Why it does not work? Metaheuristic Task Allocation Approaches In Fog-enabled Internet of Drones

Saeed Javanmardi[a], Georgia Sakellari[b], Mohammad Shojafar[c], Antonio Caruso[a]

[a]*Department of Mathematics and Physics, University of Salento, Lecce, Italy*
[b]*Faculty of Engineering and Science, University of Greenwich, London, United Kingdom*
[c]*Faculty of Engineering and Physical Sciences, University of Surrey, Guildford, England, United Kingdom*

Abstract

Several scenarios that use the Internet of Drones (IoD) networks require a Fog paradigm where the Fog devices provide time-sensitive functionality such as task allocation, scheduling, and resource optimization. Efficient task allocation/scheduling is critical for optimising Fog-enabled Internet of Drones performance. It leads the researchers to devise metaheuristic-based task allocation approaches. While promising in the academic area, metaheuristic algorithms may have limitations in real-time environments due to their high execution time, resource-intensive nature, increased time complexity, and inherent uncertainty in achieving optimal solutions, as supported by empirical studies, case studies, and benchmarking data. In recent years, many articles have employed metaheuristic approaches for task scheduling/allocation in Fog-enabled IoT-based scenarios, focusing on network usage and delay, ignoring execution time. As execution time is a critical factor for the productivity of a task allocation method in time-sensitive Fog-enabled IoT scenarios like IoD scenarios, we target IoD and aim to show how a simple method overcomes state-of-the-art metaheuristic approaches in execution time. To this end, this article proposes a simple and lightweight task allocation method named F-DTA that is used as the fitness function of two metaheuristic approaches: Particle Swarm Optimization (PSO) and The Krill Herd Algorithm (KHA). We keep all the settings the same for a fair evaluation and only focus on the execution time, which is ignored by the other articles. We compare our proposed method by simulation using the iFogSim2 simulator, and the results confirm the superior performance of F-DTA over metaheuristic approaches regarding execution time. The experiments indicate that by varying the number of IoT devices (tasks), and the number of Fog devices (resources), the execution time of F-DTA could be improved by

99%, compared to the metaheuristics.
Keywords: IoT-Fog networks, Fog-enabled Internet of Drones, Task allocation, Metaheuristic algorithms, Execution Time

1. Introduction

The proliferation of connected *things* (e.g., vehicles, drones, and wireless sensors) linked in a collaborative network has resulted in the evolution of Internet of Things (IoT). In such environments, intelligent *things* integrate with their surroundings, sharing data across media to interact with each other [1]. As a result, scientific knowledge managers, administrations, and investigators are working hard to invent approaches allowing widespread IoT deployment to sustain various case studies in multiple scenarios [2]. Drones have become widely used in various applications, including surveillance, object tracking, disaster investigation, and environmental monitoring. The Internet of Drones (IoD) refers to the integration of drones into IoT networks in which drones act as IoT devices [3].

IoD-Fog networks, in which we deploy Fog devices close to drones, make IoD application implementation more suitable for time-sensitive tasks. Fog devices are connected to Fog gateways to store servers at the network's edge and execute time-sensitive drones' requests to reduce execution time. Drones are part of IoD-Fog networks in an operation involving numerous computationally challenging duties. For example, a drone gathers data, renders tasks and allocates their processing to Fog devices for execution at corresponding Fog regions. The processed outcomes are then returned to the drones and delivered to the intended end users [4].

Efficient task allocation is an inseparable part of the IoD-Fog network. While metaheuristic algorithms have played a key role in computational problem-solving, their productivity in IoD-Fog time-sensitive applications is questionable due to high execution time [5, 6]. These algorithms may not be practical in real environments because they are computationally expensive and require many resources. It can lead to poor performance in terms of execution or processing time, which is

Email addresses: saeed.javanmardi@unisalento.it (Saeed Javanmardi), g.sakellari@greenwich.ac.uk (Georgia Sakellari), m.shojafar@surrey.ac.uk (Mohammad Shojafar), antonio.caruso@unisalento.it (Antonio Caruso)

a critical metric in real-time IoD-Fog applications. As the number of tasks and resources increases, the optimization problem becomes more complex, and the algorithms may not find optimal solutions within a reasonable time.

1.1. Motivation

The primary motivation of this research article is to discuss challenges and considerations that limit the practicality of metaheuristic algorithms for Fog-enabled IoT applications like IoD-Fog task allocation. In the context of IoD, a proper task allocation algorithm should minimise execution time. While existing research has explored the use of metaheuristic algorithms, there is a need to reevaluate their practicality in execution time. Using such algorithms is practical in some environments with sufficient computational resources to run the algorithms. In IoT-Fog networks, we may implement these algorithms in Fog gateways with good computational capacities; however, metaheuristic algorithms do not guarantee an optimal answer, and their results may be semi-optimal. In other words, while metaheuristic algorithms have been used for IoT-Fog task allocation in some research studies, they may not be suitable for real-world applications owing to the time complexity (High execution time), uncertainty of real environments, and computational cost.

Metaheuristic algorithms are not inherently designed for time-sensitive applications with strict time constraints. They may require a considerable amount of time to converge to solutions, which is not suitable for applications that demand immediate responses [6, 7, 8]. Accordingly, they often have high execution times, which can be challenging in time-sensitive applications where quick decision-making is crucial. Here, we introduce the F-DTA method and compare it with metaheuristic algorithms such as PSO and KHA. We aim to illustrate why metaheuristic approaches are unsuitable for time-sensitive IoD-Fog applications; instead, a light method with low execution time is more practical.

1.2. Contribution

We devise a fuzzy-based method (F-DTA) that simultaneously uses the characteristics of resources and the drone's tasks. Then, we put it in the fitness function of two well-known metaheuristic approaches (PSO and KHA) to illustrate that heuristic methods are impractical in the time-sensitive real environments for Fog-enabled IoD applications regarding execution time. These contributions can be summarized as follows:

- proposing a lightweight function and employing it in the two metaheuristic approaches' fitness functions, PSO and KHA;
- Comparing PSO and KHA algorithms in respect to their execution times and illustrating why these approaches are impractical for Fog-enabled IoD networks.
- Discussing some challenges in devising, evaluating and implementing metaheuristic approaches in IoD-Fog networks.

This study illustrates the practicality of lightweight methods such as F-DTA in addressing the multifaceted challenges of task allocation in Fog-enabled IoD networks. As a result, we hope that this paper serves as a valuable resource for researchers seeking to advance the practical approaches in IoT-Fog networks.

1.3. Organization

We manage the article as follows: Section 2 studied related literature on Fog-enabled IoT and IoD task allocation employing metaheuristic methods. Section 3 presents an overview of the reference architecture, problem statement, and the F-DTA, PSO, and KHA task allocation approaches. Section 4 examines how the metaheuristic approaches evaluated. Section 5 discusses the challenges related to our work that may pave the way for future research directions. Finally, Section 6 concludes our study.

2. Related works

This section examines the state-of-the-art articles about task allocation in IoT and IoD. As drones act as IoT devices, we explain relevant articles about task allocation in IoT, IoD and UAV.

In our former works, we employed metaheuristic approaches, PSO, MOPSO, and NSGA-III algorithms, for FPFTS [9], FUPE [10], and S-FoS [11] projects for resource management in IoT-Fog networks. In FPFTS, we employed a single objective optimization for resource efficiency, while we used a multi-objective optimization to balance security and resource efficiency in FUPE. Finally, we used NSGA-III for performance optimization in a secure resource management system. Zhang et al. [12] developed a multi-UAV task assignment technique based on a clone selection algorithm in UAV clustering. The authors contended that metaheuristic methods, instead of thoroughly exploring every potential option, can swiftly identify nearly optimal solutions for intricate optimization issues, including multi-UAV job distribution.

A PSO-based algorithm was put forth by Min Deng et al. [13] to address the task assignment issue in dynamic scenarios, including UAVs and digital twins. To increase the effectiveness and diversity of solutions, it integrates metaheuristic initialization, adaptive mutation, and subgroup techniques. Shufang Xu et al. [14] proposed a task allocation algorithm based on the Multi-Discrete Wolf Pack Algorithm (MDWPA) for UAVs. As the authors used MDWPA, their approach can quickly find near-optimal solutions for multi-UAV task allocation in the simulation. Jie Zhu et al. [15] employed NSGA algorithm for the task scheduling in a UAV-enabled Mobile Edge-Computing. They also employed a simulated annealing local search in the crossover operation.

The authors in the article [16] proposed a metaheuristic strategy for IoT-Fog-Cloud networks based on Modified Harris Hawks Optimization (MHHO). This paper aims to improve resource usage in the Fog and Cloud layers while lowering makespan time (for Cloud computing), job execution costs, and power consumption. In multi-UAV-enabled mobile edge computing, Yong Wang et al.'s focus [17] was on optimizing joint deployment and work scheduling for large-scale mobile users. The authors suggest a joint deployment and job scheduling optimization greedy method to reduce mobile users' latency. Schwarzrock et al. [18] developed a Swarm intelligence solution from a generalized assignment problem algorithm to task allocation for multiple UAVs in a decentralized way. Their method scales well under conditions of high task density, making it appropriate for large-scale networks.

2.1. The comparison and the positioning of our work

In our former works, FPFTS, FUPE, and S-FoS [9, 10, 11], we used the simulators (iFogSim, Matlab, and IoTSim-Osmosis), which allowed us to explore and develop our approaches. While, these works are good regarding delay and network usage, they did not present any solutions for execution time.

The optimal solution depends on the algorithm's parameters and the problem's features; the metaheuristic approach article [12] utilized did not guarantee the discovery of the optimal solution. Evaluating the algorithm's performance in the article [13] is ultimately challenging because it needs to provide a thorough comparison with other cutting-edge algorithms regarding performance measures.

Article [14] employed the MDWPA algorithm. In this work, various variables, like the problem's size, the constraints' difficulty, and the quantity of UAVs assigned to the tasks, affect how long MDWPA takes to execute. Consequently, the MDWPA's execution time may hinder its widespread use in real-world settings. Article [15] incorporated a Simulated Annealing algorithm within the NSGA for task scheduling in a UAV-enabled MEC (Multi-access Edge Computing) system. The authors evaluated their approach in Java without considering the network layers and IoT features. Accordingly, the metrics do not include the characteristics of computer networks. Moreover, While this approach may offer advantages in optimizing solutions, utilizing a Simulated Annealing algorithm can lead to extended execution times.

Article [16] presented a hybrid heuristic method and conducted comparisons with other heuristic approaches regarding execution cost and energy consumption. As stated in detail in article [17], metaheuristic techniques have the potential to outperform their greedy algorithm in solving task scheduling problems. But compared to their greedy algorithm, the metaheuristic approach has a much higher computational time complexity. This is because a metaheuristic method uses an iterative process to find the best solution. According to article [18], heuristic techniques often result in tasks not being completed, even when UAVs are equipped with sufficient resources to carry them out.

Even though the articles [17, 18] mentioned the disadvantages of metaheuristic methods in task allocation in IoT, we aim to study the execution time of these approaches in IoD-Fog networks and illustrate why they can not be practical in time-sensitive real-time IoD applications. The primary drawback of the mentioned articles is that they did not emphasize the importance of execution time, which is vital in determining the practicality of any approach, particularly in time-sensitive applications. Metaheuristic algorithms, as noted in the literature [6, 7, 8], often need extended convergence times, making them less suitable for real-time, time-sensitive tasks.

F-DTA, in contrast, places a strong emphasis on minimizing execution time to consider the productivity of the proposed approach. We have designed our approach to meet the requirements of time-sensitive applications through extensive optimisation and efficiency enhancements. As a result, it demonstrates a marked advantage over metaheuristic methods in this critical aspect. By reducing execution time, we address a fundamental issue that can impact our approach's feasibility in real-world settings.

3. Task Allocation Approaches

This section explains the proposed function and the metaheuristic algorithms that employs it in their fitness functions. To that end, we describe the IoD-Fog architecture. Following that, we state the problem the presented approaches addressed, and finally, we explain the fuzzy function and metaheuristic approaches.

3.1. Fog-enabled IoD Architecture

This section explains the reference architecture, which uses a Fog-enabled Internet of Drones to execute tasks via a broker approach. To meet drone requirements for IoD-Fog networks, we use a three-layer architecture as the typical architecture in IoT-Fog networks [9, 19, 20]. In the flying plane (i.e., device layer), a drone (IoT device in IoT) launches to finish an expedition over some device layer Fog regions. The Fog layer comprises a collection of Fog devices at the network's edge. The drones hover above the Fog regions, gather information (e.g., recording voice for audio translation service), and generate several tasks. It then sends them to the Fog gateways to assign them to the Fog devices to use their computing resources. When the drone moves to another Fog region, it repeats the same behaviour as before.

In the reference architecture, in case of overloading in a Fog device, it may offload tasks to the Fog devices inside the Fog region or the distant Cloud data center [21]. We assume infinite computing resources are contained in data centers at the Cloud layer and complete the offloaded tasks. Fig. 1 depicts the architecture the presented scheduling approaches employ. The Fog devices in our scheme are grouped into Fog regions and connected by Fog gateways. Our scheme's

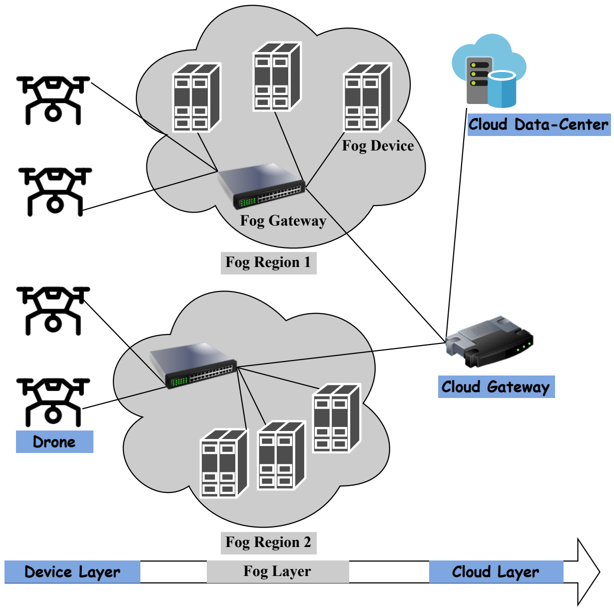


Figure 1: The reference architecture.

task manager is located on the Fog gateway. For task allocation, we use a decentralized broker management strategy [22]. The task scheduler modules are in the Fog gateways, and they assign the drones' tasks to the Fog devices.

By defining this reference architecture, we create a common environment for evaluating the performance of metaheuristic techniques in the complex and dynamic environment of IoT-Fog task allocation within IoD scenarios. In subsequent sections, we will investigate the comparative analysis of these techniques within drone scenarios.

3.2. Problem Statement

The task allocation problem in Fog-enabled IoD aims to assign drone tasks to Fog to enhance resource utilisation. Given a set of drones and Fog devices, the goal is to allocate tasks to Fog devices to minimise execution time. While researchers have made significant progress using metaheuristic algorithms for IoD task allocation in academic areas, their productivity may fade due to high execution time. To illustrate the limitations of metaheuristic approaches, we conducted experiments using the PSO, KHA, and F-DTA methods. We used the F-DTA method in the PSO and KHA fitness functions and kept the settings the same for a fair comparison. The goal is to show that PSO and KHA have much higher execution times than the simple method (F-DTA), making them impractical in time-sensitive IoD applications. In real-world IoT scenarios, the capacity of Fog devices plays a crucial role in ensuring efficient task execution. Real-time and time-sensitive tasks necessitate careful consideration of Fog device limitations. In the following, we define the formal definitions of the problem statement. In the formal definitions, m, k, t_i, f_i, and F_m^k define the number of tasks, the number of Fog devices, task number i, Fog device number i, and the Fog device m that the method selects to run task number k, respectively.

Formal Definitions: Input: Let $T = \{T_1, T_2, \ldots, T_k\}$, and $F = \{F_1, F_2, \ldots, F_m\}$ be set of drones' tasks, and set of Fog devices, respectively, as the input parameters. **Constraints:** Each task must be assigned to one Fog device: $\sum_{j=1}^{m} X_{i,j} = 1,\ \forall i \in \{1, 2, \ldots, k\}$. Besides, let capacity constraint for each Fog device, denoted as C_k, where i represents the index of the Fog device. The total number of tasks assigned to Fog device k should not exceed its capacity: $\sum_{j=1}^{m} X_{i,j} \leq C_k$. **The objective function:** $Minimise\ (\sum_{i=1}^{k} \sum_{j=1}^{m} X_{i,j} \times Execution\ Time(t_i, f_i))$. In the real-time scenarios, we can set a penalty for exceeding the time limitations as follows: $Penalty \times \sum_{i=1}^{k} max(0, \sum_{j=1}^{k})$. Let $C_{i,j}$ be the cost associated with assigning tasks. Accordingly, the objective function in the real-time scenarios considering penalties can be as follows: $Minimise\ ((\sum_{i=1}^{k} \sum_{j=1}^{m} C_{i,j}.X_{i,j}) \times Execution\ Time(t_i, f_i) + Penalty \times \sum_{i=1}^{k} max(0, \sum_{j=1}^{k}))$. It is worth mentioning that recognizing the parallel execution of tasks across different Fog devices is crucial for optimizing real-time response and sensitivity in IoD scenarios. In the objective function, we add a parameter $T_{i,j}$, which indicates that tasks assigned to different Fog devices can run in parallel. As a result, the final objective function, considering time and Fog device capacities constraints and parallelism, is as follows: $Minimise\ ((\sum_{i=1}^{k} \sum_{j=1}^{m} C_{i,j}.X_{i,j}.T_{i,j}) \times Execution\ Time(t_i, f_i) + Penalty \times \sum_{i=1}^{k} max(0, \sum_{j=1}^{k}))$. **Output:** $F = \{F_1^t, F_2^t, \ldots, F_m^k\}$.

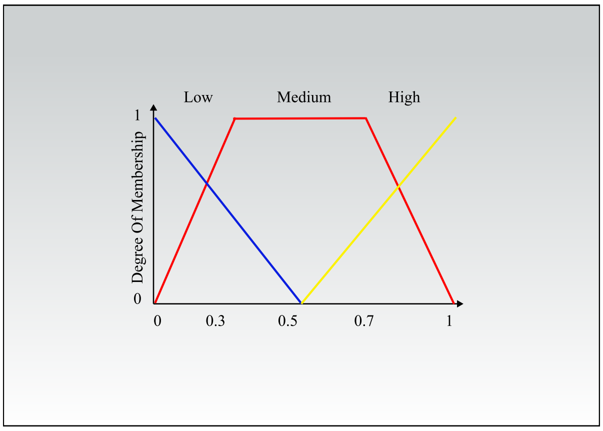
The formal definition should guarantee that the solution obtained by any optimization algorithm is admissible. So, it has to have a constraint in the optimization problem. Accordingly, we define the penalty for exceeding the predefined time and the parallelism to enforce this property. For example, if the allocation produced by the methods is not permissible and the task allocator does not execute the task on time, we set a penalty.

3.3. *Fuzzy-based method (F-DTA):*

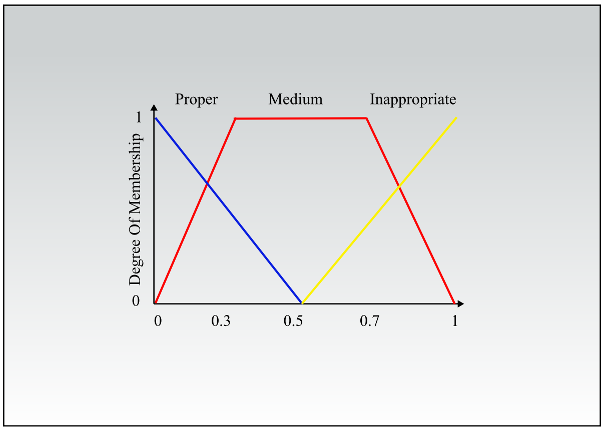
As previously stated, the task manager's role inside the Fog gateways is to allocate the drones' tasks to the most suitable Fog devices. The Fog device assigned to the drones' tasks should minimise execution time. Our proposed method employs a lightweight algorithm to optimise resource utilisation. It is worth mentioning that, like the former works, FPFTS, FUPE, and S-FoS [9, 10, 11], we employed a broker approach for node communications. As we discussed the architecture in section 3.1, the task managers inside the fog gateways receive the drones' tasks and assign them to the most suitable Fog device inside the Fog region. As drones can travel inside the Fog regions, they send new requests to the Fog gateways that are responsible for task allocation inside the newly travelled Fog region. Accordingly, the assigned Fog devices are near the drones.

Resource utilization: IoT-Fog literature demonstrates that efficient task scheduling and allocation can be accomplished by simultaneously considering the resources' computing features and the tasks' CPU requirements [23, 9, 10, 11, 24, 25]. Therefore, we use the CPU requirements of tasks and the available CPU of Fog devices as input values to fuzzy functions to optimize the performance. Mamdani is a popular fuzzy inference engine that employs sets and rules based on prior experience or predefined premises [9, 11]. We create three overlapping fuzzy sets that allocate the input values in multiple sets simultaneously. As a result, each input value is located in at least two fuzzy sets with varying degrees of membership. For instance, consider Fig. 2a. The blue line (low set) goes from (0,1) to (0.5, 0), and the yellow one (high set) goes from (0.5, 0) to (0,1). They overlapped with the medium set in red line. It means the input parameters between 0 and 0.5 are low and medium with two different degrees of membership. For instance, 0.3 is low and medium, with the degree of membership at 0.7. The point of intersection of two overlapped fuzzy sets indicates the degree of membership in the vertical axis.

For mindful readers, the question may arise that our proposed method is incomplete, as this would mean disregarding all aspects concerning the actual deployment of the tasks once they have been allocated and the delay and network usage. The contribution of this article is to focus on execution time and ignore delay, latency, energy consumption, and network delay to show the disadvantages of classic metaheuristic methods. As we used a simple Mamdani fuzzy function, we can add more input parameters, such as link bandwidth, nodes' energy consumption or other criteria, proposing a modified version of the proposed approach.



(a) Input parameters for fuzzy function.



(b) Output parameter for fuzzy function.

Figure 2: Fuzzy sets

The fuzzy sets for the parameters above and the result parameter are as follows:

- $\underline{Task}$: $\in$ {Low; Medium; High}
- $\underline{Fog\ Device}$: $\in$ {Low; Medium; High}
- $\underline{Result}$: $\in$ {Proper; Medium; Inappropriate}

We use *Task* and *Fog Device* in the above fuzzy sets to represent the tasks' CPU requirement and the Fog devices' available CPU, respectively. Moreover, the fuzzy rules and fuzzy sets used in the fuzzy function are shown in Tab. 1 and Fig. 2. In this work, we define nine fuzzy rules and based on the input values, some are fired. The input values for both input fuzzy sets must be within the specified range for triggering the fuzzy rule. The centroid approach builds a non-fuzzy value as the outcome of the fuzzy function in the aggregation step using all of the values of the fired rules. A non-fuzzy number is the outcome of the fuzzy function, a number between zero and one. The task manager assigns the task to the fog device that has the higher value. In our former work, S-FoS [11], we discussed the difference between the triangle fuzzy functions and the isosceles trapezoid fuzzy functions. Accordingly, with the lessons we learned from FPFTS and S-FoS projects, we implemented an isosceles trapezoid fuzzy function. Besides, we explained how the fuzzy function obtained the results in the FUPE project by some numerical examples [10]. Moreover, we discussed defining the fuzzy settings and fuzzy rules in the FPFTS and S-FoS projects [9, 11].

Table 1: Fuzzy rules.

Rule number	Tasks' CPU need	Fog devices' available CPU	Result
1	Low	Low	Proper
2	Low	Medium	Medium
3	Low	High	Inappropriate
4	Medium	Low	Medium
5	Medium	Medium	Proper
6	Medium	High	Medium
7	High	Low	Inappropriate
8	High	Medium	Medium
9	High	High	Proper

Mamdani fuzzy inference consists of five stages: fuzzification of the input variables, carrying out fuzzy operations and fuzzy reasoning, carrying out fuzzy inferences, aggregation of the fired rules and defuzzification of the results. It uses Tab. 1 and Figure 2 in all the mentioned five steps to obtain the output non-fuzzy number. As the scope of our article does not discuss the details of fuzzy logic, we refer enthusiastic readers to the S-FoS article [11] for more information about how the Mamdani fuzzy inference engine works. Alg. 1 indicates the algorithm of F-DTA method for IoD task allocation. In the algorithm, NF, NT, F, T, t, f, R_i^j, and *Best Fog device for Task* are integers. Moreover, we use array for $PP[t]$, $PP[f]$, $T[i]$, and $F[j]$. Besides, we use the Two-Dimensional array for $P[i][j]$. Finally, $PP[t]$, $PP[f]$, $T[i]$, $F[j]$, and $P[i][j]$ are the available CPU of the current Fog device, CPU need for the current task, current task, current Fog device, and the result of the fuzzy engine for current Task and Fog device.

How to use F-DTA method for Task allocation: We have a set of drone tasks and a set of Fog devices. When assigning a task to a Fog device, we run F-DTA for the task and each Fog devices

Algorithm 1 F-DTA

INPUT: F, T, f, t

NF: `Number of Fog devices`

NT: `Number of Tasks`

F: `Fog device`

T: `Task`

t: `Fog devices’ available CPU`

f: `Tasks’ CPU need`

OUTPUT: $Best\ Fog\ device\ for\ Task$

Define isosceles trapezoid fuzzy function as the membership function
Define the rules for the fuzzy inference system
Define the centroid method as defuzzification to obtain the crisp output value.
for $i = 1$ to NT **do**
    for $j = 1$ to NF **do**
        Use the fuzzy inference system to determine the value of $P[i][j]$ based on $PP[t]$ and $PP[f]$
        Assign $T[i]$ to the $F[j]$ with the highest value of $P[i][j]$ and put it in the R_i^j
        $Best\ Fog\ device\ for\ Task = R_i^j$
    end for
end for
if Execution time ≥ Predefined time **then**
    Give the user a penalty
end if
return $Best\ Fog\ device\ for\ Task$

to find the most proper one. We assign a Fog device to the task with the highest number, similar to the previous work, FPFTS [9]. Finally, as we aim to illustrate a simple, lightweight approach that considers the features of tasks and the resources much more practical and has less execution time than metaheuristic approaches such as PSO and KHA, we employed the F-DTA method in the PSO and KHA fitness functions.

3.4. Metaheuristic Approaches

In the literature, researchers have employed metaheuristic approaches such as NSGA [26], PSO [27], Firework algorithm (FWA) [28], Whale optimization algorithm (WOA) [29], Bee life algorithm (BLA) [30], Harmony Search (HS) [31], and Tabu Search (TS) [32] for IoT applications. PSO is one of the most acceptable ones, and KHA is almost the newest one that reduced the iterations, so we chose them as the employed metaheuristic ones.

Particle Swarm Optimization (PSO): PSO is a popular optimization algorithm inspired by the collective behaviour of birds. In a PSO algorithm, a population of potential solutions, known as ”particles,” explores a solution space in search of the optimal solution. Each particle represents a potential solution and adjusts its position based on its own experience and the experiences of its neighbouring particles [33]. The algorithm refines the particle positions by moving them towards the best solutions found so far. This process employs how a flock of birds cooperatively adapts to find the most suitable direction. While PSO is a popular optimization algorithm with various applications, its suitability for online, real-time, and time-sensitive tasks is limited due to its inherent characteristics and computational needs.

Krill Herd Algorithm (KHA): KHA is a bio-inspired optimization algorithm inspired by the collective behaviour of krill, small marine crustaceans. KHA is a population-based optimization technique that simulates krill's social interactions and movements in search of optimal solutions. In KHA, each potential solution is represented as a krill, and these individuals collectively explore the solution space by adjusting their positions. Krill update their positions based on various factors, including their experience and other neighbouring krill's influence [34]. The algorithm aims to improve the quality of solutions over time by employing the swarming behaviour of krill, where individuals cooperate to find more suitable solutions. KHA offers certain advantages over PSO.

One key advantage is KHA's ability to adapt to dynamic and complex solution spaces. KHA's collective behaviour, inspired by krill swarming, allows it to better handle problems with varying environments. Additionally, KHA often requires fewer tuning parameters than PSO, making it more suitable for practical applications.

PSO and KHA fitness functions: In the PSO and KHA algorithms, the fitness function is a crucial component that determines the suitability of a Fog device to run the drone's tasks. The primary purpose of the fitness function is to evaluate how well a particular Fog device satisfies the optimization objectives and constraints. As our aim is to study the execution time of the metaheuristic algorithms, we used the proposed F-DTA method in their fitness function to have a fair comparison. We refer the enthusiastic readers to read the article [35] for more information about the Metaheuristic algorithms and fitness functions.

4. Performance Evaluation

In this section, we clarify the evaluations we performed to assess the performance of the approaches. The performance evaluation depicts the impact of devising a task manager that considers resource utilization by employing metaheuristic techniques and a simple method (i.e., F-DTA). To implement our approach, we used iFogSim2 [36], a java-based simulator built on the CloudSim framework. We use this simulator because it supports mobility and clustering and is quite acceptable for task allocation approaches for Fog-enabled IoT applications. Moreover, it integrates real-world datasets into the simulation.

4.1. Simulation Setup

We used the EUA dataset of iFogSim2 for the simulation environment because it supports mobility of the drones. We also used XFuzzy tool [37] to define the fuzzy rules and fuzzy sets. We employed six Fog gateways spread across six Fog regions. Besides, we used a broker approach and put the algorithms in the Fog gateways. The Fog gateways are the broker between the drones (things in the IoT) and the Fog devices in the Fog regions. Drones have a path, and the simulation will allow them to create several tasks at random points so they offload to the region brokers, and finally, Fog gateways assign them to the Fog devices. The scenarios that are actually running in the simulation contain drones flying to multiple Fog regions and also the simulation grid if formed by multiple Fog devices. We used *random_usersLocation_melbCBD_1.csv*, which contains the drone's mobility traces and represents the drone's path during the simulation and *edgeResources-melbCBD.csv* for fog layer's nodes configurations.

We used the particular features of the scenarios listed in Tab. 2 in order to simulate the methods. As we don't use Fog device to cloud data-centre data offloading in our simulation, we put zero for its features in the table. The simulation setup that we employ for evaluation is shown in this table. It displays the CPU, RAM, and bandwidth capacities. The computational capability and bandwidth (i.e., the amount of CPU, RAM, and bandwidth) of the cloud data centre and Fog devices are displayed. The flows show how much RAM, CPU, and bandwidth they require to run. We use the iFogSim2 entities to implement this functionality. Furthermore, we fixed the range of fuzzy sets for the security portion of our proposed task manager between zero and one. Next, we took the information out of the EUA dataset and divided it by the maximum value to normalise it. As a result, the fuzzy algorithm's actual value range falls between zero and one. After that, we defined the fuzzy sets and fuzzy rules using XFuzzy. Finally, we assessed the approaches using the iFogSim2.

Table 2: Entity Requirements.

Requirements	**Cloud**	**Fog device**	**Task**
RAM	0	40 GB	10 GB
CPU	0	44800 Mips	200 MIPS
Bandwidth	0	200 Mbps	100 Mbps

4.1.1. Simulation Metrics

- <u>Execution time:</u> It is the primary metric for the evaluation of a task management approach. It is the time a task management unit takes to complete a task once it has received a request. It includes processing time but not the time for the response to travel back to the drone. For the execution time, we should consider the optimisation result (the execution time of the tasks on the Fog devices) and the time it takes to execute the optimisation itself. In our experiments, we considered both of them. But, it is worth mentioning that we kept all the settings the same for all three methods. We used a star topology, and the distance between the Fog devices and the Fog gateways and their configurations (links and Fog devices) are the same; the differences between the execution times for the three algorithms are mainly due to the second one.

4.1.2. Implementation scenarios

Metaheuristic approaches require a ready workload to choose the best answer among the many answers for the various drones. In the real environment, we cannot wait to have a huge workload. We should assign the most available and proper fog device to the request. That is why some real-world IoT applications still use First-Come-First-Serve (FCFS) scheduling algorithms. For instance, article [38] uses FCFS priority scheduling to detect and allocate empty parking spaces in a real-time manner. We implement a small network scale. The main reason is that we want to show that metaheuristic approaches don't have any merits when the size of the network is small or when we don't have a ready huge workload. Over the following various drones, and Fog devices scenarios, we compare our proposed approach to PSO and KHA approaches:

- Scenario-1: Comparing approaches based on various number of drones: The number of Fog devices in this scenario is 12 in 6 Fog regions. We vary the number of drones to adjust the number of tasks (requests) to study the effects of the number of requesters on PSO and KHA and compare the execution time with the F-DTA method we use in their fitness functions.

- Scenario-2: Comparing approaches based on various number of Fog devices: The number of drones in this scenario is one with ten tasks. This scenario aims to illustrate the effects of the number of Fog devices on PSO and KHA and compare the execution time with the F-DTA method that we use in their fitness functions.

4.2. Evaluation Results

This section shows the implementation results for the metaheuristic approaches and the F-DTA method. As this research aims to illustrate that metaheuristics are unsuitable for time-sensitive Fog-enabled IoD applications, we keep the settings the same for the three approaches. We used the F-DTA method in the PSO and KHA fitness functions. We just show the result of the execution time and discuss the network utilization and delay, stating that their results are sufficient for our research report.

First, we discuss the evaluation for the first scenario, comparing approaches based on various numbers of drones. In this scenario, we have 12 Fog devices, and we test the result of the methods by varying the drone numbers from 1 to 11. Table 3 summarizes the execution time of the F-DTA, PSO, and KHA methods. As they illustrate, there is a clear upward trend in execution time across all methods. There are more requests than there are drones, which means that the task management should distribute more work to the Fog devices.

The significantly lower execution time of the F-DTA method in the context of IoD task allocation is due to its simplicity. F-DTA, as a custom-designed method, likely involves straightforward calculations and minimal data processing, making it faster to evaluate. On the other hand, the KHA and PSO have more execution time. However, KHA showcases a lower execution time than PSO due to using the K-means algorithm. KHA is a nature-inspired optimization algorithm that emphasizes a more streamlined approach to population movement, often leading to quicker convergence towards a solution. In contrast, PSO involves more complicated mechanisms for particle update, global best position tracking, and computational overhead, contributing to a relatively longer execution time [39].

Table 3: Execution Time (Seconds).

Number of Drones' Tasks	F-DTA approach	PSO approach	KHA approach
30	0.82	1402	720
50	1.36	2039	1102
70	1.53	3807	1613
90	2.05	4234	1956
110	2.38	4944	2408
150	2.98	5450	2717
200	4.18	6031	3119

As we observed from simulation, The *network usage* of the three approaches was the same. The reason is that the network usage is primarily determined by the communication requirements of the tasks and the data transfer between the Fog gateways and the drones. All three approaches allocate the same tasks to the same Fog device (due to using F-DTA method in the PSO and KHA fitness functions), resulting in similar network usage across these approaches. In other words, the allocation of tasks to drones is the same, so the network usage, which depends on these task assignments, remains unchanged. Moreover, when we have more drone tasks, the links should transfer more data, and accordingly, we see an increase in network usage.

Finally, we discuss the evaluation for the second scenario, comparing approaches based on various numbers of Fog devices. In this scenario, we have a drone with ten tasks, and we test the result of the methods by varying the Fog device numbers from 18 to 180. Table 4 summarizes the execution time of the F-DTA, PSO, and KHA methods.

Table 4: Execution Time (Seconds).

Number of Fog Devices	F-DTA approach	PSO approach	KHA approach
18	0.96	908	414
36	1.15	1696	857
60	1.69	2224	1060
90	2.37	3731	1544
120	2.60	3980	2244
150	3.50	6002	2702
180	4.45	7736	3074

Some notable results emerged when we employed the F-DTA, PSO, and KHA methods with varying numbers of Fog devices. As the number of Fog devices increases from 18 to 180, the execution time for all three methods experiences an increase. The main reason is that, as the algorithms should consider more resources, it takes more time to select the proper one. However, comparing the execution times reveals that F-DTA consistently outperforms PSO and KHA across all scenarios. F-DTA exhibits significantly shorter execution times. In contrast, PSO and

KHA, while effective optimization methods show notably longer execution times. This outcome indicates the advantage of using the F-DTA method for IoT task allocation, as it consistently provides quicker results even as the scale of the problem increases, making it a valuable choice for time-sensitive and resource-constrained IoD-Fog environments.

In the evaluation scenario where the F-DTA, PSO, and KHA methods are employed for drone task allocation with varying numbers of Fog devices distributed across six Fog regions, a consistency emerges regarding *network usage*. Despite the increase in Fog devices, ranging from 18 to 180 across these regions, the network usage for all three methods remained constant. This result indicates that when we have very few requests (IoD tasks) when assigning to the resources (Fog devices), adding the Fog devices does not affect the network utilization. The reason is that we have six Fog regions, and each of them has a Fog gateway. We use the broker approach, and the instances of the algorithms are in the Fog gateways. More importantly, we used a star topology and the distance between the Fog devices, and the Fog gateways and their configurations (links and Fog devices) are the same. As a result, network usage remains the same.

In our experimental results, we evaluated execution time and discussed network usage. As the result of the *delay* in a common simulator could be far from reality in the real-world, we did not assess it. The main reason is that the simulators simplify real-world requirements such as processing delay, transmission delay, propagation delay, queuing delay, sensing delay, task queuing delay, task execution delay, and load balancing delay to make them computationally feasible. These simplifications can lead to a significant difference between the simulation results and the real-world results. In the discussion section 5.1, we discuss the problems of obtaining delay in common simulators. Still, to pave the way for the other researchers, we anticipate that the outcomes of the three approaches are almost the same in terms of delay. We anticipate delay remains nearly identical across the three methods, despite variations in execution times. The reason why we anticipate equivalent delays across these methods is due to employing F-DTA in the PSO and KHA fitness functions [40].

Time complexity: We use metaheuristics if the problem is so complex that precise optimization takes too much time. It is usually proved by showing that the problem is NP-HARD. If the problem is simpler and an efficient polynomial solution exists, metaheuristics are unmotivated. For the time-sensitive Fog-enabled IoD applications, the time complexity should be very low, and Fog gateways don't have enough capacity to run metaheuristics. The task manager should assign the tasks to the most available Fog device, and can not wait to gather a huge amount of tasks, and then repeat the iterations and find the best Fog device. Accordingly, their practicality fades away in real scenarios. As the primary goal of our article is to show the execution time of the mentioned algorithms, to wrap up this section, we discuss the time complexity of the PSO, KHA, and F-DTA methods. The time complexity of a Mamdani fuzzy method is $O(1)$ due to performing all the steps in a parallel manner [41]. But as the F-DTA assigns each task to a Fog device, the complexity is linear with the number of tasks. As the result, the complexity of F-DTA for optimization is $O(T)$. The time complexity of the PSO and KHA methods are $O(I \times P \times F)$, where I, P, and F are the number of iterations, the population size (i.e., number of Fog devices), and fitness function, respectively. As the employed PSO and KHA methods used F-DTA as the fitness function, the complexity of their fitness function is in order of $O(T)$. As a result, the time complexity of the PSO and KHA methods are $O(I \times P \times T)$.

5. Discussion

In this section, we discuss some challenges in devising, evaluating and implementing metaheuristic approaches in IoD-Fog networks that inspire researchers and pave the way for future research directions for developing practical IoD applications.

5.1. The limitations of IoT simulators:

In our study, the utilization of metaheuristic methods for IoD-Fog task allocation was explored, and we encountered particular challenges inherent in using common simulators focusing on execution time. We acknowledge that, at times, the choice of simulator is constrained, and in our case, we opted for a Java-based simulator. However, it is imperative to highlight that the results obtained from such simulators may not truly mirror real-world scenarios, thus potentially impacting the validity of our proposed approach [42]. The unreliability of common IoT simulators can be attributed to several factors. Firstly, these simulators often need the incorporation of essential IoT features and network layers, which makes it challenging to replicate the characteristics of real-world settings. Additionally, the parameters used in these simulators are frequently based on assumptions and approximations, potentially failing to capture the nuanced conditions of the network accurately [43].

To take an example, consider the delay metric. Many elements that are difficult to accurately model in a simulator, such as packet loss, and network congestion, affect the delay parameter. common simulators frequently obtain delay based on approximations and assumptions that may not accurately represent the actual conditions of the network. Besides, the simulators do not consider the computation delay of a Fog gateway, but in reality, it tends to be far different due to caching in processors. In a nutshell, the absence of network layers, network-level features, and the simplified IoT and network models in the simulator significantly limits its ability to model and evaluate delays in real-world scenarios accurately. The simulator's architecture does not capture the characteristics of communication protocols and networking dynamics, which are critical factors in determining the delay in IoT task allocation.

5.2. IoD simulators:

In addition to the commonly used simulators, there are several simulation tools, namely IoD-Sim, AirSim, Gazebo, and RealFlight's drone simulator. These simulators do not have abilities to implement task allocation approaches and evaluate drone task allocation metrics, as their primary purpose is to simulate drone movement and interactions within an environment. For instance, IoD-Sim creates realistic simulations of the UAV by extending the features of ns-3 to cover various aspects of IoD, including mission design, trajectory planning, hardware and application configuration, mobile wireless communication, and energy consumption models [44, 45]. A well-liked simulator for testing and simulating robotic systems, including drones, is the Gazebo. Gazebo, however, is primarily concerned with mimicking automated systems' sensors and physical components. It is particularly good at simulating drone dynamics, sensor data, and environmental interactions [46].

5.3. *The productivity of IoD task allocation approaches:*

Metaheuristic approaches such as PSO and KHA have been widely explored and refined by researchers seeking to optimize task allocation in IoT applications. However, their practical productivity often needs to improve when applied to time-sensitive applications. Although they may yield excellent solutions in controlled, non-real-time environments, the time required for these methods to converge can be prohibitive in time-sensitive scenarios such as drone operations. Consequently, the high execution time of metaheuristic approaches can significantly hinder their productivity and practical utility in time-sensitive IoD applications.

5.4. *Challenges in Bridging Academic Theory and Practical Productivity:*

This academic research helps build a foundation of knowledge that can eventually lead to more practical and efficient solutions. Although metaheuristic approaches may not be immediately suitable for time-sensitive Fog-enabled IoD applications because of their high execution time, research in academia serves as a stepping stone for future work. The theoretical insights gained from studying metaheuristics can inform the development of hybrid methods or improved algorithms that better balance theoretical considerations and practical applications. While these approaches might not have direct productivity in real-world applications, they contribute to the academic area, enabling a deeper understanding of optimization methods and inspiring further innovation that may eventually bridge the gap between academic theory and practical productivity in time-sensitive IoD applications, such as drone operations.

6. Conclusions and future directions

Practical work allocation and scheduling are essential for achieving optimal performance in the fog-enabled Internet of Drones. Numerous researchers have developed metaheuristic-based task allocation techniques. Empirical studies, case studies, and benchmarking data support the notion that metaheuristic algorithms while promising in the academic realm, may have limitations in real-time environments because of their high execution times, resource-intensive nature, increased temporal complexity, and inherent uncertainty in reaching optimal solutions. This paper presented the F-DTA, a lightweight and straightforward task allocation method that serves as the fitness function for two metaheuristic methods: the Krill Herd Algorithm (KHA) and Particle Swarm Optimisation (PSO). We used the iFogSim2 simulator to simulate our suggested methodology, and the findings validate that F-DTA performs better than metaheuristic methods in terms of execution time. From a research perspective, as our goal is to point out the possible directions of future research, the modified versions of the classical metaheuristic approaches may reduce the iterations and time complexity, such as enhancing the intensification and diversification mechanisms.

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