stable, and reliable solution for resource management and traffic unloading in heterogeneous and high-density wireless networks.

INTRODUCTION

In today's world, with the rapid growth of the need for large data transmission and the use of numerous devices connected to wireless networks, resource management in wireless networks has become one of the fundamental challenges in the design and implementation of communication systems [1]. Especially in overlapping Wi-Fi and LTE networks that operate simultaneously in a common environment, optimal resource allocation can have a great impact on the overall network performance and quality of service (QoS) [2].

Wi-Fi and LTE networks are widely used for communication in urban, commercial, and residential environments. These networks often operate in an overlapping manner; meaning that different nodes and stations use two networks with shared bandwidth and energy resources [3]. In such environments, managing and allocating resources simultaneously to optimize throughput and energy efficiency becomes a complex and multidimensional problem [4].

In Wi-Fi and LTE overlapping networks, resource allocation can have a significant impact on network efficiency and service quality due to resource sharing and competition among users [5]. Especially in high-traffic networks, bandwidth and energy are limited resources that must be allocated properly to avoid traffic congestion and data transmission speed degradation. In addition, high energy consumption in wireless networks is a major problem, especially for devices with limited energy [6]. These challenges increase the importance of optimizing resource

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allocation. In overlapping networks, users must use network resources efficiently. In these situations, optimization algorithms can operate effectively and allocate limited resources in the best way. In particular, metaheuristic algorithms with the ability to search complex search spaces are able to solve optimization problems in such environments [7-9].

Resource allocation in overlapping networks faces many challenges. One of the most important challenges is the multi-objective nature of the problem, because in overlapping networks, throughput (which is related to the data transfer rate) and energy efficiency (which is related to the energy consumption during data transfer) must be optimized simultaneously. These two objectives may be in conflict with each other; for example, optimizing throughput may require increasing energy consumption and vice versa [10]. Therefore, the main goal in this paper is to find the optimal balance between these two objectives to maximize network performance on the one hand and reduce energy consumption on the other. Another issue is the complex search space [11]. In overlapping networks, the number of users and network nodes may be very large, and the search space grows exponentially. This makes classical algorithms unable to solve these problems effectively due to computational limitations [12]. To solve resource allocation optimization problems in overlapping networks, metaheuristic algorithms, especially evolutionary algorithms, are used. Due to their features such as global search (exploration) and exploitation, these algorithms are very suitable for solving complex problems with large search spaces. In this regard, algorithms such as genetic algorithm (GA) [13], particle swarm algorithm (PSO) [14]and nature-inspired algorithms have been widely used [15].

In this paper, two important metaheuristic algorithms, namely Aquila Optimizer (AO) [16] and Fossa Optimization Algorithm (FOA) [17], are reviewed, each of which has its own capabilities in searching for optimal solutions to optimization problems. The AO algorithm is specifically inspired by the behavior of bird predators and is able to perform a large search in the search space through features such as competition and cooperation between agents. However, AO faces challenges in finding more precise and focused solutions in specific parts of the search space. On the other hand, FOA, inspired by the behavior of the fossa, a Madagascar predator, is particularly capable of searching more precisely and solving local problems. This algorithm can help identify local optima in more complex search spaces. However, FOA has limited performance in terms of global search in the search space, especially in high-dimensional problems, and may face difficulties in optimizing global solutions. Considering these challenges, the combination of AO and FOA can effectively reduce the limitations of each and help to optimize better in overlapping networks. AO uses its global search capabilities to move more widely in the search space, and FOA can achieve greater precision and search more precisely in specific regions of the search space. This combination can effectively optimize throughput and energy efficiency in overlapping networks simultaneously.

The purpose of this paper is to present a hybrid method that uses AO and FOA to optimize multi-objective resource allocation in Wi-Fi and LTE overlapping networks. In particular, this paper explores how to combine these algorithms to increase throughput and reduce energy consumption in overlapping networks. In other words, the aim of this research is to find the best balance between two different optimization objectives and solve complex resource allocation problems. Accordingly, the innovations of the paper are as follows.

Combination of two meta-heuristic algorithms for multi-objective resource allocation: This paper combines AO and FOA for the first time to simultaneously optimize throughput and energy efficiency in Wi-Fi and LTE overlapping networks. This combination effectively uses the global search and finer search properties of the algorithms for optimization.

Solving Resource Allocation Challenges in Overlapping Networks: This paper examines the resource allocation challenges in overlapping Wi-Fi and LTE networks and presents novel solutions for managing resource contention, reducing interference, and improving system efficiency in these networks.

Introducing a New Hybrid Method for Multi-Objective Problems: In this research, a new hybrid method for multi-objective optimization is introduced that specifically addresses the challenges of optimizing throughput and energy consumption in overlapping networks, and simulation results show that this combination performs better than independent algorithms.

This paper is organized as follows. In Section 2, the theoretical foundations and previous studies in the field of resource allocation and meta-heuristic algorithms are reviewed. Section 3 is dedicated to the methodology, which explains in detail the AO and FOA algorithms and how to combine them to optimize resource allocation. Section 4 presents experimental results and analysis of the results, where the performance of the hybrid algorithm is examined in comparison with other algorithms. Finally, Section 5 is devoted to conclusions and suggestions for future research.

LITRATURES REVIEW

Resource allocation in overlapping wireless networks such as Wi-Fi and LTE is one of the complex issues in the design and optimization of communication systems. This challenge becomes more complex, especially with the increase in the number of users and the need for different services in these networks. Since resources such as bandwidth, power, and energy are limited, optimizing resource allocation is of great importance. In this regard, metaheuristic algorithms, especially metaheuristic algorithms, have been used to solve complex problems. These algorithms have provided effective solutions to these challenges due to their capabilities in global search of the search space and avoiding getting stuck in local optima. One of the notable researches in this field is the multi-objective optimization method for spectral resource allocation in heterogeneous and cognitive-based wireless networks. In this study, the spectrum allocation problem is formulated as a multi-objective model that simultaneously pursues objectives such as increasing spectrum efficiency, reducing interference, and improving QoS.

These algorithms have been able to manage the conflict between these objectives and achieve balanced and efficient solutions in the parameter space, but the need for high computational resources and high complexity in modeling are some of their disadvantages [18]. In another study, the combination of fuzzy optimization with meta-heuristic algorithms has been proposed for resource allocation in a large parameter space. This approach uses fuzzy methods as a multi-criteria decision-making tool to better balance between different objectives. These algorithms have been able to simultaneously improve different objectives such as energy efficiency, throughput, and latency, but the long computational time at large scales is still a major challenge in this approach [19].

Also, hybrid algorithms such as particle swarm optimization, and honeybee have been introduced for resource allocation in wireless networks, especially in cellular and Wi-Fi networks. These hybrid algorithms have been able to simultaneously optimize bandwidth, transmission power, and quality of service, and help improve accuracy and convergence time. However, in complex or variable networks, these methods may have lower accuracy than other methods [20]. In the context of 5G networks, combining PSO with DDPG (Deep Deterministic Policy Gradient) has been proposed for resource allocation. In this method, PSO is used to search the initial parameter space and DDPG is used to dynamically adapt policies in the network environment. This approach has been able to improve the quality of service (QoS) and reduce energy consumption. However, since this approach is more complex than traditional methods, it may pose challenges in implementation [21]. In the following, the combination of Grey Wolf GWO, PSO and Ant ACO is proposed for resource allocation in VANET networks (Connected Vehicle Networks). These hybrid algorithms are able to simultaneously improve latency, energy consumption and spectrum efficiency and provide better performance compared to single-algorithm algorithms. However, due to the long computational time in large networks, they may face problems at large scales [22].

The use of the Integrated African Vultures with Grasshopper Optimization Algorithm IAVGOA for network selection and resource allocation in 5G networks is also an interesting approach. This algorithm has been able to effectively balance between different objectives such as reducing communication cost, optimizing spectral resources and power, but it requires fine-tuning to balance between different objectives [23]. In other methods, meta-heuristic algorithms are used for channel and power allocation in wireless networks, especially in dynamic environments. These algorithms are particularly effective in reducing interference and improving throughput, but in high-interference environments, the optimization may not fully converge [24]. In the context of 5G networks, the use of extended PSO for resource allocation has been able to reduce transmission costs and increase network efficiency. However, the need for fine-tuning of parameters and input data is one of the limitations of this method [25]. In other studies, the combination of evolutionary and population algorithms for resource allocation in underground sensor networks has shown that this method can save energy and reduce latency along with increasing spectrum efficiency. However, the long computational time in large networks is one of the main challenges of these methods [26]. Recent simulation results show that the use of meta-heuristic algorithms for power allocation in wireless networks has been able to increase throughput and maintain quality of service. However, in high-interference environments, more precise optimization settings are required [27]. These studies and approaches indicate the increasing use of meta-heuristic algorithms and hybrid methods to solve complex

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resource allocation problems in overlapping Wi-Fi and LTE networks. Given the complexities of these problems and the need for multi-objective optimization, meta-heuristic algorithms are considered as efficient tools for optimizing network performance, especially in future networks such as 5G and 6G [28, 29]

1) ***Table (1):Hybrid metaheuristic algorithms applied to optimize resource allocation in wireless networks***

Ref	Proposed Method	Advantages	Disadvantages
[18]	Multi-objective optimization for spectrum resource allocation in heterogeneous and cognitive wireless networks	- Improved throughput and QoS - Managing trade-offs between conflicting objectives	-High computational resources required - High model complexity
[19]	Combining fuzzy optimization and metaheuristic algorithms for resource allocation	- Simultaneously optimizing multiple objectives - Optimizing large parameter space	- Long computation time for large scales
[20]	Hybrid combination of PSO and ABC algorithms for resource allocation in wireless networks	- Improved accuracy and convergence time - Simultaneous optimization of bandwidth, transmit power, and QoS	- Lower performance in highly complex or variable networks
[21]	Combining PSO with DDPG for resource allocation in 5G networks	- Dynamic policy adaptation - Improved QoS and reduced energy consumption	- More complex implementation compared to traditional methods
[22]	Hybrid GWO-PSO-ACO for resource allocation in VANET networks	- Improved delay, energy consumption, and spectrum efficiency - Better performance compared to single algorithms	- Long computation time for large networks
[23]	IAVGOA algorithm for network selection and resource allocation in 5G networks	- Reduced communication cost - Simultaneous optimization of spectrum and power resources	- Requires fine-tuning for balancing between objectives
[24]	Using metaheuristic algorithms for channel and power allocation	- Reduced interference and improved throughput - Simultaneous optimization of multiple objectives	- May not fully converge in dynamic environments
[25]	Using developed PSO for resource allocation in 5G networks	- Effective and precise optimization in search space - Reduced transmission costs	- Requires fine-tuning of parameters and input data
[26]	Hybrid combination of evolutionary and population-based algorithms for resource allocation in underground wireless sensor networks	- Energy saving and reduced transmission delay - Increased spectrum efficiency and network performance	- Long computation time in large networks
[27]	Using metaheuristic algorithms for power allocation in wireless networks	- Increased throughput and QoS maintenance - Reduced transmission costs	- May require more precise adjustments in interference-heavy environments
[28]	Using hybrid metaheuristic algorithms for resource allocation in PD-NOMA networks	- Improved network performance in terms of power and reduced interference - Improved fairness among users	-Computational complexity and long execution time in problems with many parameters

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[29]	Using PSO for resource allocation in 5G networks	- Improved QoS - Reduced transmission costs and increased network efficiency	-Requires precise parameter and input data adjustments

According to the comparison table 1, various methods of hybrid metaheuristic algorithms have been applied to optimize resource allocation in wireless networks. These methods have been successful in improving throughput, quality of service, and energy efficiency. However, many of these methods face computational challenges and long convergence times. The proposed research method, which is a combination of AO and FOA algorithms, can effectively optimize resource allocation in a complex search space and simultaneously provide better performance in terms of convergence time and efficiency in overlapping Wi-Fi and LTE networks. Therefore, this approach is superior in terms of accuracy and execution time compared to other methods.

PROPOSED METHOD

In this section, a proposed method is presented for solving the resource allocation problem in Wi-Fi/LTE overlapping networks. The main idea of the proposed method is that, given the nonlinear, constrained, and multivariate nature of the problem (performance dependence on the number of active users in each time interval and simultaneous interaction of two technologies), using a single meta-heuristic approach may either encounter slow convergence or get stuck in local optima. Therefore, a hybrid framework is designed in which diverse search mechanisms and the heuristic power of AO are combined with the power of local optimization and exploitation (FOA) to achieve a better balance between exploration of the search space and gradual improvement of solutions. In the following, first, the solution representation and the method of coding the decision variables are introduced, then the steps of the hybrid algorithm (initial population generation, evaluation, updating, and selection) are described, and finally the method of applying the constraints and stopping criteria of the algorithm is explained.

Model System: Figure 3.1 shows the topology and framework of the studied system for resource allocation in Wi-Fi/LTE overlapping networks. In this model, a macro cell is considered consisting of an eNB and multiple Wi-Fi access points (APs) whose coverage areas overlap with each other and with cellular coverage. Mobile users are located within the coverage area of the APs and are simultaneously connected to both technologies (dual connectivity/inter-network collaboration scenario), such that part of the users' uplink traffic can be sent over the Wi-Fi path and the remaining part over the LTE path. From the perspective of resource allocation, the main decision-making involves scheduling users' use of Wi-Fi in different time slots and determining each user's share of access resources in each AP; consequently, the number of active users and their contention in each time slot have a direct impact on the final network performance. Therefore, the purpose of the model system in Figure 1 is to provide a unified framework for describing user interactions with Wi-Fi APs and eNBs and to pave the way for designing an optimization method that can manage resource allocation under conditions of overlap, contention, and user variability. Table 2 describes the variables used in the model system.

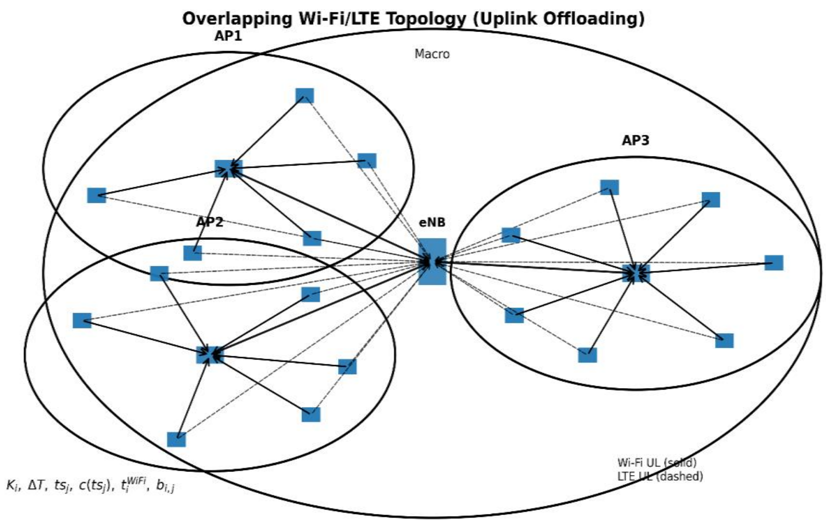

Figure 1. Proposed system model

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Table (2) Parameters and definitions related to the system model

parameter	Description
α_u	Upload connection transfer capacity in Mbps
β	LTE base power
R_{LTE}^{ul}	LTE reception rate
P_{LTE}^{ul}	User LTE interface power level
N	Number of users competing for an access point
S	Average user throughput
Ptr	Probability of at least one transmission in a time slot
Ps	Probability of successful transmission
E[P]	Average packet size
σ	Time slot length
Ts	Successful transmission duration
Tc	Collision duration
EE	User energy efficiency
Ei	User energy consumed during idle period
Es	User energy consumed during successful transmission
Ec	User energy consumed during collision
TH	Transmission time of physical and MAC headers
TE[P]	Average packet transmission duration
Pidle	Wi-Fi interface power level when idle
PTx	Wi-Fi interface power level during transmission
PRx	Wi-Fi interface power level during reception
K_i	Traffic per user
ti	Time period allocated for exclusive access
EC	Energy consumption
ΔT	Total time slot
M	Total number of time slot slots
Kmax	Maximum data volume
ts_j	Each time slot ΔT
c(m_j)	Number of associated users With AP during m_j
$b_{i,j}$	user presence in each time slot

The uplink access approach in IEEE 802.11 DCF is related to the communication between users who have data to transmit over Wi-Fi using the window support algorithm of difference. Using Bianchi analysis [30] for saturated traffic conditions and validation by simulation, we conclude that the throughput of a user transmitting data traffic over Wi-Fi is significantly affected by the number of users under the coverage of an access point. . have. The throughput of each user S (N), where N is the number of users competing for each Wi-Fi access point, which is expressed as:

$$S(N)=\frac{P_s(N)P_{tr}(N)E[P]}{N[(1-P_{tr}(N))\sigma+P_s(N)P_{tr}(N)T_s+(1-P_s(N))P_{tr}(N)T_c]} \quad (1)$$

Throughput of each user S(N) in the saturated state, when N users compete for an AP, is in bit/s. $P_{tr}(N)$ is the probability that at least one transmission occurs in a time slot. $P_s(N)$ is the probability that a transmission is successful. E[P] is the average packet/payload size in bits. σ is the slot time and T_s is the channel occupied time in a successful transmission. And finally T_c is the channel occupied time in a collision. $P_{tr}(N)$ is the probability that at least one transmission occurs in a given time slot, $P_s(N)$ is the probability of a successful transmission, which is defined as:

$$P_{tr}(N)=1-(1-\tau)^N \quad (2)$$

$$P_s(N)=\frac{N\tau-(1-\tau)^{N-1}}{P_{tr}(N)} \quad (3)$$

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τ is the probability of a user transmitting in a slot (Transmission probability per slot). The user energy efficiency (EE(N)) is expressed as a function of the number of users in bits/joules:

$$\mathrm{EE}(N)=\frac{P_s(N)P_{tr}(N)E[P]}{N\big[\big(1-P_{tr}(N)\big)E_i+P_s(N)P_{tr}(N)E_s+\big(1-P_s(N)\big)P_{tr}(N)E_c\big]} \tag{4}$$

EE(N) is the energy efficiency of each user as a function of (bit/Joule) and E_i is the energy consumed in idle and non-transmission mode. E_s is the energy consumed in successful transmission and E_c is the energy consumed in collision. Also, the successful transmission time and collision time are obtained from the following equations:

$$T_s=T_H+T_{E[P]}+T_{sIFS}+T_{ACK}+T_{DIFS} \tag{5}$$

$$T_C=T_H+T_{E[P]}+T_{DIFS} \tag{6}$$

T_H is the time to send physical and MAC headers, $T_{E[P]}$ is the time to send the payload with the average size E[P], T_{DIFS} is the short interval between frames, T_{ACK} is the time to send the ACK, T_{DIFS} is the interval, and T_s is the total channel occupancy time in successful transmission. Considering these, to obtain the energy consumption, we express the following for equation 5 as follows:

$$E_s=P_{Tx}(T_H+T_{E[P]})+P_{idle}(T_{sIFS}+T_{DIFS})+P_{Rx}T_{ACK} \tag{7}$$

$$E_C=P_{Tx}(T_H+T_{E[P]})+P_{idle}T_{DIFS} \tag{8}$$

$$E_i=\sigma T_{idle} \tag{9}$$

$P_{Tx}$is the power consumption of the Wi-Fi card in transmit mode (Transmit power level). P_{idle} is the power consumption of the Wi-Fi card in idle/listening mode (Idle power level). P_Rx is the power consumption of the Wi-Fi card in receive mode (Receive power level). The energy consumption of the i-th user in Wi-Fi mode is calculated as follows:

$$\mathrm{EC}_{\mathrm{i}}^{\mathrm{WiFi}}=\sum_{\mathrm{i=1}}^{M}\frac{b_{i,j}ts_j\,\mathrm{S}(\mathrm{c}(ts_j))}{\mathrm{EE}(\mathrm{c}(ts_j))}\quad[\text{Joule}] \tag{10}$$

$\mathrm{EC}_{\mathrm{i}}^{\mathrm{WiFi}}$ is the energy consumed when the transmission results in a collision. $\mathrm{EE}(\mathrm{c}(ts_j))$ is the user energy efficiency when the number of competitors is . Where, if the i-th user uploads via Wi-Fi during tsj, the element $b_{i,j}=1$and if the i-th user is disconnected during tsj, $b_{i,j}$=0. Furthermore, the energy consumption of the i-th user's network interface card in LTE conditions is expressed as:

$$\mathrm{EC}_{\mathrm{i}}^{\mathrm{LTE}}=\Big(K_i-\sum_{\mathrm{j=1}}^{M}b_{i,j}\,ts_j\mathrm{S}(\mathrm{c}(ts_j))\Big)\frac{P_{LTE}^{ul}}{R_{LTE}^{ul}}\ [\text{Joule}] \tag{11}$$

$\mathrm{EC}_{\mathrm{i}}^{\mathrm{LTE}}$ is the energy consumed by user i to send a piece of data via Wi-Fi, M is the number of time slots in ΔT, ts_j is the length of the jth time slot, $b_{i,j}$ is the presence index of user i in slot j, which is 1 if the user uploads in that slot, otherwise it will be 0 $\mathrm{c}(ts_j)$is the number of active/competing users in slot ts_j and $\mathrm{S}(\mathrm{c}(ts_j))$is the throughput of the user when the number of competitors is $\mathrm{c}(ts_j)$From the DCF model, the average energy efficiency can be expressed as follows:

$$EE\big(N,M,t_i^{WiFi},ts_j\big)=\frac{\sum_{i=1}^{N}K_i}{\sum_{i=1}^{N}\big(EC_i^{WiFi}+EC_i^{LTE}\big)}=\frac{\sum_{i=1}^{N}K_i}{\sum_{i=1}^{N}\Big(\sum_{\mathrm{i=1}}^{M}\frac{b_{i,j}ts_j\,\mathrm{S}(\mathrm{c}(ts_j))}{\mathrm{EE}(\mathrm{c}(ts_j))}+\big(K_i-\sum_{\mathrm{j=1}}^{M}b_{i,j}\,ts_j\mathrm{S}(\mathrm{c}(ts_j))\big)\frac{P_{LTE}^{ul}}{R_{LTE}^{ul}}\Big)} \tag{12}$$

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$EE\left(N,M,t_i^{WiFi},ts_j\right)$ is the average energy efficiency of the system over the entire ΔT, where numerator is the sum of the total user traffic and denominator is the sum of the users' energy consumption in Wi-Fi and LTE. t_i^{WiFi} is the time allocated to user i for Wi-Fi access. The resource allocation decision is made. In addition, the throughput can be obtained for different values of M, N, t_i^{WiFi} and tsj as follows:

$$S\left(N,M,t_i^{WiFi},ts_j\right) = \sum_{j=1}^{M}\left(\frac{P_s\left(c(ts_j)\right)P_{tr}\left(c(ts_j)\right)E[P]}{N\left[\left(1-P_{tr}\left(c(ts_j)\right)\right)\sigma + P_s\left(c(ts_j)\right)P_{tr}\left(c(ts_j)\right)T_s + \left(1-P_s\left(c(ts_j)\right)\right)P_{tr}\left(c(ts_j)\right)T_c\right]}\right) \tag{13}$$

To formulate the resource allocation problem in uplink data offloading, in addition to the system functional relations (relations 1 to 13), it is necessary to define a set of temporal and logical constraints so that the scheduling process and the presence of users in the time slots are physically feasible and consistent with the system model. Since the offloading time interval ΔT is divided into M time slots ts_j, the sum of the slot lengths must be exactly equal to ΔT so that the defined scheduling does not exceed the system time boundary. Therefore, the following constraint applies:

$$\Delta T = \sum_{j=1}^{M} ts_j \tag{14}$$

Also, to avoid selecting unrealistic slots (too small or too large) and to ensure the scheduler is implementable in practice, the length of each time slot must lie between the allowed bounds:

$$ts_j^{mib} \leq ts_j \leq ts_j^{max} \tag{15}$$

In the presented model, the effect of user contention on Wi-Fi and DCF performance is directly dependent on the number of active users in each time slot, which is represented by $c(ts_j)$. Since the presence of user i in time slot ts_j is specified by the variable $b_{i,j}$,the number of active users in each time slot is defined as the sum of user presences to establish a connection between scheduling/allocation and throughput/energy efficiency calculation:

$$c\left(ts_j\right) = \sum_{j=1}^{N} b_{ij} \ ,\forall \mathrm{j} \tag{16}$$

On the other hand, since b_{ij} represents the presence/absence status of the user in the slot, this variable must be binary to avoid unrealistic values:

$$b_{ij} \in \{0,1\} \ \forall \mathbf{i},\mathbf{j} \tag{17}$$

From the perspective of time allocation to users in Wi-Fi, each user has an access time $t_i^{WiFi_i}$ for uploading data, which must be limited to the unloading time interval. Therefore, the time constraint for $t_i^{WiFi_i}$is considered as follows:

$$0 \leq t_i^{WiFi_i} \leq \Delta T \ ,\forall \mathrm{i} \tag{18}$$

Also, to be consistent between the allocated time $t_i^{WiFi_i}$ and the user's presence in different time slots, the Wi-Fi access time of each user should not exceed the sum of the times the user is active in the slots. Hence, the following constraint applies:

$$t_i^{WiFi_i} \leq \sum_{j=1}^{N} ts_j b_{ij} \ ,\forall i \tag{19}$$

Finally, to avoid unrealistic allocation that leads to sending more than the user's traffic demand (and consequently, the LTE part in equation (11) becomes negative), the total amount of data offloaded via Wi-Fi for each user must not exceed K_i . Therefore, the no-sending-more-than-demand constraint is defined as follows:

$$\sum_{j=1}^{M} ts_j b_{ij} S\left(c\left(ts_j\right)\right) \leq K_i, \forall i \tag{20}$$

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By applying the above constraints, the resource allocation problem is defined as an optimization problem with a weighted objective function according to equation (14), whereλ_2 and λ_1 are the weighting coefficients to determine the relative importance of energy efficiency and throughput. To achieve maximum discharge performance through the selection of t_i^{WiFi} and tsj, we need to define an optimization problem according to the equations presented. The problem formulation including the objective function and the relevant constraints can be defined as follows:

$$\mathcal{OF} = \min(\lambda_1.\frac{1}{EE} + \lambda_2.\frac{1}{S}) \tag{21}$$

Where λ1 and λ2 are the coefficients for selecting the importance of each criterion from the objective function. Equation 21 can be solved using optimization algorithms. In this research, metaheuristic algorithms are used to optimize the resource allocation problem in uploading data unloading.

Aquila Optimization Algorithm: To solve the resource allocation problem in Wi-Fi and LTE overlapping networks, our goal is to find the optimal values of the decision variables such that the objective function defined in equation (21) is minimized. Since the objective function includes two opposing criteria, namely energy efficiency and throughput, and also the system performance relations (1) to (13) and constraints (14) to (20) create a nonlinear, combinatorial, and complex structure, it is difficult to use classical analytical methods to find the optimal solution, and the use of a metaheuristic algorithm such as the Aquila Optimizer (AO) is justified. In AO, each candidate solution is represented as a decision vector in the search space, and a population of solutions evolves simultaneously to obtain the minimum of the objective function.

In the AO algorithm, first a population of candidate solutions is generated with the symbol X according to equation (22); So that each row of the matrix X_i represents a candidate solution X_i and each corresponding column is one of the components of the decision vector. The initialization is done randomly between the lower and upper bounds to provide a suitable coverage of the search space:

$$X = \begin{bmatrix} x_{1,1} & \cdot\cdot & x_{1,j} & \cdot\cdot & x_{1,Dim} \\ \vdots & & \vdots & & \vdots \\ x_{i,1} & \cdot\cdot & x_{i,j} & \cdot\cdot & x_{i,Dim} \\ \vdots & & \vdots & & \vdots \\ x_{N,1} & \cdot\cdot & x_{N,j} & \cdot\cdot & x_{N,Dim} \end{bmatrix} \tag{22}$$

$$X_{i,j} = rand \times \left(UB_j - LB_j\right) + LB_j \ , \ \ i = 1,2, \dots, N \ , J = 1,2, \dots, Dim \tag{23}$$

In the resource allocation problem, the decision vector must be defined in such a way that it is possible to generate the values $t_i^{WiFi_i}$ and ts_j (and in the case of explicit modeling of the presence schedule, the binary variables b_{ij} are also extracted from this vector). Therefore, for each solution b_{ij} , a mapping (Decoding) is defined to transform the continuous components of b_{ij} into the decision variables of the problem; then constraints (14) to (20) are applied. Specifically, the time decomposition constraint (14) ensures that the sum of slots is equal to ΔT, constraint (15) controls the allowed range of each ts_j, relation (16) extracts the number of active users c(ts_j) from b_{ij} , constraint (17) ensures the binary presence, and constraints (18) and (19) establish the time consistency of $t_i^{WiFi_i}$with the presence in the slots. Finally, constraint (20) prevents sending more than K_i traffic so that the LTE part of relation (11) is not negative.

After initialization, in each iteration of the AO algorithm, the objective function value is calculated for each solution X_i. For this purpose, first, using the number of competing users, the user throughput in Wi-Fi is obtained according to equations (1) to (3) and the times $T_C$and T_s according to (5) and (6). Then, the energies of different states E_s, E_c and E_i are calculated from equations (7) to (9) and the Wi-Fi energy efficiency is extracted according to equation (4). With these values, the Wi-Fi and LTE energy consumption of each user is calculated from equations (10) and (11), respectively, and the average energy efficiency of the system is obtained from equation (12) and the aggregate throughput is obtained from equation (13). Finally, the system objective function is calculated according to equation (21) as the minimization of the inverse weighted sum of the criteria.

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In AO, after evaluating the population and determining the best answer up to iteration t, denoted $X_{best}\ (t)$, the population positions are updated with the four hunting behaviors of the eagle. The algorithm dynamically switches between the exploration and exploitation phases; if $t < \frac{2}{3}T$, the exploration behaviors, including steps X_1 and X_2, are activated, and otherwise the exploitation behaviors, namely steps $X_3$and X_4, are executed. In the extensive exploration phase, the eagle surveys the area from a high altitude and moves based on the best answer and the population mean:

$$X_1(t+1) = X_{best}\ (t) * \left(1 - \frac{t}{T}\right) + (X_M(t) - X_{best}(t) * rand) \tag{24}$$

where $X_M(t)$ is the mean of the population positions at iteration t:

$$X_M(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t)\ , j = 1,2, \dots, Dim \tag{25}$$

In the limited exploration phase, AO performs a more precise exploration around promising areas using Lévy flight and spiral movement to prepare for approaching the optimal solution:

$$X_2(t+1) = X_{best}\ (t) * Levy\ (D) + X_R(t) + (y - x) * rand) \tag{26}$$

where Levy(D) and the parameter σ are calculated according to [16]. Creating the spiral component in the search, x and y and the spiral radius r are determined according to [16]. After the exploration phase is complete, the algorithm enters the exploitation phase to intensify the search around the best identified areas. In the extensive exploitation phase, the locations are updated with a combination of distance from the population mean and a controlled random component:

$$X_3(t+1) = (X_{best}\ (t) - X_M(t)) \times \alpha - rand + ((UB - LB) \times \mathrm{rand} + \mathrm{LB})) \times \delta \tag{27}$$

where α and δ are the operation tuning parameters. In the final stage, i.e., constrained operation, AO performs near-target moves using the quality function GF and control parameters G_1 and G_2 to make the solutions more accurate around $X_{best}\ (t)$:

$$GF\ (t) = t^{\frac{2*rand\ (\ \ )-1}{(1-T)^2}} \tag{28}$$

$$G_1 = 2 * rand\ (\ \ ) - 1 \tag{29}$$

$$G_2 = 2 * (1 - \frac{t}{T}) \tag{30}$$

After updating each situation, the new solution is discarded/repaired to constraints (14) to (20) and then the value of the objective function (21) is recalculated. If the new solution produces a lower value for $\mathcal{OF}$, it replaces the previous solution and if it is superior to the best recorded solution, $X_{best}\ (t)$ is also updated. This process continues until a stopping condition is reached, for example t=T, and finally, $X_{best}\ (t)$is reported as the best resource allocation policy including the values $t_i^{WiFi_i}$ and ts_j and the presence structure b_{ij} according to the constraints) that provides the minimum of the objective function and simultaneously creates a favorable balance between increasing energy efficiency and increasing throughput in overlapping Wi-Fi/LTE networks. Algorithm 1 shows the pseudocode of the AO method in optimization.

Algorithm 1:AO for Optimizing OF in Wi-Fi/LTE Overlapping Resource Allocation

Input: N, T, LB, UB, λ1, λ2, system parameters, constraints on $t_i^{WiFi_i}$, ts_j , b_{ij} , ΔT

Output: X_best → $t_i^{WiFi_i}$, ts_j, b_{ij} , and OF($X_{best}\ (t)$)

1. **Initialize**
   - Generate population X = X_i with size N uniformly within [LB, UB].
   - For each X_i: Decode(X_i) → $t_i^{WiFi_i}$, ts_j, b_{ij} then Repair to satisfy all constraints.
   - Evaluate OF(X_i) for all candidates and set X_{best} as the best one.
2. **Main loop** for t = 1 … T
   - Compute population mean X_M.
   - For each solution X_i:

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- If $t < \frac{2}{3}T$ (**Exploration**):
  - Generate X_i_new using either wide exploration or narrow exploration (random long moves).
- Else (**Exploitation**):
  - Generate X_i_new using either wide exploitation or narrow exploitation (refinement moves).
- Apply **bound control** to keep X_i_new inside [LB, UB].
- Decode(X_{inew}) → → $t_i^{WiFi_i}$, ts_j, b_{ij} and **Repair** to satisfy constraints.
- Evaluate OF(X_{inew}).
- **Selection:** if OF(X_{inew}) improves OF(X_i), replace $X_i \leftarrow X_{inew}$.

  - Update X_best if a better solution is found.

3. **Return**
   - Return X_{best} and OF(X_{best}).

Objective function Optimization for model system using FOA: In order to optimize the resource allocation in overlapping Wi-Fi and LTE networks, the goal is to find the optimal values of the decision variables $t_i^{WiFi_i}$ and ts_j and, if considered in the time planning, the user presence status b_{ij} , so that the weighted objective function of the system is minimized. Since the system performance indicators (relations (1) to (13)) and the time/logical constraints (constraints before relation (21)) have a nonlinear structure and depend on the competition of users, in this section a meta-heuristic method such as the Fosa optimization algorithm (FOA) is used. In FOA, each "Fosa" represents a candidate solution in the search space and moves towards the optimal solution by imitating the hunting behavior of Fosa (attack/explore and chase/exploit).

In FOA, the initial population of solutions is represented by a matrix X, where each row is a candidate solution X_i and each component $x_{i,d}$) represents one of the decision variables. The initialization is done randomly between the lower and upper bounds:

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N*M} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & & \vdots & & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & & \vdots & & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix} \tag{31}$$

$$x_{i,d} = lb_d + r\,.(ub_d - lb_d) \tag{32}$$

Then, each solution X_i is assigned to the decision variables of the decision problem ($t_i^{WiFi_i}$ and ts_j , that is, b_{ij} and after applying the constraints (the constraints before equation (21)), the objective function value is calculated for it. In order for FOA to directly minimize the objective function of your system, the objective function value of each solution is defined as the FOA fit value; therefore, the fit vector is as follows:

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N*1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N*1} \tag{33}$$

In other words, after calculating E and S^ from the system relations (1) to (13) and considering the scheduling ts_j and the time allocation $t_i^{WiFi_i}$ and the effect of the presence of users b_{ij} on $c(ts_j)$, the value of OF is considered as the quality criterion of the solution X_i in FOA and FOA seeks to minimize it.

Phase 1 of FOA: Attack and move towards the lemur (exploration)
In the exploration phase, for each foci i, a set of "candidate lemurs" is defined as solutions with a better objective function value; that is:

$$CL_i = \{X_k : F_k < F_i \ nad \ k \neq i\} \\ i = 1,2,..,N \ and \ k \in \{1,.2,...N\} \tag{34}$$

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Then FOA assumes that Fossa randomly selects one member of this set as the target $SL_{i,j}$ and creates the new position in the attack phase:

$$x_{i,j}^{P1} = x_{i,j} + r_{i,j}\,(SL_{i,j} - I_{i,j}\,x_{i,j}) \tag{35}$$

After generating the new position $x_{i,j}^{P1}$, this Decode solution and constraints are applied; then the value of F$(x_{i,j}^{P1})$is calculated. If the value of the objective function is improved, the replacement is performed:

$$X_i = \begin{cases} X_i^{P1}, F_i^{P1} < F_i \\ X_i, other \end{cases} \tag{36}$$

Phase 2: FOA Lemur Chase (Exploitation)
In the exploitation phase, FOA intensifies the search around promising areas with smaller, more controlled changes. The new Fosa position in this phase is generated as follows:

$$x_{i,j}^{P2} = x_{i,j} + (1 - 2r_{i,j})\,\frac{ub_d - lb_d}{t} \tag{37}$$

As in the previous phase, after decoding and applying constraints, the value of $X_i^{P2}, F_i^{P2}$is calculated and, if improved, replacement is performed:

$$X_i = \begin{cases} X_i^{P2}, F_i^{P2} < F_i \\ X_i, other \end{cases} \tag{38}$$

At the end of each iteration, the best observed solution is stored as the current optimal solution, that is, the solution with the lowest OF(Xi). Thus, by repeating the two phases of exploration (attack) and exploitation (tracking), FOA optimizes the set $t_i^{WiFi_i}$, ts_j, b_{ij} ,, in such a way that the objective function of the model system (relationship (21)) is minimized and at the same time a suitable compromise between increasing EE and increasing S^ in overlapping Wi-Fi/LTE networks is achieved. Algorithm 2 shows the optimization pseudocode in this way.

Algorithm 2 :FOA for Minimizing OF in Wi-Fi/LTE Overlapping Resource Allocation

Input: N, T, LB, UB, λ1, λ2, system parameters, constraints on $t_i^{WiFi_i}$, ts_j, b_{ij} , ΔT

Output: X_{best} decoded as $t_i^{WiFi_i}$, ts_j, b_{ij} , and OF($X_{best}\ (t)$)

Algorithm: FOA-OF Minimization

1. **Initialize population**
   - Generate population X = X_i with size N uniformly within [LB, UB].
   - For each X_i:
     - Decode(X_i) → $t_i^{WiFi_i}$, ts_j, b_{ij}
     - Repair(X_i) to satisfy all constraints (time consistency, bounds on ts_j, binary b_{ij} , consistency of $c(ts_j)$, feasibility of offloaded traffic)
     - Evaluate F(X_i) where F(X_i) ≡ OF(X_i).
2. **Set initial best**
   - Set X_{best} = arg min F(X_i) among all i = 1..N.
3. **Main loop** for t = 1 … T
   - For each candidate X_i in the population:

     (A) Build candidate-lemur set
     - Construct CL_i = X_k | F(X_k) < F(X_i) and k ≠ i.

     (B) Exploration: Attack step
     - If CL_i is not empty:
       - Randomly select one target solution SL_i from CL_i.
     - Else:
       - Select SL_i as X_best (fallback target).
     - Generate X_i^{P1} using FOA attack movement toward SL_i.
     - Apply bound control to keep X_i^P1 inside [LB, UB].
     - Decode(X_i^{P1}) → $t_i^{WiFi_i}$, ts_j, b_{ij}
     - Repair(X_i^{P1}) to satisfy constraints.
     - Evaluate F(X_i^{P1}).

     Selection after attack
     - If F(X_i^{P1}) < F(X_i), then set X_i ← X_i^{P2}.

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(C) Exploitation: Chase step

- Generate X_i^{P2} using FOA chase movement (small controlled adjustment).
- Apply bound control to keep X_i^{P2} inside [LB, UB].
- Decode(X_i^{P2}) $\rightarrow t_i^{WiFi_i}, ts_j, b_{ij}$
- Repair(X_i^{P2}) to satisfy constraints.
- Evaluate F(X_i^{P2}).

Selection after chase

- If F(X_i^{P2}) < F(X_i), then set $X_i \leftarrow X_i^{P2}$.

  - Update X_{best} as the solution with minimum F(X_i) in the current population.

4. **Return**
   - Return X_{best} and OF(X_{best})

PROPOSED HYBRID METHOD

In this section, the combination of two powerful optimization algorithms, AO and FOA, is investigated to solve the resource allocation problem. Each of these algorithms has its own strengths and weaknesses: Aquila is very effective in global search and can efficiently navigate large search spaces, but it may encounter problems in the accuracy and final optimization of solutions. In contrast, Fosa is very effective in local exploitation and precise optimization around promising solutions, but in complex and multidimensional spaces it may get stuck in local optimizations. By combining these two algorithms, we can take advantage of the global search capabilities of Aquila and the local optimization capabilities of Fosa and overcome these weaknesses. This hybrid approach allows us to obtain a more optimal solution to the resource allocation problem in overlapping networks, so that both energy efficiency and throughput are improved simultaneously.

To combine AO and FOA, the goal is to use the advantages of both algorithms in simultaneous search and exploitation. In this hybrid approach, the two algorithms operate simultaneously, where AO initially explores the search space broadly, and then FOA is used for exploitation and local search in promising regions.

Simultaneous interaction of the two algorithms

At each stage of the optimization, a population of AO and FOA interact with each other. First, AO is used for large-scale space search (exploration), at which point AO uses its large population to explore the search space more broadly. Then, FOA comes in to improve local search (exploitation) in promising regions. This method makes the search faster and uses both algorithms effectively.

Adaptive Weighting Scheme

In this method, the weights are adjusted adaptively. In the early stages, when searching a large space is more important, the weight of AO is greater than that of FOA. But gradually, as the optimization progresses and the optimal regions are approached, the weight of FOA increases.
To calculate the weights at each stage, the following formula is used:

$$Weight_{AO} = \frac{1}{t+1} \tag{39}$$

$$Weight_{FOA} = 1 - Weight_{AO} \tag{40}$$

where t is the number of iterations performed. In the early stages, the weight of AO is higher, and as t increases, the weight of FOA increases.

Hybrid AO-FOA algorithm

In this hybrid method, the populations from AO and FOA are updated simultaneously. Specifically, at each stage of optimization, individuals from both algorithms are updated alternately, using the optimal choices. The hybrid algorithm works as follows:
Starting with the AO population First, an initial population of potential solutions is generated by AO. This population is randomly distributed in the search space

$$X_{AO} = [X_1 \quad \cdots \quad \cdots \quad X_N] \tag{41}$$

where X_i denotes a solution from the AO population.

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Population Update with FOA After the initial search phase by AO, FOA is used to exploit promising regions in the search space. At this stage, the population update is performed as follows:

$$X_{FOA} = [X'_1 \quad \cdots \quad \cdots \quad X'_N] \tag{42}$$

where X'_i is the new solution obtained through FOA.
Selecting the most optimal individual from both populations: In each iteration, the best individual is selected from both AO and FOA populations. The optimal individual is selected according to the objective function

$$X_{best} = \arg\min(OF\ (X_{AO}), OF\ (X_{FOA})) \tag{43}$$

where OF is the objective function to be minimized.

Choosing a search strategy (Exploration vs. Exploitation)
During the optimization process, AO is used for exploration and FOA is used for exploitation, depending on the optimization situation. In this method, if the distance from the best solution (OF) is large, AO is used for a wider search, but if we are close to the optimal region, FOA is chosen for a more precise search. The goal of this hybrid method is to minimize the objective function shown in equation (21).

This method has the following advantages:
Balance between exploration and exploitation: This method finds a good balance between searching in a large space and accurately exploiting the optimal regions.
Reduced convergence time: Using AO and FOA simultaneously reduces the optimal convergence time.
Dynamic weight changes: Adaptive weights that change during the optimization process allow the best features of both algorithms to be used at each step.
Finally, the use of the combination of the two algorithms AO and FOA in this hybrid method effectively helps in searching and exploiting the solution space and leads to a more optimal and faster solution of the resource allocation problem in overlapping Wi-Fi and LTE networks. Algorithm 3 shows the proposed hybrid method.

Algorithm 3 : The proposed hybrid method.

1. Initialize AO and FOA populations:
- Generate initial AO population (X_{AO})
- Generate initial FOA population (X_{FOA})

2. Set parameters:
- MaxIter = Maximum number of iterations
- λ1, λ2 = Weights for energy efficiency (EE) and throughput (S)
- $Weight_{AO} = 1$, $Weight_{FOA} = 0$ (Initial weights)

3. For each iteration t = 1 to MaxIter:

a. For each individual in X_{AO}:
- Apply AO update rules (exploration)

b. For each individual in X_{FOA}:
- Apply FOA update rules (exploitation)

c. Combine AO and FOA populations:
- Select the best individual (X_{best}) from X_{AO} and X_{FOA}

d. Dynamically update weights:

$$\boldsymbol{Weight_{AO} = \frac{1}{t+1}}$$

$$\boldsymbol{Weight_{FOA} = 1 - Weight_{AO}}$$

e. Calculate objective function (OF):

$$\boldsymbol{\mathcal{OF} = \min(\lambda_1 . \frac{1}{EE} + \lambda_2 . \frac{1}{S})}$$

f. Select the best solution based on the objective function

g. Update X_{AO} and X_{FOA} with the selected solutions

4. Return the best solution after MaxIter iterations

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SIMULATION AND EVALUATION RESULTS

The proposed method aims to improve the allocation in overlapping networks by optimally allocating resources. The simulation of the proposed method will be performed in MATLAB 2020Rb software. For this purpose, data offloading will be used. Here, we can define the offloading performance metrics. The first metric is the offloading efficiency, which is given by the number of APs K (γK) and can be defined as the ratio of the total amount of offloaded traffic (ω_{offl}) to the total amount of traffic generated without offloading ((ω_{ov}) and can be expressed as

$$\gamma^K = \frac{\omega_{offl}}{\omega_{ov}} = \frac{\sum_{j=1}^{K} \omega_j^D}{\sum_{j=1}^{M\times M} \omega_j^S} \tag{44}$$

To evaluate the impact of each AP in a discharge scenario, we define another metric called the average discharge efficiency (γ_{av}^K):

$$\gamma_{av}^K = \frac{\gamma^K}{K} \tag{45}$$

The third metric is operational efficiency. This metric is defined as the ratio of the average power delivered to Wi-Fi and mobile users and can be expressed as:

$$\eta^K = \frac{S_W^{user-K}}{S_C^{user-K}} \tag{46}$$

Parameter Tuning:In the parameter tuning section, the goal is to achieve better performance in resource allocation in Wi-Fi and LTE overlapping networks by selecting optimal values for various parameters of the algorithms used in the proposed method. In general, parameter tuning plays an important role in improving the accuracy and efficiency of the algorithms. In this research, the algorithms FOA and AO, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been used for comparison. Each of these algorithms requires specific parameters that are optimally tuned. For this purpose, the initial values of the parameters are selected using empirical methods or network search to create a combination of accuracy and efficiency in the optimization algorithms. Finally, the results of these parameter tunings will be evaluated using different criteria of unloading performance, average unloading efficiency and operational efficiency to compare different algorithms. Table 3 shows the values of the tuned parameters for each algorithm and the comparison with the GA and PSO algorithms.

Table (3) Values of set parameters

Algorithm	Parameter	Value
FOA	Population Size	50
	Max Iterations	1000
	Crossover Rate	0.9
	Mutation Rate	0.1
	Search Range	[0, 1]
	Convergence Rate	-
	Levy Parameter	0.01
	Dimensions	2
	Random Walk Steps	-
GA	Population Size	50
	Max Generations	1000
	Crossover Rate	0.8
	Mutation Rate	0.01
	Selection Rate	0.5
	Selection Method	Tournament (Tournament)
	Search Range	[0, 1]
	Dimension	2
PSO	Population Size	50
	Max Iterations	1000
	Inertia Weight	0.9
	First Inertia Coefficient C1	1.5
	Second Inertia Coefficient C2	1.5

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	Search Range	[0, 1]
	Velocity	-
	Dimensions	2
	Random Factor	0.7
AO	Population Size	30 to 50
	Max Iterations	100 to 500
	Convergence Rate	0.8 to 0.9
	Selection Rate	0.6 to 0.8
	Random Variable	rand (0 to 1)
	Max Position Bound	0 to 1
	Position Update Rate	0.5 to 0.7
FOA + AO	Population Size	50
	Max Iterations	1000
	Crossover Rate	0.9
	Mutation Rate	0.1
	Random Walk Steps	-
	Convergence Rate	0.05
	Search Range	[0, 1]
	Inertia Weight	0.9
	Levy Parameter	0.01
	Selection Rate	0.5
	Dimensions	2
	Personal Learning Parameter (AO)	1.5
	Social Learning Parameter (AO)	1.5

System Model Specifications: In this section, the system model specifications are presented for simulating resource allocation in overlapping Fi-Wi and LTE networks. This model specifically addresses the configurations of Wi-Fi (using the IEEE 802.11n standard) and LTE wireless networks in overlapping environments and uses key parameters to perform accurate simulations. These parameters include fixed frequencies for each node, channel width, PHY data rates, and propagation models, all of which are set to evaluate the optimization of throughput and energy efficiency in overlapping networks simultaneously. In addition, the settings related to the load model and delay evaluation in this model are also designed to allow the system performance to be examined under different conditions of resource contention and interference. This specification generally provides a framework for designing and implementing simulations that help improve resource allocation and increase performance in overlapping Fi-Wi and LTE networks.

Table (4) System Model Specifications (Fi-Wi and LTE Overlapping Networks)

Parameter	**Value / Setting**
Wireless Technology	Wi-Fi and LTE
Frequency Band (Wi-Fi)	2.4 GHz, 5 GHz
Frequency Band (LTE)	700 MHz, 1800 MHz
Channel Width (Wi-Fi)	20 MHz, 40 MHz
Channel Width (LTE)	10 MHz, 20 MHz
PHY Data Rate (Wi-Fi)	65 Mbps, 150 Mbps
PHY Data Rate (LTE)	10 Mbps - 100 Mbps
Propagation Model	Log-Distance, Free-Space
Path-Loss Exponent (Wi-Fi)	n = 2.7 - 3.5
Path-Loss Exponent (LTE)	n = 3.0
Transmit Power (Wi-Fi)	15 dBm, 20 dBm
Transmit Power (LTE)	23 dBm
Receiver Sensitivity (Wi-Fi)	-85 dBm
Receiver Sensitivity (LTE)	-100 dBm
AP Placement	Uniform Random
Mobility Model	Random Waypoint, Static
Simulation Area	1000m x 1000m

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Number of Users (LTE)	50 - 100
Number of Users (Wi-Fi)	10 - 30
Load Model (Wi-Fi)	Uniform random (1-3 Mbps)
Load Model (LTE)	Uniform random (2-6 Mbps)
Delay Model	Distance-dependent under Log-Distance
Traffic Model	Constant Bit Rate (CBR), Poisson
Load Update	Constant per run
Simulation Duration	100s - 500s

Figure 2 shows that the hybrid approach achieves a better final quality solution in minimizing the objective function, which is also meaningful from the perspective of the evaluation criteria. A better solution in this context means a policy that improves the "offloaded volume relative to the base traffic" and therefore γK and Kγav are expected to improve. Also, this better quality is usually accompanied by a more effective balance between the throughput of the Wi-Fi path and the cellular path, so ηK is also driven towards a more efficient use of Wi-Fi while maintaining the role of LTE. Overall, the superiority of the hybrid approach in the final result shows that using a hybrid approach for offloading scenarios is more effective in achieving more stable and efficient policies than standalone algorithms.

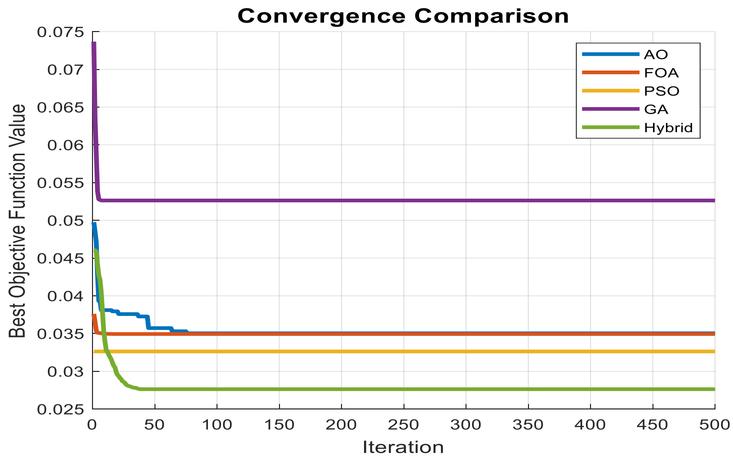

Figure 2. Comparison of the changes of the best objective function value during iterations for different algorithms.

Figure 3 compares the overall offloading efficiency for different optimization algorithms and shows that the hybrid method provides the highest level of effective traffic offloading compared to other methods. This behavior indicates that the proposed method was able to offload a larger portion of the generated traffic via Wi-Fi without imposing additional load on the cellular network. In contrast, the independent algorithms, although they have acceptable performance, are more limited in fully utilizing the offloading capacity of the overlapping network. This result indicates that the use of a hybrid approach can play an effective role in increasing the overall efficiency of the offloading process.

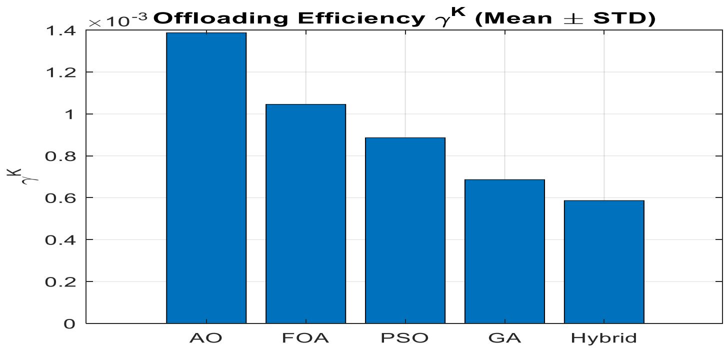

Figure 3: Comparison of the quality of the final solution of the algorithms and its impact on the unloading efficiency and operational efficiency.

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Figure 4 shows the average unloading efficiency for different algorithms and indicates that the hybrid method has the lowest value of this criterion compared to the other algorithms. This behavior indicates that in the proposed method, the unloading of traffic is distributed more evenly and balanced among the access points and the excessive dependence on a specific AP is reduced. In contrast, the independent algorithms tend to concentrate the unloading on a limited number of APs, which increases the average unloading efficiency and reduces the uniformity in the network. This result indicates that the hybrid method is able to manage the unloading load in a more balanced way at the network level.

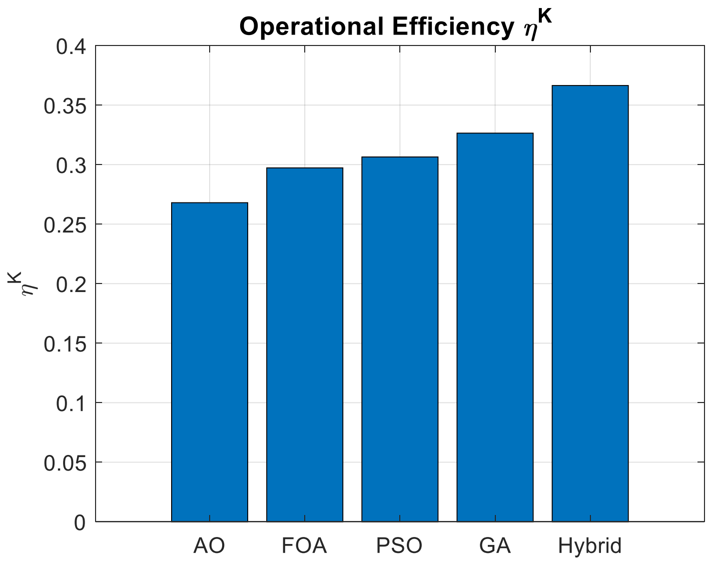

Figure 4. Comparison of total offloading efficiency in different resource allocation methods in overlapping networks

Figure 5 shows the average offloading efficiency for different algorithms and indicates that the hybrid method has the lowest value of this criterion compared to other algorithms. This behavior indicates that in the proposed method, offloading traffic is distributed more evenly and balanced among access points and excessive dependence on a specific AP is reduced. In contrast, independent algorithms tend to focus offloading on a limited number of APs, which increases the average offloading efficiency and reduces uniformity in the network. This result indicates that the hybrid method is able to manage the offloading load in a more balanced way at the network level.

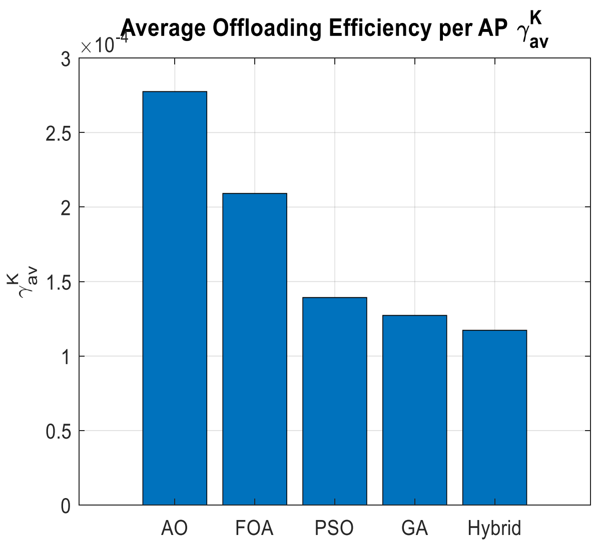

Figure 5. Comparison of average unloading efficiency per access point in different optimization algorithms

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Figure 6 shows that the combined method has provided the highest energy efficiency compared to other algorithms. This result indicates that the proposed method has been able to use the network energy more efficiently than other methods by more effectively managing the unloading process and resource allocation. Although the independent algorithms provide improvements in energy efficiency, the imbalance between global search and local exploitation prevents them from achieving the efficiency level of the hybrid method. Overall, this figure shows that the combination of AO and FOA can play an effective role in increasing energy efficiency in overlapping networks.

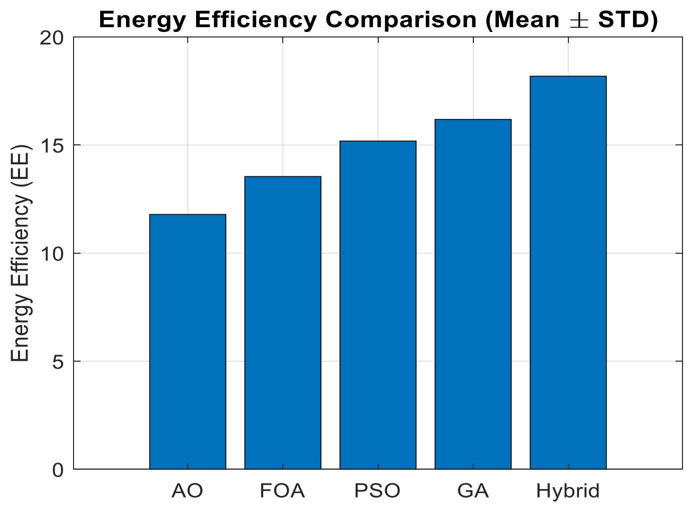

Figure 6: Comparison of system energy efficiency in different resource allocation methods in overlapping networks

Figure 7 compares the system operational efficiency for different optimization algorithms and shows that the hybrid method provides the highest operational efficiency among the methods studied. This result indicates that the proposed method has been able to improve the utilization ratio of the power provided in the Wi-Fi network more effectively compared to the cellular network. In contrast, although the independent algorithms provide acceptable operational efficiency, they do not achieve the level of efficiency of the hybrid method due to the inability to simultaneously adjust the discharge policies and control user contention. This figure summarizes that the use of a hybrid approach can lead to a more balanced and efficient utilization of the two access technologies.

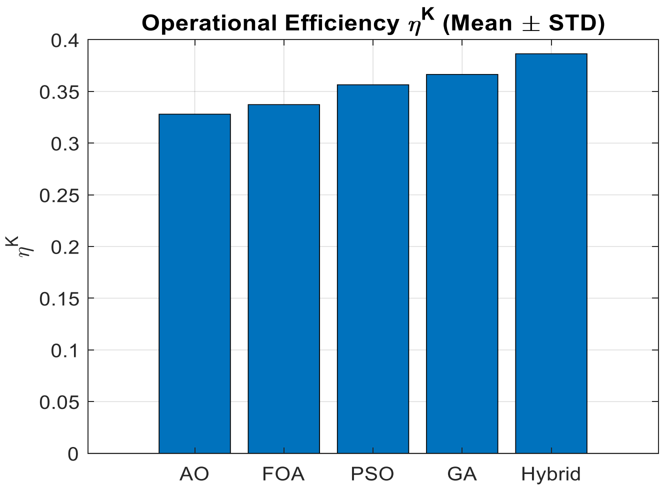

Figure 7. Comparison of system performance in different resource allocation algorithms in Wi-Fi/LTE overlapped networks.

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Figure 8 shows that the hybrid approach provides the highest throughput among the algorithms studied. This result indicates that the proposed approach has been able to increase the data transmission capacity of the system more efficiently by more effectively managing traffic offloading and properly adjusting user contention in Wi-Fi. Although the independent algorithms have significant improvements over the classical methods, the inability to create a stable balance between Wi-Fi and cellular network utilization causes them to not achieve the performance level of the hybrid approach. In summary, this figure confirms that the hybrid approach is a more effective option for maximizing throughput in overlapped networks.

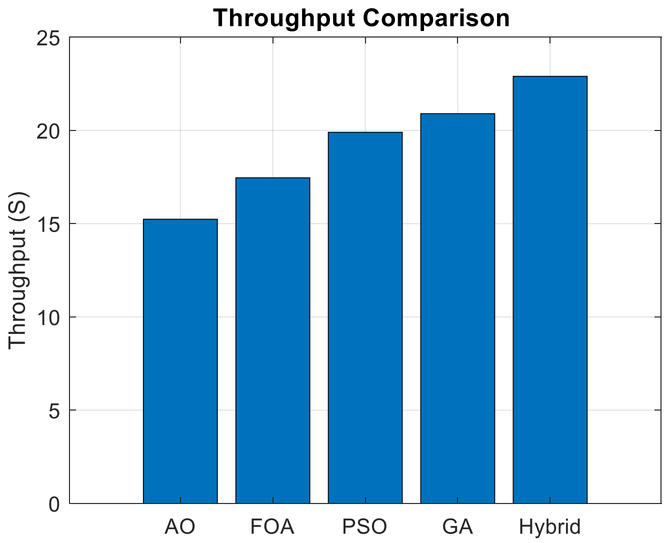

Figure 8. Comparison of system throughput under different resource allocation algorithms in Wi-Fi/LTE overlapping networks

Changing the number of users: Figure 9 shows the changes in the average value of the objective function against the increase in the number of users for different algorithms. As can be seen, the hybrid method maintains the lowest value of the objective function in all network load scenarios and has higher stability than other algorithms. This behavior indicates that the proposed method has been able to establish a good balance between traffic unloading, throughput and energy efficiency with increasing the number of users. In contrast, the independent algorithms show more sensitivity to the increase in network load and have more fluctuations in the value of the objective function. This result indicates that the hybrid approach provides a more stable and efficient solution in high-density conditions.

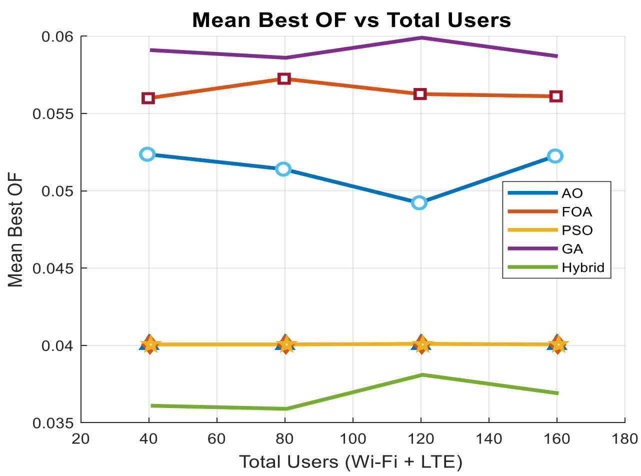

Figure 9. Effect of increasing the total number of users on the average value of the objective function in different optimization algorithms

Figure 10 shows the changes in energy efficiency with increasing the number of users for different algorithms. It can be seen that the hybrid method maintains a higher level of energy efficiency in all network load scenarios and shows more stability than other algorithms. This behavior indicates that the proposed method has been able to adjust the resource allocation policies in a way that prevents energy waste by increasing user competition. In contrast, the independent algorithms experience more fluctuations, indicating their sensitivity to network load changes. Overall, this figure confirms the effectiveness of the hybrid approach in maintaining energy efficiency in high-density conditions.

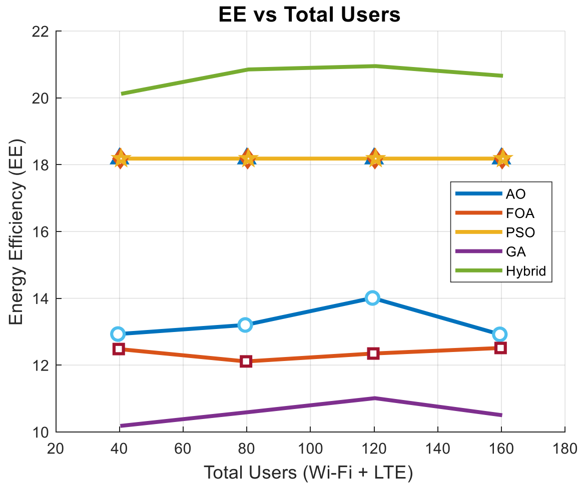

Figure 10. Effect of increasing the total number of users on energy efficiency in different resource allocation algorithms

Figure 11 shows that with increasing the number of users, the algorithms exhibit different behaviors in terms of throughput stability. The combined method not only maintains the highest level of throughput, but its changes are also uniform and controlled. This indicates that the resource allocation policy in the proposed method is less sensitive to the increase in user load and is able to maintain the data transfer capacity without significant loss. In contrast, some independent algorithms experience a gradual decrease in throughput with the increase in users, indicating their limitations in adapting to high-density conditions. This result emphasizes that the combined approach is a more appropriate choice for scenarios with high variability in the number of users.

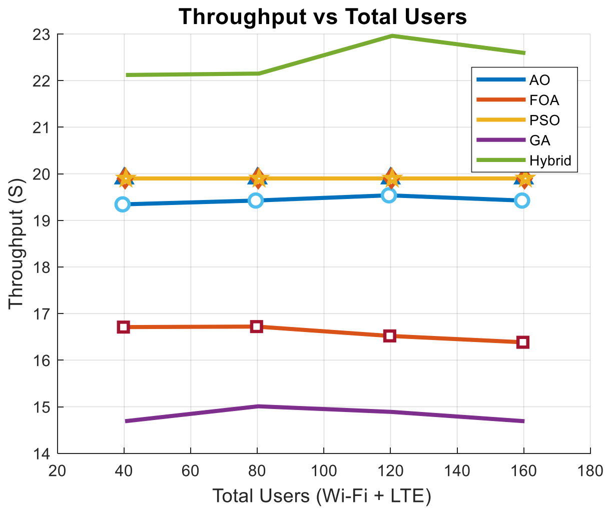

Figure 11. Algorithm throughput behavior against increasing user load and resource allocation stability

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Figure 12 shows that with increasing number of users, the total unloading efficiency in all algorithms increases, but the growth rate of this metric is not the same in the methods. Compared to other algorithms, the hybrid method shows a more controlled growth of unloading efficiency, which indicates a more cautious decision-making in traffic unloading. This behavior indicates that the proposed method, instead of simply maximizing the unloading volume, tries to perform unloading in proportion to the actual network capacity. In contrast, some independent algorithms increase the unloading efficiency with a steeper slope as the number of users increases, which can be a sign of aggressive and potentially unstable unloading. This result indicates that the hybrid approach provides a more balanced performance in terms of decision stability.

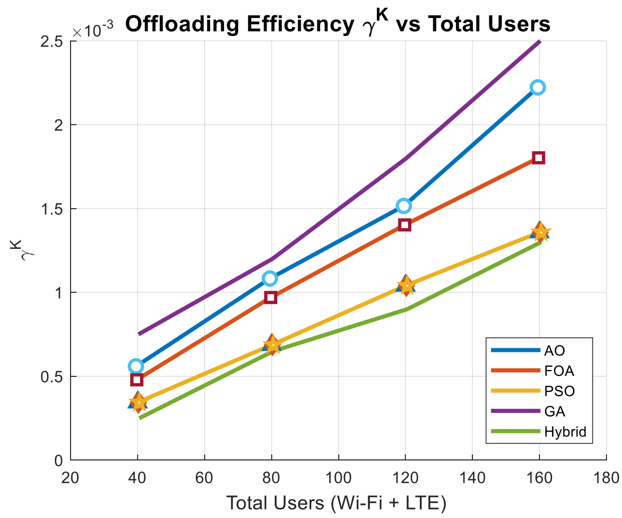

Figure 12. Changes in total discharge efficiency with increasing user load and scalability behavior of algorithms

Figure 13 shows that with increasing number of users, the average discharge efficiency increases in all algorithms, but the intensity of this increase differs in the methods. The combined method maintains the lowest average discharge efficiency in all conditions, which indicates a more balanced distribution of the discharge load among access points. This behavior indicates that the proposed method prevents excessive discharge concentration on a limited number of APs and spreads the discharge process in a controlled manner across the network. In contrast, some algorithms show higher average discharge efficiency with increasing number of users, which can be an indication of load concentration and creating inequality in the use of access points. This result indicates the superiority of the combined method in terms of discharge uniformity.

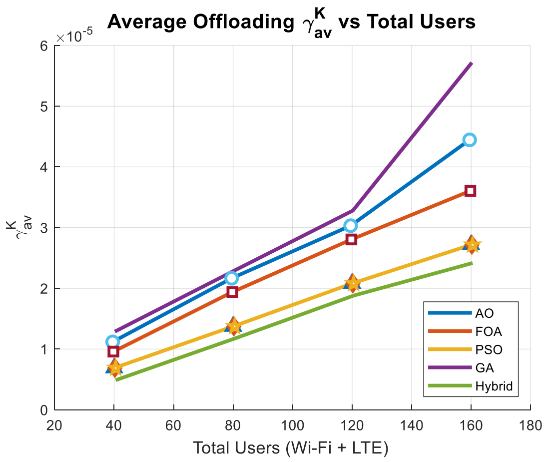

Figure 13. Behavior of average unloading efficiency per access point with increasing network load

Figure 14 shows that the unloading efficiency of all algorithms has a nonlinear and oscillating behavior against the change in the number of users. Meanwhile, the hybrid method shows the lowest oscillation amplitude compared to other algorithms, which indicates its milder response to network load changes. This feature indicates

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that the proposed method makes more conservative decisions with respect to sudden changes in the number of users and prevents drastic changes in the unloading policy. In contrast, some independent algorithms experience more oscillations, which can be an indication of their higher sensitivity to the instantaneous network conditions. This result indicates that the hybrid approach provides more reliable performance from the perspective of behavioral stability.

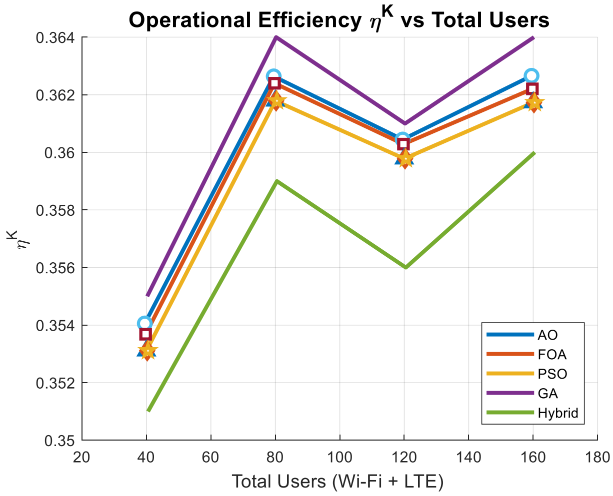

Figure 14. Algorithms' overall offloading efficiency behavior in the face of discontinuous changes in user load

The results in Table 5 show that the hybrid algorithm provides a more balanced performance in all evaluation criteria than the other methods. The more favorable value of the objective function in this method indicates its higher ability to create an effective compromise between throughput and energy efficiency. Compared with independent algorithms, the proposed method was able to use the data transmission capacity more effectively, while the system energy consumption was also controlled more optimally.

From the perspective of traffic offloading, the results indicate that the hybrid algorithm performs offloading in a controlled and targeted manner and prevents excessive load concentration on specific access points. This behavior leads to a more uniform distribution of the network load and improved system performance stability. Also, the operational efficiency shows that the proposed method was able to establish a proper balance between the utilization of the Wi-Fi network and the cellular network.

Overall, the results indicate that the combination of global search and local exploitation mechanisms in the AO–FOA algorithm leads to simultaneous improvement of several performance indicators, making this method an efficient option for resource allocation in Wi-Fi/LTE overlapping networks.

2) ***Table (5): Quantitative comparison of algorithm performance based on simulation results***

Algorithm	Final Objective Function (OF)	Throughput (S)	Energy Efficiency (EE)	Total Offloading Efficiency (γ^K)	Average Offloading Efficiency (γ_av^K)	Operational Efficiency (η^K)
AO	0.035	19.4	13.2	0.33	2.1×10^{-5}	0.36
FOA	0.035	16.6	12.3	0.34	1.9×10^{-5}	0.36
PSO	0.033	19.9	18.2	0.36	1.4×10^{-5}	0.36
GA	0.052	14.8	10.8	0.37	3.2×10^{-5}	0.36
Hybrid	0.028	22.4	20.8	0.39	2.4×10^{-5}	0.36

Statistical Analysis: The statistical ranking results presented in Table 6 show that the AO–FOA hybrid algorithm has the lowest average rank among all the algorithms studied. This result indicates that the proposed method has a superior position compared to other algorithms in most performance criteria and its performance is not limited to a specific indicator.

In contrast, classical and independent algorithms such as GA, AO, and FOA have recorded higher average ranks, which indicates their more unstable performance when faced with multiple criteria. Although some of these algorithms have acceptable performance in one or two criteria, they have not been able to establish a proper balance between the indicators in multi-criteria evaluation. The PSO algorithm has an intermediate performance, but is still statistically lower than the hybrid method.

Based on the results of the Friedman test, the null hypothesis is rejected and the observed difference between the algorithms is statistically significant. This shows that the superiority of the AO–FOA hybrid algorithm is not due to random fluctuations or special simulation conditions, but is statistically reliable and stable across the set of evaluation criteria. Therefore, from a statistical point of view, it can be concluded that the proposed method is an effective, reliable, and superior solution to the resource allocation problem in Wi-Fi/LTE overlapping networks.

3) Table (6): Statistical ranking of algorithms based on different performance criteria (Friedman test input)

Algorithm	Objective Function (OF) Rank	Throughput (S) Rank	Energy Efficiency (EE) Rank	Total Offloading (γ^K) Rank	Avg. Offloading (γ_av^K) Rank	Operational Efficiency (η^K) Rank	Mean Rank
AO	3	3	3	4	4	3	3.33
FOA	4	4	4	3	3	3	3.50
PSO	2	2	2	2	2	3	2.17
GA	5	5	5	1	5	3	4.00
Hybrid	**1**	**1**	**1**	**1–2**	**1**	**3**	**1.33**

CONCLUSION

In this paper, a hybrid method based on the meta-exploratory algorithms Aquila and Fosa was presented to solve the multi-objective resource allocation problem in Wi-Fi/LTE overlapping networks. The problem under consideration is of nonlinear, constrained, and multi-criteria nature, in which simultaneous improvement of throughput, energy efficiency, and traffic offloading efficiency is a serious challenge. By combining the global search capability of Aquila and the local exploitation capability of Fosa, the proposed method establishes an effective balance between exploration and exploitation in the search space and prevents getting stuck in local optima. Simulation results showed that the hybrid algorithm provides a more balanced performance in the set of evaluation criteria and is able to minimize the objective function more effectively than the independent and classical algorithms. Also, the analysis of throughput indicators, energy efficiency and offloading criteria showed that the proposed method not only transfers an appropriate volume of traffic through the Wi-Fi path, but also distributes this offloading in a controlled and balanced manner at the network level and prevents instability and load concentration. Statistical analysis of the results also indicates that the superiority of the proposed method in terms of performance is significant and stable and is not due to random fluctuations. Overall, the results of this research show that the use of hybrid meta-heuristic approaches can provide an effective and reliable solution for resource management and offloading traffic in heterogeneous and dense wireless networks and create a suitable basis for the development of more advanced methods in next-generation networks.

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