Volume 19, Issue 1, 192505 (1-7)

Majlesi Journal of Electrical Engineering (MJEE)

https://doi.org/10.57647/j.mjee.2025.1901.05

Performance improvement of data offloading using Krill herd optimization algorithm

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Original Research

Received:
3 September 2024
Revised:
11 November 2024
Accepted:
5 December 2024
Published online:
1 March 2025

Abstract:

The new pattern of user traffic generation in recent years and the variety of traffic services including data, voice and video have led to a large load in the access of cellular networks. One of the promising solutions in the field of reducing this traffic load is data offloading, which is based on exploiting the unused bandwidth of wireless technologies overlapping with the cellular network. As a widespread technology, Wi-Fi networks have been proposed as a suitable solution for data offloading in cellular networks. Considering the effect of access points (APs) on the performance of Wi-Fi networks, deploying APs can affect the efficiency and cost of Wi-Fi-based data offloading. This issue is the main research part of the current paper. In this paper, an optimization problem is proposed to find the best location for the Wi-Fi APs, providing the maximum performance metric for offloading. Two optimization algorithms are proposed to solve the problem: the Krill Herd Algorithm (KHA) and the Greedy algorithm. The evaluation results indicate that the feature of global optima in the exploration phase of the KHA algorithm leads to finding a better location of the APs than the Greedy algorithm.

Keywords: Offloading; Cellular network; Performance; Deployment

1. Introduction

The number of smart mobile devices (SMD) is increasing exponentially. More than 5 billion people in the world currently use smartphones and there are nearly 11 billion mobile connections. IoT-connected devices will be around 42 billion in 2025, generating 80 zettabytes of data. Internet usage is experiencing a significant growth in coverage and consumption annually. Cisco [1] predicts access to 66% of the world's population. The same reports predict that the number of IP-based devices will triple by 2025. This increase in Internet consumption and the number of connected devices along with the variety of online services on the Internet creates a significant volume of data traffic [2]. Bandwidth limitation in wireless networks is one of the main challenges of this increase in data traffic. Therefore, the bandwidth management of wireless networks seems to be a critical issue, and one of the effective solutions in this field without reducing the quality of service (QoS) is data offloading [3]. With the help of data offloading, mobile operators will be able to provide seamless connectivity while maintaining the quality of service to users by exploiting complementary wireless technologies [4]. In this technique, in the overlapping areas of mobile and complementary wireless technology, the unused bandwidth of the former is exploited by the latter, which leads to improved network performance in the data traffic of cellular networks [5]. One of the complementary wireless technologies is Wi-Fi networks, which are widely established and have significant coverage with cellular networks in urban and domestic areas. In addition, smartphones equipped with Wi-Fi technology, as well as the cheapness of Internet through Wi-Fi compared to mobile Internet, are other advantages of this technology as a complementary wireless technology to mobile networks. It seems that the deployment of access points (APs) is a very important point in data offloading using Wi-Fi networks. The investment and maintenance cost of APs along with their impact on improving various network performance indicators are important issues in network design. The location of AP deployment is effective in improving network service quality. Choosing the right place for the optimal deployment of APs is one of the important activities in strategic planning for the maximum coverage of fifth-generation networks and even higher. Locating APs is a multi-criteria decision-making process, which includes both quantitative and qualitative deployment criteria. Due to the complexity of positioning in fifth-generation networks, traditional positioning methods cannot be used effectively. In this paper, we propose two optimization algorithms: the Krill herd algorithm (KHA) and the Greedy algorithm to find the best location of APs in an offloading scenario. The main contributions of this paper are the following:

1. The problem of Wi-Fi APs in data offloading is proposed in the context of an optimization problem.
2. A new optimization solution method is applied to the problem: Krill herd algorithm (KHA).
3. The comparison of the KHA and existing solution method (Greedy) is performed in different situations of networks.

The rest of the paper is organized as follows: Section 2 presents the related works. A system model based on the Greedy algorithm is described in section 3. In Section 4, an evaluation of the proposed algorithm will be presented. Section 5 concludes the paper and presents the future directions.

2. Related works

According to the research [1], existing systems are classified into small mobile data offloading, Wi-Fi data offloading, opportunistic data offloading, and data offloading in heterogeneous networks. In addition, it takes a complete classification of the technologies dependent on mobile data and examines the merits and disadvantages of different solutions. On the other hand, the authors divide common techniques into two groups based on their obligations to content delivery: delayed, delayed transfer. In addition, they discuss technical and efficient items in each region. In [5] the author analyzes the status of data offloading during work and according to the position. The issue of data offloading in heterogeneous networks is also investigated in [6], in which the authors divide the available techniques into two main groups: strategies based on structure and non-structure. Subsequently, the technical factors are discussed in different situations. The authors [7] have developed a new framework for the mirroring of data on the Internet.
In the study of Lee et al. [8], the mathematical framework for analyzing mobile traffic has been suggested by several data items in a realistic environment for delayable tolerable networks (DTNs). In this study, the authors confirmed that the data was not of the same type or size of the same content. They have also emphasized the design of efficient schemes of offloading, taking into account the various demands and interests of mobile data. According to their research, delayed tolerant networks are limited due to issues such as storage and battery capacity for opportunistic communications. Research analysis or simulations based on actual tracking have been approved for the system performance in human and vehicle environments.
In another study [9], the limits of Wi-Fi capacity have been investigated. This study is based on tracking experiments and simulations and they indicate the efficiency of delayed and non-delayed categories. However, this simulation ignores the impact of network load change and network bandwidth. Although their implementation is specific to the device and the test, it offers a good perspective on offloading. The results have shown that most of the offloading will be delayed and improved by delayed energy efficiency. These simulations have been done for limited and long delays with the time-offloading scheme.
The authors in [10] proposed a reinforcement learning method for cost-effective data simultaneously in terms of cost and energy. However, this implementation is based on the issue of Wi-Fi only from the perspective of mobile users. Exploration methods of multiple mobile users for further implementation remain. Authors have shown that reinforcement-based learning algorithm performs better when the model is unknown. The results have shown that the possibility of completion of the transfer is more aware of the delay. Existing energy and costs are reduced by using dynamic programming-based reinforcement learning implementation.
Zhou et al. in [11] consider the economic dimensions of Wi-Fi-based warranty. Their study has shown the effect of using Wi-Fi for data and multiple pricing-based income dimensions. The authors have used traffic demand parameters and the willingness to pay, the possibility of Wi-Fi connectivity and the relationship with the main station to analyze the results of delayed and without delay. The results are shown with specific device-based databases for optimal economic reflection in implementation. In [12], a mechanism of incentives for optimal mobile traffic is proposed. The main objective of this study is to the balance between traffic congestion and users' satisfaction in delayed tolerant applications in Wi-Fi networks. In addition to the delay tolerance, the potential of users is also intended to design an incentive mechanism. This framework has minimized the cost of incentive distribution using the winning strategy on the mobile network. The authors have also considered reliability, personal rationality, and low-complexity algorithms.
In another study conducted by Hui Yan et al. [13], data was used for the Unmanned Aerial Vehicle (UAV) network of communication and the Internet of Things. In this study, two metrics of fairness and service quality are considered, which are provided using a dynamic and motivational-based optimization framework. The simulation results indicate the superiority of the proposed optimization model in terms of service quality, energy efficiency and throughput.
Nevertheless, none of the existing works considered an efficient APs deployment when dynamic traffic is imposed by the users. In this paper, we employ two optimization algorithms to find the best locations of APs in order to maximize the offloading metric.

3. System model

Consider a cellular network as shown in figure 1 including a cellular BS in the center and a number of cellular users

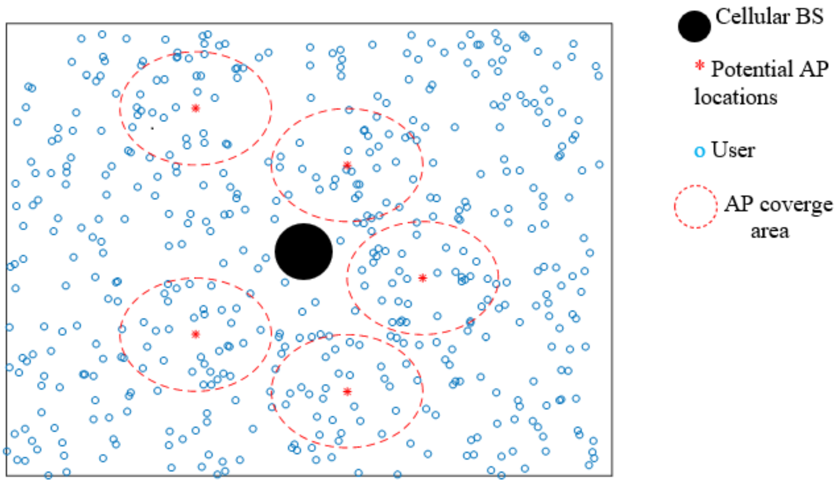


Figure 1. System model.

with the ability to connect Wi-Fi and cellular at the same time. We have N_{ov} users which are located uniformly in the cell. For every user i can provide a random value of traffic t_i ($0 < t_i < 1$). Suppose that n_j number of users under the coverage of one Access Point j (AP_j) and they create a traffic of T_j ($T_j = \sum t_i$) where $1 < j < M$ and M is the maximum number of APs located in the cell area without any overlapping. Now, the problem is how to locate K number of APs. For this purpose, we need to define a metric of offloading. The proposed metric is throughput ratio which is the ratio of average throughput provided for Wi-Fi and cellular users and it can be expressed as:

$$\beta^K = \frac{S_W^K}{S_C^K} \tag{1}$$

Where S_W^K and S_C^K denote the average user Wi-Fi throughput and the average user cellular throughput when K number of APs are deployed and they can be expressed as follows:

$$S_W^K = \frac{\sum_{j=1}^{K} S_{AP_j}}{\sum_{j=1}^{K} n_k^D} \tag{2}$$

$$S_C^K = \frac{S_C}{N_C} = \frac{S_C}{N_{ov} - \sum_{j=1}^{K} n_k^D} \tag{3}$$

Where S_{AP_j} and S_C denote the throughput of AP_j and the cellular bandwidth respectively. To analyze the Wi-Fi throughput of AP_j, we use the Markov chain model in [14] which provides DCF mechanism modeling. In the following of this section, we will apply the optimization algorithm to find the best location of the K number of APs provided the required performance metric.
Moreover, we need a metric to evaluate the performance of offloading mobile data traffic to Wi-Fi access points (APs). The offloading ratio (γ^K) is defined as the ratio of the total offloaded traffic (ω_{offl}) to the total traffic generated without offloading (ω_{ov}). This metric provides a quantitative measure of the effectiveness of a Wi-Fi deployment strategy in reducing cellular network load. It can be expressed as

$$\gamma^K = \frac{\omega_{offl}}{\omega_{ov}} = \frac{\sum_{j=1}^{K} T_j^D}{\sum_{i=1}^{N_{ov}} T_i} \tag{4}$$

3.1 Optimization problem

To achieve the maximum performance of offloading through the Wi-Fi APs' deployment, we need to define an optimization problem according to the metric of Eq. 1. The problem formulation including the objective function and related constraints can be defined as follows:

$$OF = \max(\beta^K) \tag{5}$$

Subject to:

$$|S_C^K - S_W^K| > 0$$

$$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} > R$$
$$i, j = 1 \ldots K (i \neq j)$$

Where x_i, x_j, y_i and y_j are the coordinates of AP_i and AP_j. In the next section, the optimization algorithms for solving the Eq. 14 will be presented.

3.2 Optimisation algorithms

To solve the optimization problem of Eq. 4, we will apply a new optimization algorithm: *Krill herd algorithm (KHA)* [15]. Then, we will compare the results with a basic algorithm (e.g. Greedy algorithm [16]) which is applied to the system model.

3.2.1 Krill herd algorithm (KHA)

This algorithm was introduced as the bio-inspired optimization algorithm to solve optimization problems. In this algorithm, two phases including exploration and exploitation are used for random and local search, respectively. In KHA, the objective function is defined as the distance of food from each krill individual and the highest density of the herd by the three main actions including movement induced by other krill individuals, foraging activity, and random diffusion. Based on this, the Lagrangian model of the Krill herd in the n-dimensional search space will be as follows:

$$\frac{dX-i}{dt} = N_i + F_i + d_i \tag{6}$$

Where N_i is movement induced by other krill individuals, F_i is foraging activity and d_i is random diffusion.
The first section is the movement induced by other krill individuals which is found by the following expression:

$$N_i^{new} = N^{max} \times \alpha_i + \omega_n \times N_i^{old} \tag{7}$$

Where α_i = α_i^{local} + α_i^{target} In these equations, N^{max} is the maximum induced speed, ω_n is the inertia weight of the motion induced in the range [0, 1], $\times N_i^{old}$ is the last motion induced, α_i^{local} is the local effect provided by the neighbors and α_i^{target} is the target direction effect provided by the best krill individual.
To find α_i^{local} the following equations are used:

$$\begin{cases} \alpha_i^{local} = \sum_{j=1}^{NN} X_{ij} \times K_{ij} \\ X_{ij} = \frac{X_j - X_i}{\|X_j - X_i\| + \varepsilon} \\ K_{ij} = \frac{K_i - K_j}{K^{worst} - K^{best}} \end{cases} \tag{8}$$

Where X_i and X_j are the positions for i and j krill, K_i and K_j are the objective function value for i and j krill, K^{worst} and K^{best} are the worst and best value for the objective function and NN is the number of neighborhoods.
To find α_i^{target} the following equations are used:

$$\alpha_i^{target} = C^{best} \times K_{i,best} \times X_{i,best} \tag{9}$$

Where C^{best} is the effective coefficient of the krill individual. The second section is a foraging activity which is found by:

$$F_i = V_f \times \beta_i + \omega_f \times F_i^{old} \tag{10}$$

Where β_i = β_i^{food} + β_i^{best}. In these relations, V_f is the foraging speed, ω_f is the inertia weight of the foraging motion in the range [0, 1], F_i^{old} is the last foraging motion, β_i^{food} is the food attractive and β_i^{best} is the effect of the best fitness of the ith krill so far.
To find β_i^{food} and β_i^{best} the following equations are introduced:

$$\begin{cases} \beta_i^{food} = C^{food} \times K_i^{food} \times X_i^{food} \\ \beta_i^{best} = K_{i,best} \times X_{i,best} \end{cases} \tag{11}$$

Where C^{food} is the food coefficient.
The third section is related to random diffusion. This section is used to avoid local optimum (like mutation in GA). This activity is modeled by:

$$D_i = D^{max} \times (1 - \frac{I}{I_{max}}) \times \delta \tag{12}$$

Where D^{max} is the maximum diffusion, δ is the random directional vector, I and I_{max} are current and maximum iterations.

So, by finding $\frac{dX_i}{dt}$, the current position of krill I means X_i is obtained:

$$X_i(t+\Delta t) = X_i(t) + \Delta t \times \frac{dX_i}{dt} \tag{13}$$

Where,

$$\Delta t = C_t \sum_{j=1}^{NV} (UB_j - LB_j) \tag{14}$$

UB and LB are the upper and lower bounds of variables. Figure 2 indicates the operation of the KHA method when it is applied to the proposed optimization problem. The first step is the initialization of the KHA method using the random numbers. Then the objective function of Eq. 4 is calculated. In the next step, three actions of associated movements are performed. The new positions of the krills are updated according to Eq. 12. After checking the last iteration, the process is finished and the results are measured or it goes to the calculation of Eq. 4 in step 2.

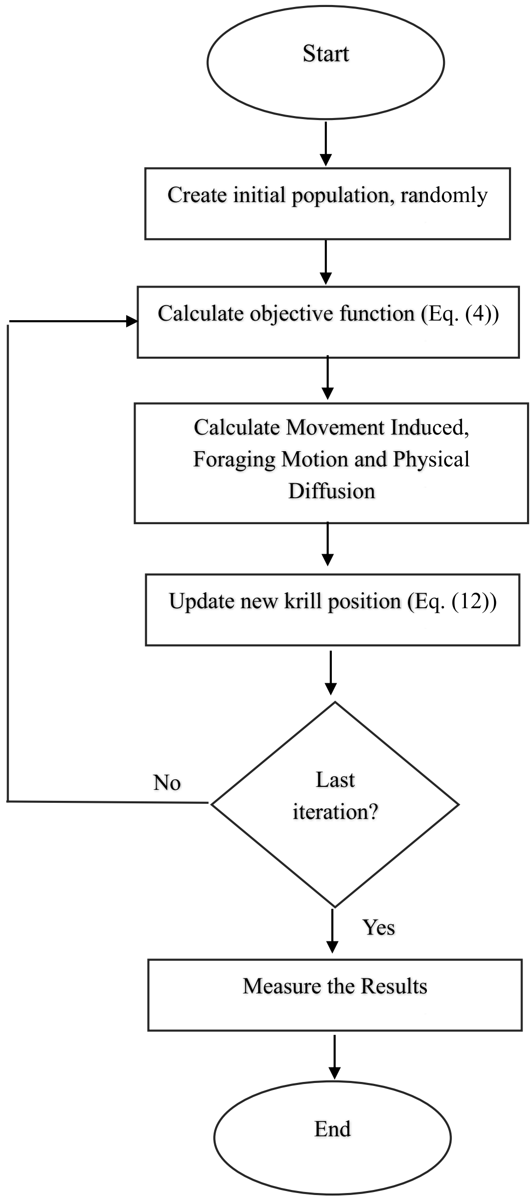


Figure 2. The flowchart of the KHA method.

3.2.2 Greedy algorithm

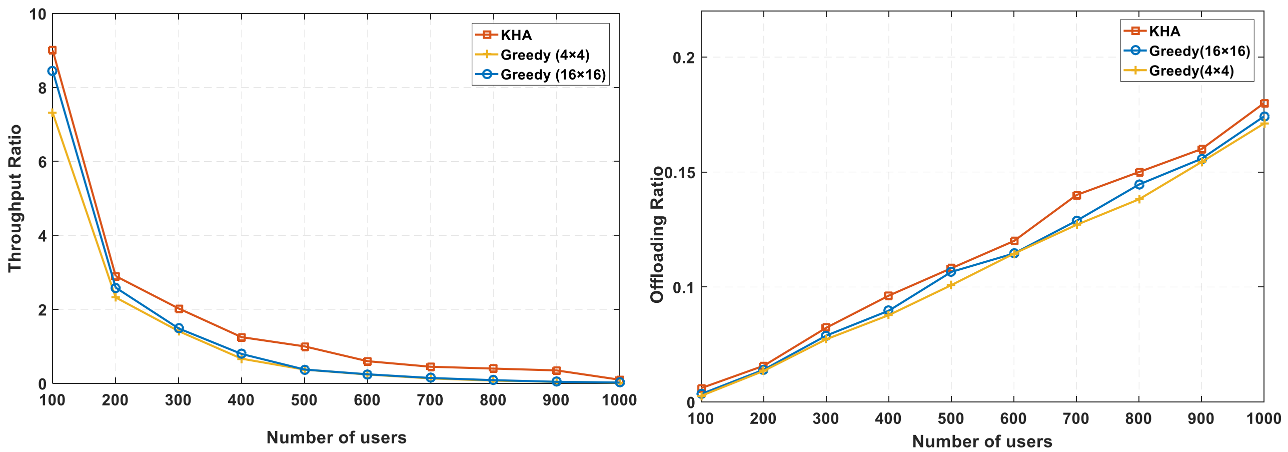
This algorithm was implemented for APs' deployment in an offloading scenario in [17]. In this algorithm, a grid-based greedy approach [16] has been proposed in which the area of the cell is divided to a grid of S×S. The first it calculates the number of users in each grid. Note that according to the coverage range of Wi-Fi APs, two neighbor grids should not overlap together. Therefore, this condition should be satisfied that the distance between two neighbor APs is more than two Wi-Fi coverage ranges. Then, the grids are sorted by the number of users. The first AP is placed in the grid with the most users and this placement continues until the K number of APs are placed. This means that in each new placement, Wi-Fi throughput and cellular throughput are calculated, and as the number of K increases, the ratio between these two throughputs is compared, and the corresponding throughput ratio will be obtained.

4. Evaluation results

In this section, the evaluation of the proposed algorithms for finding the best location of K number of APs. For Wi-Fi networks, IEEE 802.11n standard has been used and LTE is the cellular network. Table 1 summarizes the setting parameters of the simulation required for the Markov chain model in [28] and the LTE parameters. For evaluation, we measure two metrics: 1) Throughput ratio: The ratio of Wi-Fi throughput to cellular throughput; and 2) Offloading ratio: The ratio of Wi-Fi traffic (offloaded) to cellular traffic. In the first scenario, we consider a constant value of APs (K = 3) when the number of users varies from 100 to 1000. Then we apply the KHA and Greedy algorithms. To evaluate the impact of grid dimension, two models of grids are used: 4×4 and 16×16. Figure 3a indicates that the performance of KHA is better than the Greedy algorithms. The reason is the accuracy of KHA in finding the locations with high traffic load. The fixed pattern of grid-based greedy algorithms leads to throughput ratio degradation. However, smaller grids (16×16) can provide higher performance than larger ones (4×4). Generally, the throughput ratio reduces with the increase in user numbers due to higher collisions. This leads to performance degradation in all algorithms. However, the offloading ratio increases with an increase in the user's number (figure 3b). The reason is the larger number of users provides more traffic and consequently more offloaded traffic leading to a higher offloading ratio. The KHA algorithm provides a higher offloading ratio than the Greedy algorithm for different numbers of users due to the higher accuracy of the KHA algorithm in finding the location providing a larger traffic load. Similar to the throughput ratio, a smaller grid size (16×16) can provide a better offloading ratio than a larger grid size (4×4). Since the smaller grid size is capable of finding a more accurate traffic load for placement of the APs.
In the second scenario, the number of users is constant (Nov = 1000) and the algorithms are applied for different num-

Table 1. Setting parameters of Wi-Fi and LTE.

Parameters	Values	Parameters	Values
BS cell radius	1000 m	ACK(µs)	32.23
LTE capacity (Mbps)	56.4	PLCP (µs)	16.67
SIFS (µs)	10	MAC header (bits)	272
DIFS (µs)	28	Single date rate (Mbps)	7.2
RTS (µs)	38.89	CWmin (SlotTime)	15
CTS (µs)	32.23	CWmax (SlotTime)	1023



(a) (b)

Figure 3. The Offloading metrics for 3 APs (K = 3) and different number of users.

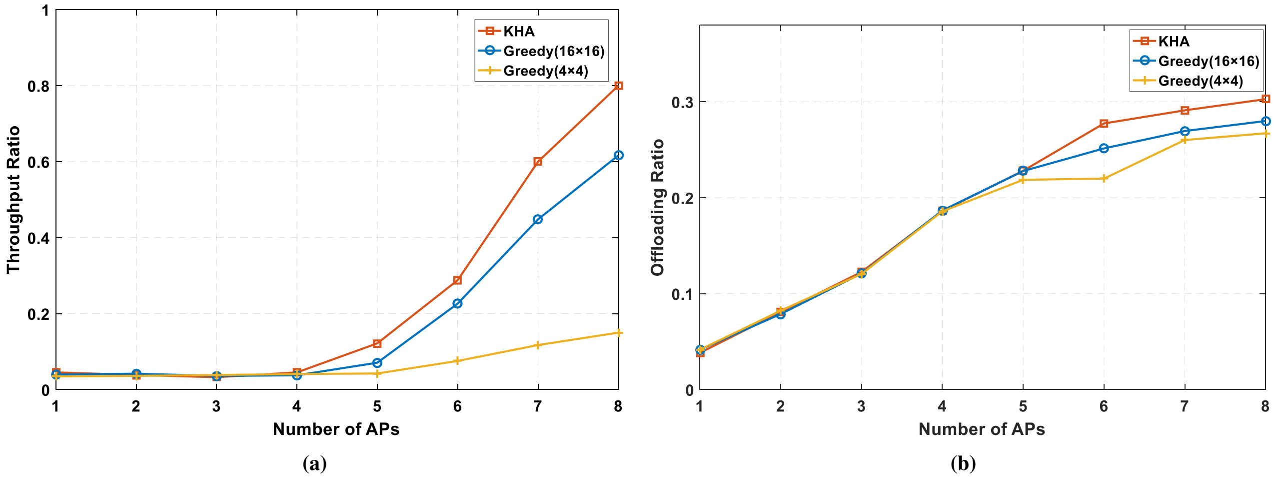


Figure 4. The Offloading metrics for 1000 users and different number of APs.

bers of APs. Figure 4a indicates the throughput ratio when different numbers of APs are employed. The throughput ratio metric of the KHA algorithm is higher than the Greedy algorithm. The KHA algorithm features provide the capability of finding the best locations having the larger traffic load leading to a higher throughput ratio. As the number of APs increases, the performance of KHA in the throughput ratio can be more considerable. For instance, the performance of the throughput ratio is mostly similar when the number of APs is smaller than 5 (K<5). However, the difference between the performance of algorithms is more when the number of AP is greater than 5 (K>5). It means that finding the primary locations (K<5) is similar for all algorithms. However, the algorithm efficiency can be more specified for a greater number of APs (K≥5). In the Greedy algorithm, the small grids provide higher performance in comparison to the large grids. The reason is that more accuracy of smaller grids in finding the best locations. Similarly, the offloading ratio of the KHA algorithm is higher than the Greedy algorithm (figure 4b) and the pattern follows the throughput ratio for different numbers of APs.
The main reason for the superiority of KHA is that the local optima are performed using the exploitation phase (which is similar to the Greedy algorithm) and it also investigates other spaces randomly in the search space (exploration phase), which leads to the global optima.

5. Conclusion

In this paper, we have proposed a KHA algorithm to find the best locations of APs in a Wi-Fi-based data offloading. For this purpose, a single optimization problem for maximizing the throughput ratio was defined and then the proposed algorithm was applied. In order to evaluate the efficiency of the proposed solution to the existing research work, the results of the KHA method are compared to the Greedy algorithm [17]. The evaluation of the KHA method and comparison to the Greedy algorithms are performed based on two metrics: throughput ratio and offloading ratio. The first metric determined the ratio of the average user's throughput in the offloaded part to the cellular part and the second metric measured the ratio of offloaded traffic to the total traffic. The similarity of finding the location with a larger traffic load to the KHA problem (searching for food from each krill) leads to the high efficiency of this algorithm in solving our problem. The evaluation results were performed in two offloading scenarios: 1) constant number of APs (K = 3) and different number of users and 2) Constant number of users (Nov = 1000) and different number of APs. Two metrics of throughput ratio and offloading ratio were measured in these two scenarios. The general pattern in the two scenarios is similar. The throughput ratio of the KHA algorithm is better than the Greedy algorithm due to KHA's capability to find the best location having the largest traffic load. In the Greedy algorithm, the smaller grid size (16×16) provides higher performance metrics in comparison to the larger ones (4×4). Both KHA and Greedy algorithms operate similarly in the phase of exploitation phase leading to local optima. However, the operation of global random searching of KHA (exploration phase) results in a higher performance in comparison to the Greedy algorithm. For future research works, the simultaneous optimization of two parameters, the Wi-Fi to cellular throughput ratio and the offloaded traffic rate can be considered in order to minimize the number of APs.

Authors contributions
All authors have contributed equally to prepare the paper.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflict of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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