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Research article

Optimal data transmission for decentralized IoT and WSN based on Type-2 Fuzzy Harris Hawks Optimization

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ABSTRACT

Due to the widespread availability of services and smart devices, the decentralized internet of things and wireless sensor network-based systems (DIoT and WSN) have drawn the attention of academics and researchers and are still under constant development. Many challenges face the DIoT and WSN networks and need to be solved. The main issue among these challenges is reducing energy consumption in order to increase network lifetime. Energy-efficient routing protocols and the clustering method are the best solutions to this problem. In this paper, Type-2 Fuzzy Harris Hawks Optimization (T2FHHO) is used to choose the best path (route) from the source (cluster head (CH)) to the destination nodes (base station (BS)). Along with this, we propose a new fitness function to find the next hop based on residual energy, distance, traffic, and buffer size. Then, we apply the T2FHHO method to get the best CH. This protocol seeks to increase the long-term reward earned by each node. The best path in terms of the minimum cost obtained using the proposed method is found. The two main contributions of this study are as follows: firstly, we present a new efficient routing approach that minimizes costs and maximizes efficiency. Secondly, we apply the T2FHHO to the network parameters of energy consumption, network lifetime, and convergence curves. The results indicate that T2FHHO outperforms competing methods. The proposed method holds the promise of significantly advancing the state of the art in energy-efficient routing for DIoT and WSN networks, with significant implications in various sectors and applications, ensuring extended network lifetimes and sustainable IoT implementations.

1. Introduction

Wireless sensor networks (WSNs) are indeed a critical subcategory of networks that consist of a multitude of distributed sensor nodes. These nodes are equipped with sensors to collect data from their environment and can be used in various systems, including Internet of Things (IoT) models, [1,2]. One of the main advantages of WSNs is their ability to be deployed easily in remote or challenging environments. These nodes are typically small and wireless, making them suitable for monitoring and collecting data in areas that are hard to reach or dangerous for humans. The power limitation of sensor nodes in these networks allows for improving energy efficiency and network lifetime by applying optimal methods for data forwarding and routing [3]. IoT and WSN systems

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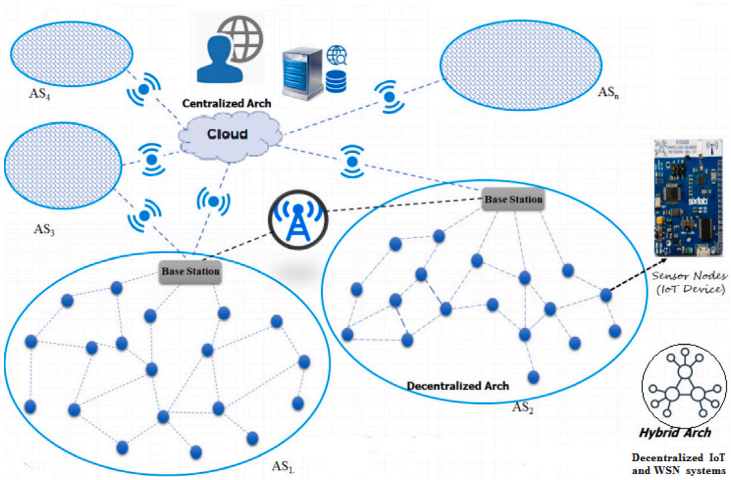


Fig. 1. Architecture for DIoT and WSN [5].

complement each other seamlessly, with WSNs serving as the foundation for data collection in IoT. This integration enhances the capabilities of IoT and opens up a vast array of applications, especially in the context of decentralized IoT (DIoT) [4].

There may be issues with an IoT with traditional centralized services in cases where there are concerns with the internet. Furthermore, a sizable portion of the workload in this architecture is placed on the server-side cloud application. Blockchain technology is another suggestion as a solution to enhance the security and reliability of this architecture. Decentralized process designs are commonly used in industrial systems because they might be more productive. As a result, distributed and decentralized architectures can be used as answers. These applications fit our definition of DIoT. WSNs are typically created using a decentralized structure. The DIoT and WSN systems are given in Fig. 1 [5].

The IoT device has the option of using a single hop or a multi-hop path (route) to transmit its packet size to the base station (BS). Multi-hop methods are widely used in distributed structures that are decentralized. All data packets are gathered by the BS and sent to a server for data analysis and end-user access. An effective mechanism of data transport is required because sensor nodes cooperate. These nodes have little battery power, bandwidth, processing power, or memory space. Hence, it is a difficult task to carry out the intricate computations at each sensor node. Nevertheless, physical limitations like the nodes' positions make charging virtually impossible. Increasing the network lifetime is the key challenge in WSN and IoT. Nodes within the network are evaluated to determine their fitness values. This evaluation considers various factors, such as energy levels, distances to the base station, and network traffic. If a node's fitness value starts at zero, it is subsequently updated based on a weighted combination of these factors [6]. Energy consumption rate is a fundamental component in these schemes since network longevity directly affects the remaining battery capacity of sensor nodes, making energy one of the most crucial resources [7].

One of the most important challenges in DIoT and WSN systems is effective resource consumption, such as energy consumption [8]. Methods to get the optimal paths while using the least amount of energy are important. In the literature to address this issue, several multipurpose routing solutions have been proposed that maintain the integrity, inclusiveness, and connectivity of the network. Finding the optimal path in a large and complex network among numerous options necessitates additional processing. Selecting suitable, efficient coefficients for the pertinent routing parameters is also difficult. These issues actually fall within the non-deterministic polynomial-time jobs [9]. It is therefore appropriate to apply optimization methods to solve this problem. Nevertheless, these methods are used throughout the entire routing process; they frequently add extra burden to the system and use some system resources inefficiently.

The meta-heuristic methods are better suited for pathfinding issues in DIoT and WSNs. These methods can be divided into three categories: physics-based, evolutionary, and swarm intelligence methods. In the first one, some studies are gravitational local search [10], charged system search [11], and the black hole algorithm [12]. In the second one, some methods are the genetic algorithm [13], differential evolution [14], evolutionary programming [15], and evolution strategy [16]. The last one is based on swarm behaviors: partial swarm optimization (PSO) [17], flower pollination (FPA) [18], whale optimization (WOA) [19], grey wolf optimization (GWO) [20], and Harris Hawk optimization (HHO) [21].

HHO is an optimization method influenced by hunting Harris Hawks. The fast convergence and global search capabilities of this method make it suitable for solving various optimization challenges. The goal of HHO is to achieve an optimal configuration that minimizes latency, reduces power consumption, and improves data reliability in a decentralized environment. In recent years, the use of metaheuristics has become very popular in IoT and WSN systems. In this paper, optimal paths and optimal cluster heads (CH) in DIoT and WSN systems are presented using the HHO method.

In this study, DIoT and WSN have emerged that provide a distributed and scalable approach to harnessing the potential of IoT. The proposed method is motivated by the need to address numerous challenges faced by DIoT and WSNs by improving energy-efficient routing and optimizing the selection of CH. The main goal of this work is to advance the state-of-the-art in energy-efficient routing and network optimization. In DIoT and WSN, data characteristics and network conditions can be highly uncertain. Therefore, Type 2 fuzzy sets (T2FS) are suitable for providing precise solutions in insecure network environments and provide greater flexibility for handling insecure data. This paper proposes a new energy-saving method to achieve the optimal path from source CH to destination node BS in DIoT and WSN and a new fitness function combining T2FS and HHO methods (T2FHHO). Then this method is applied to get the best CH. The new fitness value is found using the network parameters (residual energy, distance, traffic, and buffer size). Finally, the T2FHHO is compared with a variety of well-known methods in terms of energy consumption, network lifetime, and convergence curves.

The rest of the paper is given as follows: Section 2 includes related works. Section 3 presents the proposed method. Section 4 illustrates a detailed analysis of the experimental results. Finally, the conclusion is reported in Section 5.

2. Motivation and contribution

In DIoT and WSN, energy consumption during data transmission must be minimized. Many methods are ways to alleviate this problem and mainly focus on one energy parameter and pay less attention to other related parameters, such as quality of service, coverage, connectivity, etc. Some protocols strive to choose the best path from source to destination nodes and face challenges related to selecting the path that provides high throughput and less delay. Therefore, it is a challenge and motivation to extend the lifetime of DIoT and WSNs by considering conflicting parameters for optimal path, CH selection, and energy-efficient routing.

The main contributions of this paper are given as follows:

- Introducing a method for determining the optimal path from source to destination node and increasing the lifetime of DIoT and WSN
- The proposed method employs the HHO, derived from the hunting behavior of Harris Hawks and renowned for its rapid convergence rate and global search capabilities.
- Pathfinding efficiency is increased by using T2FHHO to identify the most appropriate coefficients for each parameter of the specified fitness function.
- A new fitness function is used to calculate the cost of each path in the network using a fuzzy method and find the next hop based on residual energy, distance, traffic, and buffer size.
- Applying the T2FHHO method to get the optimal CH selection

3. Related works

Efficient resource consumption in WSN and DIoT is one of the key fundamental issues. The methods in energy efficiency for determining the best path among many possible paths are of important value. To solve this difficulty, many multipurpose routing methods are presented. Furthermore, further processing is required to determine the best route out of many achievable paths in complex networks. Thus, meta-heuristic methods are proposed to solve this problem [22].

Finding the most efficient CH selection among many possible nodes in a wide and complex network requires further processing. It is not easy to find appropriate, effective coefficients for the relevant parameters. In fact, these issues are classified as non-deterministic polynomial-time problems (NP-hard). The authors propose a multi-factor-based routing algorithm and energy-efficient clustering for WSN, where sensors are grouped into clusters by energy-efficient heterogeneous clustering. Three parameters are used to select the best CH: (a) transmit power, the delay as a function of the node residual energy, etc.; (b) the distance between the node and the corresponding CH; and (c) the distance between the CH and the BS [8]. Address multiple conflicting factors to achieve load and power balance during data collection. The chosen CH always has a good balance of factors, which helps the network transmit data to the receiver in an energy-efficient manner. Both nodes and CHs consume less power, and the load is balanced among them, which ensures the continuity of the data collection process for a long time. Hence, this algorithm is beneficial for collecting information in remote areas over a longer period of time [23].

Any sensor node or IoT device can use a single-hop or multi-hop paradigm to transmit its data packets to the BS. Multi-hop approaches are widely used in distributed structures that are decentralized. All data packets are gathered by the BS and sent to a server (potentially in the cloud) for data analysis and end-user access [24]. An effective mechanism of data transport is required because sensor nodes cooperate. These nodes have issues with their low memory, bandwidth, computing capability, and memory space. The key challenge in WSN and IoT is increasing network lifetime. It is vital to note that resource management and network topology are crucial to network lifetime and availability.

Efficient resource application is a real requirement in WSN and DIoT schemes. In these cases, a pathfinding method can achieve this goal. Nevertheless, since this problem exists, meta-heuristic methods can be applied. Further processing is necessary in order to identify the most effective path out of numerous alternatives in a large and complicated network. Additionally, it is challenging to locate suitable, efficient coefficients for the pertinent routing parameters. To find the best paths, two routing techniques based on GWO techniques are proposed [5].

Another state-of-the-art meta-heuristic method, named ant colony optimization (ACO), has been proposed for the DIoT and WSN. The authors propose a routing protocol based on ACO in multi-agents that manages network assets in real-time. This method is applied to find the next destination for ants. However, because it doesn't operate in a fair and balanced manner, it is not seen as being highly effective in terms of energy efficiency. The fitness function utilized does not use enough parameters, which is the main cause of the issue [24].

Table 1
Comparative methods.

Methods	Problem addressed	Methodology	Application
I-GWO and Ex-GWO [5]	Optimal data transmission to find the next destination of the target	Find the best path with low power consumption to extend network lifetime in parallel and concurrent states	WSN and DIoT
ACO [24]	Multi-agent real-time pathfinding method	Finding the best path of any length for each path between source and destination nodes	WSN and DIoT
HHO [24]	CH selection	Choosing the best CH in each of the clusters in the IoT networks	IoT
Machine learning and meta-heuristic algorithms [30]	CH selection	Choosing the best CH and considering power and concentration factors as well as routing and data transmission using fuzzy clustering	IoT
Fuzzy clustering [31]	CH selection	The best CH is select by determining the maximum fitness value using a fuzzy method	WSN
Meta-heuristic algorithms [2,26]	Best CH and route	Select the best CH and the Nodes transmit the aggregated data to the best CH or BS via the best route	WSN

Choosing a suitable CH and getting the best coefficients for every parameter of a pertinent fitness function in CH are NP-hard problems that require additional processing. To find the best coefficients for every parameter, metaheuristic approaches are used [25]. The optimized CH routing method to minimize nodes' energy consumption and fast data transmission in a WSN combines both local and global search optimization techniques and uses a specific routing algorithm (Dragonfly Algorithm) for effective data transmission [26]. To improve the energy utilization in the IoT networks through an optimal CH selection using HHO algorithm [21].

Many researchers use Type-1 Fuzzy Sets (T1FS) to handle some uncertainties in DIoT and WSN, such as the estimation of the position of a node or the present status of the network. However, T1FS cannot effectively deal with uncertainties that emerge in DIoT and WSN because they employ T1FS that are essentially precise and crisp. As an extension of the concept of a T1FS, the concept of a T2FS was developed [27]. T2FS is applied to model the uncertainty and vagueness of the problem, which are common in real-world optimization problems. Using a fuzzy method in CH selection and routing can improve the efficiency of DIoT and WSN. A node seeking a higher probability of being selected as a CH is based on the values of the four descriptors it employs. The process dumps the output and uses fuzzy logic to select the best route and the best CHs [28,29]. The fuzzy logic used offers the possibility of making decisions in a real-time environment, with or without complete information [30,31].

Many other strategies have also been reported in the related literature. To optimize the network lifetime, in [32], the authors have proposed an energy-aware CH selection algorithm, an optimal clustering architecture, and a routing protocol. However, [32] has works that propose an energy-efficient fuzzy-based unequal clustering for IoT utilizing WSN. The fuzzy logic system is used in the cluster head selection process.

In a clustering protocol, the main processes are creating a cluster, choosing a CH selection, and routing between source and destination nodes. This paper provides the T2FHHO method to get the best path to increasing the network lifetime. The T2FS is highly helpful in providing the best solution for DIoT and WSN. Therefore, T2FS is used (residual energy, distance, and traffic) to find the fitness function. Hence, T2FHHO reduces energy consumption in order to increase network lifetime.

Numerous optimization techniques are proposed for choosing the appropriate path from CH to BS nodes and the best CH in DIoT and WSN based on the review of related studies. These are the restrictions: selecting the best path to the minimization and maximum of fitness function parameter values; many optimization techniques take a long time to analyze the fitness function (see Table 1).

Diversity analysis in optimization algorithms is important. To gain insights into the importance of diversity in optimization, the authors in this study [33] have explored the impact of diversity preservation mechanisms and strategies in nature-inspired algorithms. These studies provide valuable references for understanding the role of diversity in optimization and its potential implications for future research.

4. Proposed method

In this section, we apply T2FHHO to get the best path from source CH to destination BS in DIoT and WSN to increase the networks' lifetime. HHO, defining the problem as an optimization job to get the best CH in DIoT and WSN. The T2FS is highly useful because uncertainty provides an accurate solution. The fitness value is found using the network parameters (residual energy, distance, traffic, and buffer size).

4.1. Harris Hawks optimization method

HHO is an optimization method whose idea is the hunting behavior of the Harris Hawk [21]. These birds perch in the air, scout out prey from a distance, and swoop down on it in concert. In HHO, Hawks perch and explore during this time. Note that in HHO, the candidate solution is called Hawk (x), while the good solution is called prey.

A recent study indicates that HHO is an efficient optimization strategy for identifying good solutions to complicated problems more rapidly and with fewer calculations. The benefits of the HHO include avoiding local optima, showing a smooth passage from exploration to exploitation, offering high accuracy in pulling up the best parameters, and discovering a superior solution.

With optimization methods, a problem situation is searched thoroughly to determine the optimum answer from the numerous available solutions. Find out the best position (location) in the middle of hills and valleys in the search space; the meta-heuristic begins the hunting in the exploration phase. In an optimization method like HHO, the search agent is widely spread in the search space. Nevertheless, we view equal probability for both strategies [21], which is calculated as:

$$h_{n+1} \begin{cases} h_{rand}(n) - a1 \left| h_{rand}(n) - 2a2h(n) \right| & l \geq 0.5 \\ h_{rabbit}(n) - h_m(n) - a3(L + a4(U - L)) & l < 0.5 \end{cases} \tag{1}$$

where the location vector of Hawk is defined as h_{n+1}, whereas the location vector of Hawk in the first iteration is represented by $h_{rand}(n)$. Hawk's current location vector is $h(n)$, and the best location is $h_{rabbit}(n)$. The lower and upper bounds of variables are L and U, respectively. Random numbers between [0, 1] are represented by the variables a1, a2, a3, a4, and l. The formula for $h_m(n)$, which represents the mean location of the N solution, is as follows:

$$h_m(n) = \frac{1}{K} \sum_{t=1}^{N} h_t(n) \tag{2}$$

where $h_t(n)$ displays the location of the hawks after each n iteration and K shows the full number of hawks.

During the escaping actions, the power of the prey (Z) significantly decreases throughout, which causes the HHO method to switch from exploration to exploitation. The power of the prey [21], can be expressed as follows:

$$Z = 2Z_0(1 - \frac{1}{T}) \tag{3}$$

where Z denotes the prey's escape energy, T shows the number of iterations, and Z_0 shows the initial energy that varies from $[-1, 1]$ in each iteration.

Regarding the exploitation phase, it comprises four different strategies, which are formulated as follows:

The soft besiege strategy holds when $a \geq 0.5$ and $|Z| \geq 0.5$. In this phase, the Hawk updates its location [21], which is explained as:

$$h(n+1) = Dh(n) - Z \left| J h_{rabbit}(n) - h(n) \right| \tag{4}$$

$$Dh(n) = h_{rabbit}(n) - h(n) \tag{5}$$

where J = 2 (1 − a5) specifies the rabbit's jump power and $Dh(n)$ indicates the distance between the rabbit and Hawk in iteration n. Here, the random variable is r5.

The hard besiege strategy holds when $a \geq 0.5$ and $|Z| < 0.5$. In this phase, the Hawk modifies its place [21], which is formulated as:

$$h(n+1) = h_{rabbit}(n) - Z \left| \triangle\, h(n) \right| \tag{6}$$

When $|Z| ge 0.5$ and $a 0.5$ are both present, a soft besiege strategy with progressive rapid dives is still effective. Before prey may effectively flee at this phase, all hawks must choose the best posture to target the prey, which can be formulated as follows:

$$A = h_{rabbit}(n) - Z \left| J h_{rabbit}(n) - h(n) \right| \tag{7}$$

In HHO, if the movement does not approve of fighting the prey, a dive is chosen based on a levy flight (FL) [21], which is formulated as:

$$M = A + S \times FL(E) \tag{8}$$

where E shows the problem dimension. S shows a vector of random numbers with a size of $1 \times D$. The FL function [21] is written as follows:

$$FL(x) = 0.01 \times \frac{m \times \omega}{|n|^{\frac{1}{\delta}}}, \omega = \left(\frac{\tau(1-\delta) \times \sin(\frac{\pi\delta}{2})}{\tau\left(\frac{1-\delta}{2}\right) \times \delta \times 2^{\left(\frac{1-\delta}{2}\right)}} \right)^{\frac{1}{\delta}} \tag{9}$$

where $delta$ is a constant with a value of 1.5 and m and n are random variables in the range [0, 1]. The following formulation can be used to describe how Hawk positions are updated throughout the soft besiege phase:

$$h_{n+1} \begin{cases} A & \text{if } E(A) < E(h(n)) \\ M & \text{if } E(M) < E(h(n)) \end{cases} \tag{10}$$

where A and M are obtained using Eqs. (7) and (8), and both refer to the new iteration's next location.

In HHO, besiege with the progressive rapid dives strategy occurs when $|Z| < 0.5$ and $a < 0.5$ [21], which is formulated as:

$$h_{n+1} \begin{cases} A' & \text{if } E(A') < E(h(n)) \\ M' & \text{if } E(M') < E(h(n)) \end{cases} \tag{11}$$

where

$$A' = h_{rabbit}(n) - Z \left| J h_{rabbit}(n) - h(n) \right| \tag{12}$$

$$M' = A' + S \times FL(D) \tag{13}$$

where $h_m(n)$ has been obtained in Eq. (2).

4.2. Proposed method

In DIoT and WSN, T2FHHO is used to optimize various facets of the network, such as energy efficiency, data routing, and energy consumption. The HHO has many advantages, such as the distributed nature of the network to optimize performance, better convergence speed, dodging of the device at local and global extremes, and ameliorated threshold coefficients. HHO uses T2FS to handle uncertainties in the fitness value scores (see Algorithm 1).

In this paper, the T2FHHO method is used to address the critical challenge of optimizing the path selection from source to destination nodes. Our method extends beyond conventional routing methods, selecting the best CH and introducing a novel fitness function that intelligently considers parameters such as residual energy, distance, traffic, and buffer size. In this investigation, BS is taken to be the final node. To determine the most appropriate path, the BS node considers other useful criteria that are specified in the new fitness function. Consequently, T2FHHO can offer the greatest solution for obtaining the best path in search space. To put it briefly, they identify the best route among the sets of feasible paths by making multiple hops.

In DIoT and WSNs, clustering involves organizing sensor nodes into groups to improve energy efficiency. In this paper, we use fuzzy logic with triangular and trapezoidal membership functions to assign nodes to clusters based on factors such as residual energy, distance, traffic, and buffer size.

Algorithm 1 T2FHHO method

Input: Sensor nodes
Output: The best CH and the best path
Split an initial population $h_n^0 (n = 0, 1, ..., N)$
Split start number of iteration m = 1 and maximum number of iterations M
while ($m \leq M$) **do**
    Compute the fitness score
    Set h_{rabbit} as the best position of rabbit
    Update fuzzy membership for each Hawk
    for (each Hawk (h_n)) **do**
        Update jump strength J and the initial energy Z_0
        Update the E by Eq. (3)
        if ($|Z| \geq 1$) **then**
            Adapt Hawk based on movement of the group
        end if
        if ($|Z| < 1$) **then**
            if ($a \geq 0.5$ & & $|Z| \geq 0.5$) **then**
                Adapt the Hawk to the prey's movement
            else if ($a \geq 0.5$ & & $|Z| < 0.5$) **then**
                Update solution by Eq. (6)
            else if ($a < 0.5$ & & $|Z| \geq 0.5$) **then**
                Update solution by Eq. (10)
            else if ($a < 0.5$ & & $|Z| < 0.5$) **then**
                Update solution by Eq. (11)
            end if
        end if
    end for
end while

4.3. Network model

We make the following assumptions about DIoT and WSN systems:

Table 2
T2FHHO fuzzy rules.

Rule	RE	Distance	TS	BZ	FV	OP
1	Low	Close	High	Medium	Very high	Preferred
2	Medium	Medium	Low	High	Moderate	Acceptable
3	High	Far	High	Low	Low	Discouraged
4	Low	Far	Low	Medium	Moderate	Acceptable
5	Medium	Close	High	Low	High	Preferred
6	Low	Medium	Medium	High	High	Preferred
7	High	Close	Low	Low	Moderate	Discouraged
8	High	Medium	High	Medium	Very low	Acceptable
9	Medium	Far	Medium	Medium	Low	Acceptable

- The network consists of N sensor nodes randomly deployed within a square area of size $S \times S$. Each sensor node is uniquely identified by a network ID.
- BS is situated at the center of the network. All sensor nodes are assumed to have at least one neighbor, which means they are within the communication range of at least one other node. Data packets from sensor nodes can be transmitted to the BS in one or multiple hops. The maximum number of hops to reach the BS is assumed to be four.
- All sensor nodes in the network are assumed to be homogeneous. This means that they have the same initial energy level and communication range. Homogeneity simplifies the network model and allows for uniform treatment of all nodes.

4.4. CH selection

The variables used in this procedure are mapped. Because of the increased degrees of freedom and greater number of parameters (residual energy, distance, traffic, and buffer), the primary advantage of T2FS over T1FS is its improved management of uncertainty, which includes the fuzzifier, rule base, and defuzzifier tasks.

- **Fuzzifier**

A fuzzier is a tool that converts exact values into fuzzy values [34]. The fuzzy inputs in this work are residual energy, distance, traffic status, and buffer size. In a fuzzy set, the membership value and linguistic variable are crucial to describing the crisp value in a given situation. The linguistic variables in these fuzzy sets contain speeches or sentences instead of books. Similarly, for residual energy, traffic status, and buffer rate, we can establish linguistic terms as “low”, “medium”, and “high”. For distance, we can establish linguistic terms such as “close”, “medium”, and “far”.

In this work, we create membership functions for each linguistic variable using triangular and trapezoidal functions in the T2FHHO based on the characteristics of the input parameters. Triangular and trapezoidal membership functions are commonly used in fuzzy logic systems.

- **Rule Base**

In this paper, the fuzzy rules are calculated by considering the input (residual energy (RE), distance, traffic status (TS), and buffer size (BZ)) and two output parameters (fitness value (FV) and optimal path (OP)). The value of fuzzy rules is defined by the values of the linguistic and input variables. The IF-THEN rules are used to specify the fuzzy rules and are then generated using the Mamdani system. Table 2 presents the fuzzy rules.

- **Defuzzifier**

One of the stages that converts the fuzzy output into a precise value is defuzzification. The center of gravity is a defuzzification technique [29] (see Fig. 2).

In WSNs, clustering involves organizing sensor nodes into groups or clusters to enhance energy efficiency. In this paper we use the fuzzy logic to assign nodes to clusters based on factors such as residual energy, distance, traffic, and buffer size.

The maintenance of clusters can involve periodic updates of membership values, reevaluation of fuzzy rules, and adaptation to changes in the network environment. The proposed T2FHHO method likely incorporates mechanisms to handle changes in the network, ensuring that the clusters remain effective in optimizing energy efficiency, data routing, and other network objectives.

4.5. Fitness function

To assess the performance of the methods and select the optimum one, residual energy, distance, traffic and buffer size are considered. A new fitness value is developed to get the best CH and the best route, and it is used by these methods. A route is not necessary if the number of hops between CH and BS is 1. The problem caused by the multi-hop mechanism is that at that place there may be multiple paths of varying sizes and possible involvement of intermediate nodes (see Fig. 3). To solve this issue, the optimal route for any number of hops is determined at the end of each iteration based on T2FS using Eqs. (15) and (16), and the best path is chosen to utilize Eq. (17). The new fitness value using T2FHHO can help DIoT and WSN perform better by using these methods to determine the best path with the least cost between two points with T2FS. The proposed fitness function is defined in Eq. (14).

$$fitness_{ij} = (w_1 dist_{ij}) + (w_2 M_j) + \left(w_3 \frac{ValidTraffic}{k_{ij}}\right) + \left(w_4 \frac{E}{A_j} \frac{buffercapacities}{buffer_j}\right) \tag{14}$$

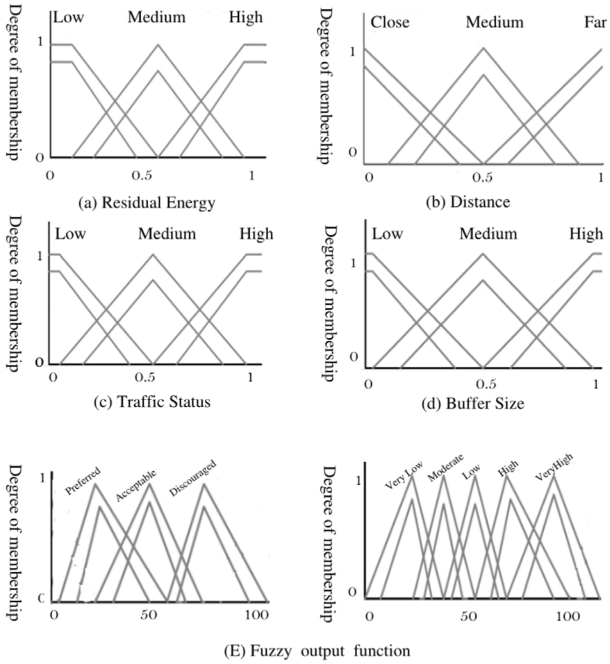


Fig. 2. Membership functions.

where the coefficients w_1, w_2, w_3, and w_4 are power parameters between 0 and 1 computed using the T2FHHO method, where $w_1 + w_2 + w_3 + w_4 = 1$ and $w_1 < w_2 < w_3 < w_4$. $dist_{ij}$ shows the distance between two nodes i and j using T2FS. M_j denotes the number of hops from CH to BS. k_{ij} indicates the current traffic intensity between them using T2FS. A_j indicates the residual energy. E indicates the current energy of the receiver node.

4.6. Pathfinding method

Pathfinding is another important aspect of DIoT and WSN systems. The major goal of this method is to identify the best route between CH and BS while considering various constraints such as node energy, distance, and transmission quality. T2FHHO can be used to optimize pathfinding by taking these constraints into account and using a combination of fuzzy logic and Harris Hawk's hunting behavior to determine the optimal route with a minimum cost (see Fig. 3). This method follows three phases (see Fig. 4):

- Phase 1: Calculation of Path Cost
  In the first one, Eq. (14) is utilized to find the path cost for every middle node between the CH and BS nodes. The T2FHHO method efficiently searches for the best coefficient numbers for each parameter in order to get the best path cost.
- Phase 2: Calculation of Candidate Path Cost
  In the second one, the method computes the cost of the candidate path using Eq. (15) [5]. Candidate paths from CH to BS are evaluated according to their cost. In turn, fuzzy logic is applied to deal with uncertainty and inaccuracies in the input data. Then, the optimum route for each hop is determined using Eq. (16) [5], utilizing the route having the smallest cost. This process is used for all hops. This selection is carried out for all hops along the path of various sizes. Select the optimal candidate of the same length.

$$totalcost_{ij} = \sum_{i=1}^{j=n} fitness_{ij}. \tag{15}$$

$$minimumcost = \min(cost^C). \tag{16}$$

- Phase 3: Select the Best Path
  Finally, the method selects the optimal CH and path between these nodes based on Eq. (17) from the found candidate paths. This path must also have the lowest cost. T2FHHO looks like the best route between CH and BS with the lowest costs.

$$overallminimumcost = \min(cost^h). \tag{17}$$

In this network, information about each node is stored in the BS. This information is acquired by sending a request data packet from the BS to the sensor nodes during the network's initialization phase. The BS stores data related to residual energy, traffic status, buffer size, distance, and the neighbor list.

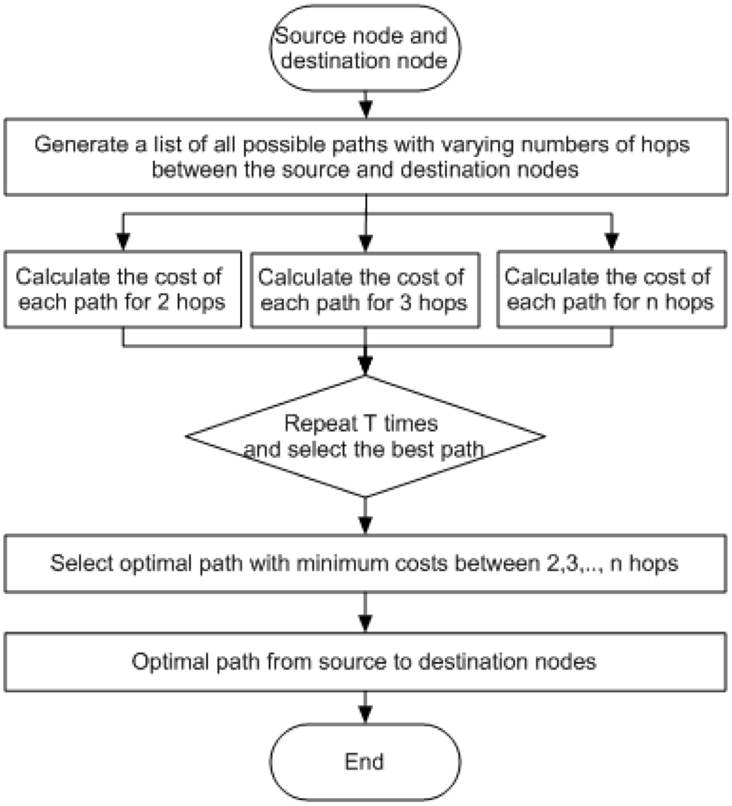


Fig. 3. Finding the optimal path.

4.7. Other features of the proposed method

In DIoT and WSN systems, multiple sources and destination nodes can communicate with each other concurrently, requiring parallel processing to handle the large amounts of data generated. In this research, the proposed node deployment method has other features besides the combination of parallel and concurrent applications, which seems well suited to handle such scenarios and allow efficient data processing in such complex systems. By utilizing parallel and concurrent processing, the algorithm can carefully search for the most efficient paths between these nodes simultaneously.

5. Results and discussion

In this section, our simulation results are developed using MATLAB R2022b. The energy consumption, convergence curves, and network lifetime are shown in order to assess the effectiveness of the strategies and select the best one. The proposed method is contrasted with the PSO [16], WOA [19], GWO [20], Energy optimization for green communication in IoT using HHO (HHO-IoT) [21], A meta-heuristic optimized cluster head selection based routing algorithm for WSN (MOCRAW) [26].

5.1. Parameter settings

Over 30 iterations of the outcomes of various optimization methods are performed. The maximum number of iterations is 50. The number of Hawks is 100, …, 5000. The initial energy is set at 0.1 J, and each packet should consume $2nj$ of energy during reception and transfer. Each packet has a size of 250 kB and is broadcast for 600 ms. There is one legitimate traffic source per edge. Each node's maximum buffer size is 10,000 kB (see Table 3).

5.2. Results

5.2.1. Energy consumption

The network must be subjected to the energy consumption test. The employed method is evaluated in situations with 10 sensor nodes of various numbers. The testing results showed that the T2FHHO was more successful in reducing the network's overall energy consumption. The search agents in the methods used in this experiment imitate the network sensor nodes' lifespan by absorbing the

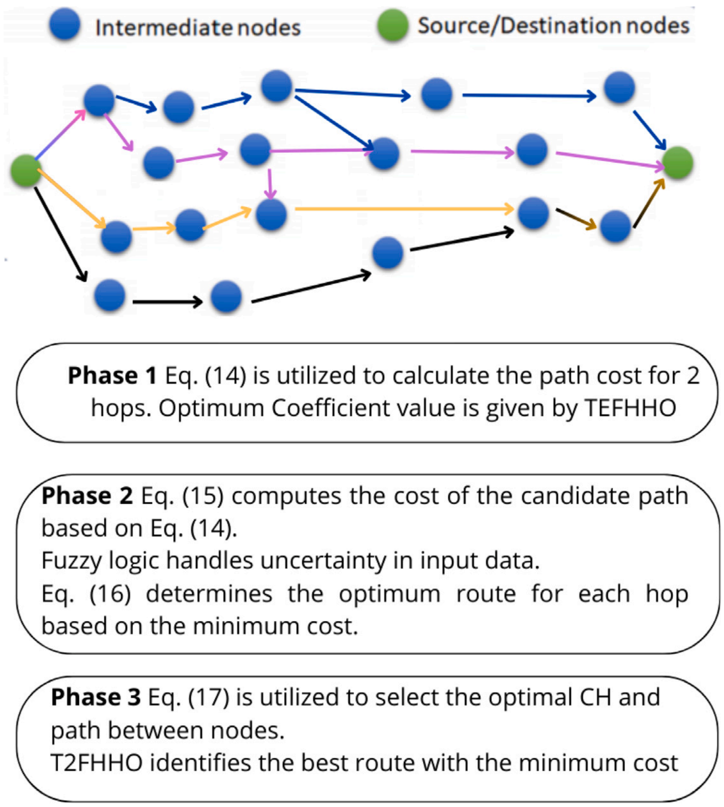


Fig. 4. The mechanism of proposed method in pathfinding.

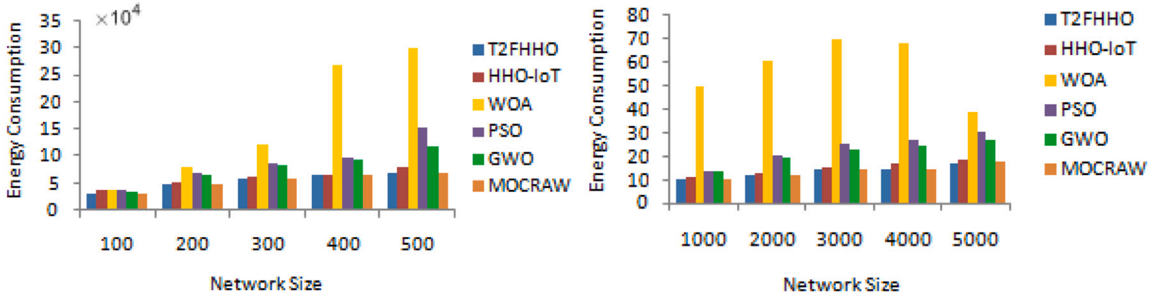
Table 3
Simulation parameters.

Parameters sets	Values
Network	100 ∗ 100 m^2
Nodes	100, …, 500–1000, …, 5000
Number of cluster	4
BS location	50∗50 m
Data packet	250 kB
α and β	0.5, 0.5
c1, c2, c3 and c4	0.15, 0.20, 0.25, and 0.4
ρ	0.5
$\tau_{i,j}(0)$	0.008

leftover energy following a predetermined number of repetitions, depending on the fitness function. The overall energy consumption for each network size is then provided. According to each network scenario, Fig. 5 indicates the overall energy usage for the T2FHHO method and four other methods. As it is obvious from Fig. 5, T2FHHO consumes the least amount of energy for all the varied networks sized from 100 to 5000, among other methods employed in this research. According to Fig. 5, which reports the overall energy consumption of the DIoT and WSN with chosen methods, the full energy consumption in the 1000-node situation with T2FHHO, HHO, WOA, PSO, GWO and MOCRAW methods is 97 456, 107 456, 488 989, 131 419, 1 133 185, and 97 459, respectively.

Fig. 6 presents the power consumption along the time, showing at least 3–4 nodes from the border with 1–2 connections, 2 nodes with few connections, 3 nodes with many connections, and the 4 nodes with the most connections. It shows that a border node with 1–2 connections uses the least power over the course of the observation. Several factors affect the power consumption of a DIoT and WSN utilizing the T2FHHO method. It is crucial to take these parameters into account when deploying the network to optimize power efficiency and guarantee the length of the nodes' battery lives.

Fig. 7 illustrates the relationship between power consumption and the size of the network in DIoT and WSN. The main concept behind energy conservation in a network is to choose the best CH and shorten the transmission route from the CH to the BS. As a result, the exploited T2FHHO outperforms other methods in energy usage as the size of the network grows.



(a) From 100 To 500 Nodes (b) From 1000 To 5000 Nodes

Fig. 5. Comparison of energy consumption between the different methods.

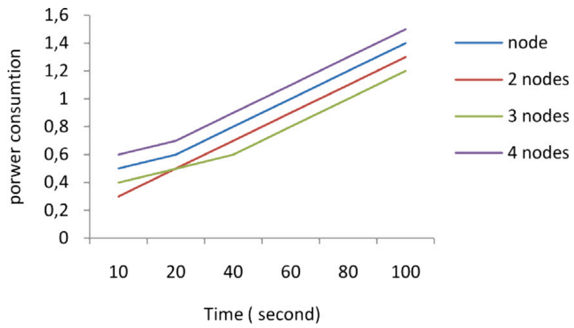


Fig. 6. Power consumption vs. time in DIoT and WSN.

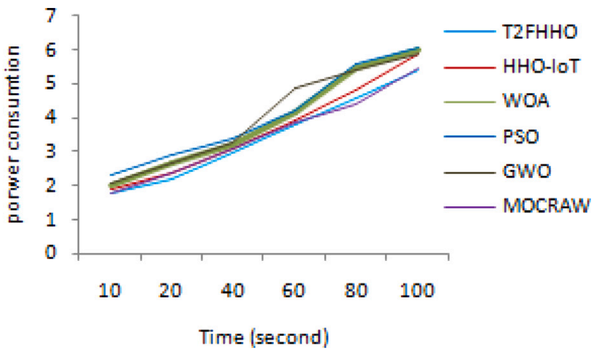


Fig. 7. Power consumption vs. time between different methods.

5.2.2. Network lifetime

One of the most crucial aspects of DIoT and WSN is the network's lifetime. The simulation results were evaluated for 100 nodes with an initial energy of 0.5 J per node, and each method was run for 100 to 5000 rounds. The simulation results presented in Fig. 8 show that T2FHHO is better in terms of network lifetime than previous methods. Specifically, the PSO depletes all the energy of the nodes before the 2000th round, while the WOA and GWO methods do so before the 3000th round. The MOCRAW and T2FHHO method lasts until the 5000th round, but its performance is inferior to that of the T2FHHO-based method.

5.2.3. Convergence rate

One of the most helpful graphics for applying an optimization method to identify the optimal solution is a convergence curve. To measure the performance of the considered methods in terms of utilizing and decreasing the fitness score to attain the lowest energy consumption rate, the convergence curves were chosen from each method after 1000 iterations to understandably assess the convergence of methods abilities. Fig. 9 shows a comparison between T2FHHO line plots of the convergence curves for all reasonable network sizes and other well-known optimization techniques. Fig. 9 illustrates that the T2FHHO approach converges to the optimum, the quickest of all methods. In this graph, the four curves are not all the same; Fig. 9a and c are distinct from Fig. 9b

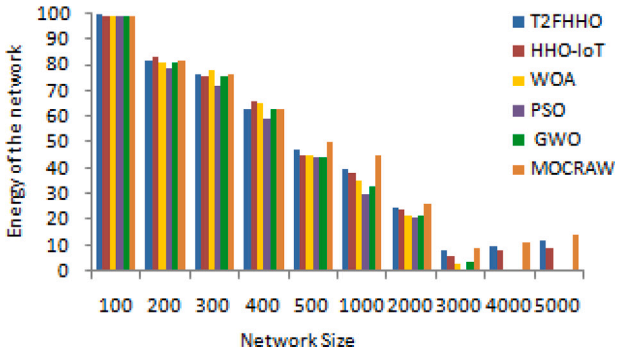
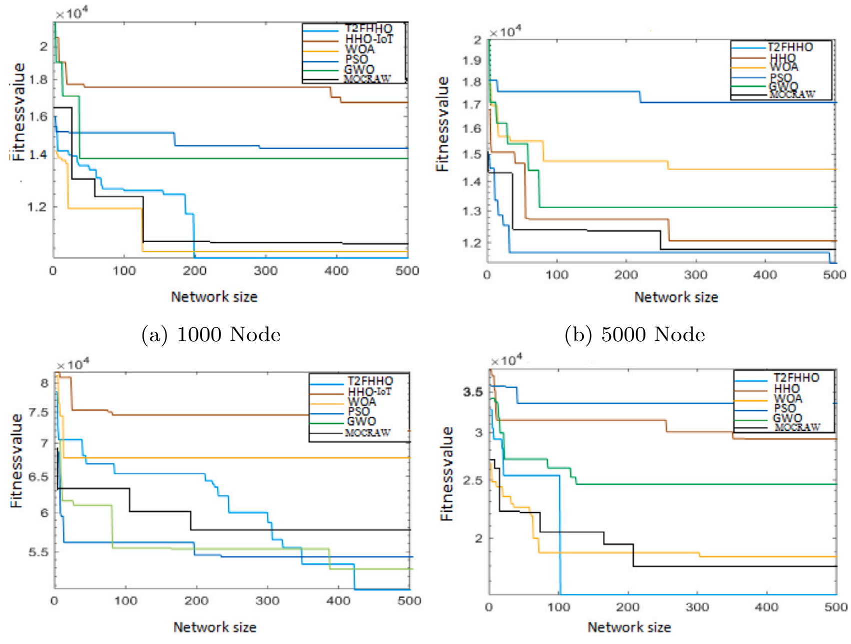


Fig. 8. Network lifetime.



(a) 1000 Node (b) 5000 Node

(c) 7000 Node (d) 10000 Node

Fig. 9. Convergence rate of the methods over 1000–10 000 sizes.

and d. This is because each curve contains a different network size. Depending on the approach, the factors in the fitness function, such as residual energy, distance, and traffic, will also vary depending on the network scale.

6. Discussion

In the experiment described in this part, network sizes ranging from 100 to 5000 nodes were used to compare the performance of the T2FHHO in DIoT and WSN. To ensure the statistical significance of the findings when compared to well-known methods like HHO, WOA, PSO, GWO, and MOCRAW, the experimentation was repeated M times. The typical evaluation measure found by the fitness function is for all possible network sizes over a set number of generations. Table 4 summarizes the performance metrics for all the competing methods and shows that the proposed T2FHHO outperformed the competing methods for all network sizes in terms of mean, best, and worst. Additionally, these empirical results support T2FHHO capability to select the best path from CH to BS.

To summarize the received statistical results, Table 5 indicates the average best and worst average evaluation metrics found by the above fitness functions according to all the considered network sizes for other methods. The T2FHHO method used accomplishes optimum performance, which demonstrates its quality to decrease the fitness function and select the best CH and route.

To examine the time consumption of the methods after 1000 iterations, Table 6 indicates that the proposed method has a faster running time than the other ways, which take longer to get the best CH and the route with low power consumption.

Table 4
Average evaluation criteria for the different methods.

Nodes	Coverage	T2FHHO	HHO-IoT	WOA	PSO	GWO	MOCRAW
	Mean	0.103	0.123	0.292	0.368	0.875	0.105
100	Best	0.111	0.121	0.126	0.322	0.420	0.119
	Worst	0.132	0.144	1.08	0.408	1.17	0.135
	Mean	0.059	0.062	0.081	0.92	0.214	0.058
200	Best	0.059	0.061	0.062	0.182	0.185	0.057
	Worst	0.078	0.080	0.205	0.232	0.867	0.079
	Mean	0.080	0.853	0.071	0.197	0.262	0.083
300	Best	0.039	0.041	0.042	0.243	0.082	0.041
	Worst	0.102	0.139	0.121	0.281	0.430	0.104
	Mean	0.030	0.034	0.037	0.149	0.200	0.033
400	Best	0.039	0.041	0.042	0.243	0.082	0.037
	Worst	0.039	0.044	0.118	0.439	0.159	0.041
	Mean	0.020	0.027	0.037	0.089	0.078	0.022
500	Best	0.021	0.024	0.025	0.028	0.070	0.023
	Worst	0.021	0.028	0.046	0.204	0.090	0.020
	Mean	0.019	0.0280	0.037	0.204	0.044	0.021
1000	Best	0.011	0.012	0.067	0.018	0.042	0.014
	Worst	0.041	0.046	0.067	0.057	0.046	0.041
	Mean	0.005	0.006	0.0088	0.009	0.019	0.008
5000	Best	0.0031	0.0033	0.0063	0.019	0.0073	0.0039
	Worst	0.0069	0.0075	0.0107	0.020	0.011	0.0071

Table 5
Average evaluation criteria for the different methods.

Coverage	T2FHHO	HHO-IoT	WOA	PSO	GWO	MOCRAW
Mean	0.021	0.037	0.061	0.119	0.194	0.023
Best	0.020	0.029	0.038	0.107	0.083	0.021
Worst	0.049	0.051	0.168	0.129	0.324	0.051

Table 6
Time consumption.

Parameters	T2FHHO	HHO-IoT	WOA	PSO	GWO	MOCRAW
Running time	5.50 ms	6.22 ms	7.77 ms	8.11 ms	7.36 m	5.91 ms
Success rate	99%	98%	94%	90%	95%	98%

The time complexity of proposed method expressed as O(M * N), where M is the number of iterations and N is the number of sensor nodes in the network.

7. Conclusion

This paper solves one of the biggest problems in DIoT and WSNs by reducing network energy consumption. The best CH and path from the source (CH) to the destination (BS) are determined by considering all potential routes that can connect any two nodes. Finding the most efficient paths between nodes can make more efficient use of resources and extend system life by reducing network energy consumption. This method calculates the cost of each network path using a fitness function that takes into account the energy consumption rate, remaining energy, distance, traffic volume, buffer size. Our proposed T2FHHO method has been used together with other well-known methods in DIoT and WSN. The results show that our method generally performs better than other methods in finding the optimal solution.

The proposed method can be applied in subsequent research to solve challenging issues in numerous disciplines, including electrical circuits, connected car networks, mobile robotics' 3D path planning, and systems' optimum node localization.

Despite the importance of this research, it is necessary to acknowledge its limitations. The study is based on simplifications and assumptions regarding grid conditions and energy models. Real-world scenarios can be considerably more complex and dynamic. Hence, future work should aim to address these limitations through more comprehensive testing and robust adaptations.

In future directions, this work can help use heterogeneous sensor nodes to support different IoT devices, integrate machine learning techniques, and enhance security and privacy measures.

CRediT authorship contribution statement

Ines Lahmar: Data curation, Investigation, Writing – original draft. **Aida Zaier:** Data curation, Investigation, Supervision, Validation, Writing – original draft. **Mohamed Yahia:** Investigation, Supervision. **Jaime Lloret:** Supervision, Writing – review & editing, Investigation. **Ridha Bouallegue:** Investigation, Supervision, Visualization.

Declaration of competing interest

Authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

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