

## Research Article

# DMTC: Optimize Energy Consumption in Dynamic Wireless Sensor Network Based on Fog Computing and Fuzzy Multiple Attribute Decision-Making

Abbas Varmaghani,<sup>1</sup> Ali Matin Nazar ,<sup>2</sup> Mohsen Ahmadi ,<sup>3</sup> Abbas Sharifi ,<sup>4</sup> Saeid Jafarzadeh Ghouschi ,<sup>3</sup> and Yaghoob Poursad<sup>5</sup>

<sup>1</sup>Department of Computer Engineering, Islamic Azad University of Hamadan, P.O. Box: 8415683111, Hamedan, Iran

<sup>2</sup>Institute of Port, Coastal and Offshore Engineering, Ocean College, Zhejiang University, Zhoushan 316021, Zhejiang, China

<sup>3</sup>Department of Industrial Engineering, Urmia University of Technology (UUT), P.O. Box: 57166-419, Urmia, Iran

<sup>4</sup>Department of Mechanical Engineering, Urmia University of Technology (UUT), P.O. Box: 57166-419, Urmia, Iran

<sup>5</sup>Department of Electrical Engineering, Urmia University of Technology (UUT), P.O. Box: 57166-419, Urmia, Iran

Correspondence should be addressed to Abbas Sharifi; [abbas.sharifi@mee.uut.ac.ir](mailto:abbas.sharifi@mee.uut.ac.ir)

Received 11 March 2021; Revised 31 May 2021; Accepted 18 June 2021; Published 1 July 2021

Academic Editor: Ihsan Ali

Copyright © 2021 Abbas Varmaghani et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Advances in wireless technologies and small computing devices, wireless sensor networks can be superior technology in many applications. Energy supply constraints are one of the most critical measures because they limit the operation of the sensor network; therefore, the optimal use of node energy has always been one of the biggest challenges in wireless sensor networks. Moreover, due to the limited lifespan of nodes in WSN and energy management, increasing network life is one of the most critical challenges in WSN. In this investigation, two computational distributions are presented for a dynamic wireless sensor network; in this fog-based system, computing load was distributed using the optimistic and blind method between fog networks. The presented method with the main four steps is called Distribution-Map-Transfer-Combination (DMTC) method. Also, Fuzzy Multiple Attribute Decision-Making (Fuzzy MADM) is used for clustering and routing network based on the presented distribution methods. Results show that the optimistic method outperformed the blind one and reduced energy consumption, especially in extensive networks; however, in small WSNs, the blind scheme resulted in an energy efficiency network. Furthermore, network growth leads optimistic WSN to save higher energy in comparison with blinded ones. Based on the results of complexity analysis, the presented optimal and blind methods are improved by 28% and 48%, respectively.

## 1. Introduction

A sensor network consists of many sensor nodes interacting strongly with the physical environment, which receives and responds to environmental information through the sensor. The connection between these nodes is wireless. Each node works independently and has specific capabilities and a certain energy level. To perform the placement operation in some methods, several nodes are equipped with higher capabilities such as higher radio range, more energy, auxiliary equipment for movement, and a GPS receiver [1]. According to the data collection methods, the wireless sensor network

can be divided into two categories: homogeneous sensor networks, including base stations and sensor nodes equipped with the same capabilities (e.g., computing power and capacity). They have the same memory. Data collection in these types of networks is based on the data structure. Heterogeneous sensor networks have a base station (complex sensor nodes equipped with advanced processing and communication capabilities) compared to conventional sensor nodes [2].

Sensor distribution (i.e., the location of sensors in the target area) is one of the leading design issues in wireless sensor networks. The location of a sensor may affect the implementation of system requirements and network performance

metrics [3]. Careful placement of the sensors can be an effective optimization tool to achieve the desired design goals. For example, the total coverage is directly related to how the sensors are adequately positioned to cover the desired area on the wireless sensor network. The sensors should not be too close to each other, not overlap, and not be overused. They also should not be too far apart to prevent the formation of coverage gaps in the network. A good distribution makes it possible to perform better in gathering information and communication [3, 4]. Some distribution methods also use stationary sensors to support the sensor location's dynamic adaptation, making it possible to reconfigure a dynamic distribution and improve network performance to minimize energy consumption [5]. During the design process of the network infrastructure, the creation of routes is affected by the sensors' energy limit because wireless transmission is directly related to the second (and higher) power of distance [6]. Using multistep delivery methods will result in less power loss, but using this method will cause problems in topology management and access control to the transmission environment [7]. Therefore, because in most networks, the sensors are randomly located in the network, it is not possible to use multipath methods [8].

Clustering in network routing can significantly affect the overall scalability of the system, lifespan, and energy efficiency [9]. Hierarchical routing is one of the most efficient ways to reduce energy consumption within a cluster and reduce the number of responses sent to the base station [10, 11]. In contrast, a single-level network may overload the gates as traffic congestion increases. In addition, a single-level architecture is not scalable for a large set of nodes because sensors are usually not able to communicate over long distances. In addition, clustering can stabilize network topology along routes and reduce overhead and overall topology maintenance costs. It means that the nodes are protected only when connected to CHs. Furthermore, they are not affected by changes in levels between CHs [12]. CHs can also implement an optimized management strategy that will drive network performance and battery and network life. A CH can schedule intracluster activities so that the nodes switch to sleep mode (low power consumption) and reduce the energy dissipation rate. Nodes can also be used in a rotating order to specify a time for sending and receiving information. As a result, data retrieval is prevented [13].

One of the main goals of wireless sensor network designs is to make data transmission work to extend the network's lifespan and prevent connections from failing through power management methods. Routing protocols in such networks are affected by some challenging factors. Tolerance against error and the ability to organize and expand have been the reasons for the success of wireless sensor networks in applications [14]. Creating an efficient architecture in distributing information between nodes can meet the time lost in the abnormal data filter. These wireless sensor networks can be created within fog computing, distributing the computational load between several nodes [15] effectively. The sensor node is first used to identify the data, and CHs should evaluate it. The tendency toward the adoption of wireless sensor networks has intensified in recent years due to its extensive

applications in a variety of industries. A wireless sensor network [16] is formed by linking a large number of sensor nodes. Prior to its actual application, the designed methodology must be tested. Having a live sensor network environment, on the other hand, is not always feasible. In that case, simulation is the only way to test the study before moving on with real-world implementation. To date, a wide range of modeling tools for WSN networks are accessible, some of which are dedicated to wireless sensor networks and others which are applicable to both wireless and wired networks [16]. The distance between the data center and the data source is the fundamental downside of cloud computing. Fog computing is a cloud computing technology that addresses these issues. It is one of the paradigms for distributed service computing. It makes full use of terminal devices' diverse computational features. It has paravirtualized architecture as well [17]. With strict energy and processing resource constraints, distributed detection is a critical challenge for WSNs. The appropriate threshold in most detection cases is determined by the noise power, which is subject to considerable variability in practice [18]. Fog computing adds to the power and benefits of cloud computing and services by extending data generation and analysis to the network edge [19]. Real-time location-based services and applications with mobility assistance are feasible because of the physical proximity of users and a high-speed internet connection to the cloud. To promote fog computing, load balancing approaches are utilized which may be done in two forms, static load balancing and dynamic load balancing [19].

Because most WSNs operate in unattended locations where human access and monitoring are nearly impossible, lifetime improvement has always been a critical concern. Clustering is one of the most effective approaches for organizing system operations in a coordinated manner to improve network scalability, reduce energy consumption, and extend network lifetime. During cluster creation, however, most of the prior techniques overload the cluster leader. To address this issue, various academics devised the concept of fuzzy logic, which is used in WSN decision-making [20]. The clustering hierarchy technique is another approach for data transfer in WSNs. This algorithm is one of the most potent ways for increasing the energy efficiency of WSNs and for maximizing the lifetime of WSNs. WSNs conserve energy by using hierarchical protocols centered on clustering hierarchy. Data might be collected and transmitted to a base station by nodes having more remaining energy. Nevertheless, earlier clustering hierarchy approaches [21] did not account for duplicated data acquired by nearby nodes or nodes that overlapped. Currently used clustering strategies include selecting cluster heads with higher leftover energy and rotating cluster heads on a regular basis to spread energy consumption across nodes in each cluster and lengthen network lifetime. Most earlier algorithms, on the other hand, did not take into account the predicted residual energy, which is then used to predict the remaining energy for selecting a cluster head and performing a round [22].

This study is aimed at working in a computational network of fog with a set of inhomogeneous wireless devices. The objective is to provide a computational distribution

method that reduces energy consumption in the nodes and satisfies the limitations of the edge delay. These nodes are dynamic and can both examine nodes and measure their communication links. The network can be used in smart cities or intelligent buildings that take information from sensors such as (traffic density or temperature) from the environment and use fog computing. Other works include network clustering and routing to reduce energy consumption and extend network life. For this purpose, fuzzy MADM algorithms are used to select optimal CHs. Therefore, the main aims are summarized as the following points:

- (i) Provide computational distribution method in Dynamic WSN
- (ii) Network routing using fuzzy MADM algorithms

The paper includes Introduction to present the main problem statement, and all need to be satisfied based on fog computing and routing WSN. Related Works provides a brief description of the literature review regarding fog computing. Methods and Materials represents the presented model and governing equations for both computation distribution and routing protocol. In Results and Discussion, the final findings and analysis results are illustrated. Finally, Conclusion summarizes the results and provides the future scope and direction of the study.

## 2. Related Works

Various methods have been proposed to analyze the spatial and temporal density of routing data; for example, the NMAST method [23] uses the ability of neighboring dynamics to measure the spatial and temporal density of data.  $k$  pathways can be utilized for visual investigation in applications such as traffic monitoring, public transit planning, and location selection as dynamic networks, unlike typical clustering algorithms that need several data-dependent hyperparameters [24]. Research of fog computing defined a new generation of support of WSN used in any aspect of smart cities, for example, using the system in the emergency system of fireman [25], traffic light control [26], agricultural system [27], and health monitoring system [28]. One of the challenges of WSN is data privacy. Gathering information and transferring to the base station needs some proper affords like designing security systems. For overcoming this challenge, the fog system is one efficient framework. In this case, an aggregator may be disconnected from the fog server and unable to send data directly. It can, nevertheless, share the encrypted data with an adjacent aggregator in order to send data to the fog server by adding its current collected data to the encrypted data. The relevant data values may be extracted by the fog server and saved in a local repository, which may then be updated in cloud repositories [29]. Storage, communication, transmission ratio, energy consumption, and resilience are all improved by the fog system [29]. As a result, job allocation and secure deduplication are two of the system's tasks. It detects data and protects against security risks. Sharma and Saini [30] proposed a Multi-Objective based Whale Optimization method for the modeling of a fog layer system for safe

data deduplication. Average latency, customer happiness, network longevity, energy usage, and security strength all increased as a result of their work [30]. Szykiewicz et al. [31] developed an energy-aware, secure sensing and computing system centered on static and dynamic clusters and edge and fog computing paradigms. The aggregated data stored at edges were transferred to the base station to analyze by gateways. The results of the implementation enhanced security and offload of data analysis [31].

The following are some examples of effective fuzzy algorithm applications in WSN. To model noisy power uncertainty, Mohammadi et al. [18] employed the fuzzy hypothesis test (FHT). Furthermore, using the Neyman–Pearson lemma on the FHT, they presented an optimum censoring strategy. It is demonstrated that the best censoring strategy may be found by comparing the energy of observed data to a threshold. The threshold would be determined by the local communication limitation and the noise uncertainty limitation, according to the findings [18]. Mohammadi et al. [32] looked at a decentralized detection problem for a WSN and utilized FHT to characterize the noise power uncertainty from a Bayesian perspective. The suggested method was assessed in terms of detection and false alarm probability. In the presence of noisy power uncertainty, simulations indicate that the suggested detector outperforms both the Anderson–Darling approach and the standard energy detector. Nayak and Vathasavai [20] looked into the pros and cons of a variety of clustering techniques. These algorithms are focused on CH efficiency, which might be adaptable, adaptable, and intelligent enough to transfer load across sensor nodes, extending the network lifetime. Menaria et al. [33] introduced an FT technique in WSN to manage faults that happen during data transmission from the sensor to the sink or base station due to link or node failure. An enhanced quadratic minimum spanning tree technique was used in the model. To increase fault tolerance in WSN, the revised technique introduced a unique approach to discover an alternate edge in the spanning tree in place of the broken or failed edge.

In a chapter, Kaur et al. [17] discussed the various aspects of cloud and fog computing platforms. In addition, both platforms' full architectures were provided, along with a comparison study. All application management techniques were examined, including resource coordination, distributed application deployment, and distributed data flow. Different load balancing algorithms were described by Singh et al. [19]. In fog computing settings, round robin load balancing is the simplest and most straightforward load balancing solution. The Source IP Hash load-balancing technique has a critical flaw in that each change might redirect to anybody with a different server, making it unsuitable for fog networks [19]. El Alami and Najid [21] developed an improved clustering hierarchy methodology for overlapping and nearby nodes based on the sleeping-waking process. As a result, data redundancy was reduced to a minimum, and network lifespan was increased. Unlike earlier hierarchical routing algorithms, which needed all nodes to gather and send data, the suggested technique just needed the waking nodes to do so. They use the method in both homogeneous and

TABLE 1: Summary of literature review of the paper.

Author	Year	Subject	Method	Application	Results
Giang et al. [34]	2020	Large scale, dynamic fog computing in WSN	Distributed node-RED	Base study	Reduce costs
Hossan & Nower [26]	2020	Fog-based WSN dynamic	Neighboring impact factor	Efficient dynamic traffic light control algorithm for multiple intersections	Reduces wait time, lowers fuel consumption, and boosts system throughput
Sharma & Saini [30]	2020	Task allocation and secure deduplication using fog computing	Hybrid Multiplier. Multi-Objective based Whale Optimization algorithm	Base study	Enhancement in average latency, user satisfaction, network lifetime, energy consumption, and security strength
Tsipis et al. [27]	2020	Latency-Adjustable Cloud/Fog Computing Architecture for Time-Sensitive monitoring	Cloud/fog computing paradigm	Environmental Monitoring agricultural activity	Improve efficiency, flexibility, and scalability of the approach in terms of latency
Zeng et al. [35]	2020	Energy powered Cyber-Physical Fog Systems	Mixed-integer linear programming	Cyber-Physical application	The high energy efficiency of our algorithm
Rani & Saini [28]	2020	Secure data collection of fog computing in WSN	The combination of fog and cloud can handle extensive data collection.	Health monitoring	Reduce the cost of data transportation and storage
Bellavista et al. [36]	2020	SDN-based multi-layer routing in fog environments	Multi-Layer Advanced Networking Environment	Smart city	Determines the most suitable path and configures the proper MLR forwarding mechanism
Jain & Goel [37]	2020	Energy efficient fuzzy routing protocol	Fuzzy C-means	Wireless sensor network	High performance, low energy consumption
Tortonesi et al. [38]	2019	Innovative information-centric service model for fog computing	Fog-as-a-service	Smart city environments	An effective platform for running fog services on heterogeneous devices
Sun et al. [39]	2019	Presenting an energy-efficient clustering method for fog computing in WSNs	Cross-layer-sensing clustering method and particles swarm optimization	Base study	Optimize the data aggregation efficiency and improve the network performance
Maatoug et al. [40]	2019	Fog computing framework for energy management	Fog computing framework	Smart building	Decreases latency and improves energy-saving and the efficiency of services among things with different capabilities
Sahith et al. [41]	2019	Face identification in fog computing framework for WSN	Radio communication module XBee, ZigBee protocol	Face identification	Data collection and the functionality of the system are good.
Mihai et al. [42]	2018	Intelligent Data Processing in fog system and WSN	Fog and mist computing approaches	Base study	Improve the information to noise ratio
Bhargava et al. [43]	2017	Fog-enabled WSN system for animal behavior analysis	Edge mining concept	Animal behavior analysis	Accuracy and suitability of the methods

heterogeneous networks. Lee and Cheng [22] suggested a fuzzy-logic-based clustering methodology with an energy prediction extension to extend the lifetime of WSNs. The suggested methodology was found to be more efficient than previous distributed algorithms in simulations. Because edge devices have restricted computing and energy resources, efficient sensor deployment and power management are critical design concerns that must be addressed in order to carry out a significant amount of computation and extend the lifespan of a sensing system to guarantee high-quality monitoring. One of the challenges of the edge-based system is data volume in edge devices. Regarding the exponential increment

of data in edges, reducing this congestion can extend the WSN lifespan and improve power consumption. For overcoming this problem, Deng et al. [44] presented a compression method base of fog computing approaches. Their autoregressive analysis method reduced data congestion significantly in conjunction with improvement in power consumption. In some ways, mobile sinks work as fog nodes to connect WSNs and cloud systems. Data are received from sensor nodes and sent to the cloud system through fog nodes(sinks) [45]. Summary of some methods and research about the use of fog computing in WSN are provided in Table 1.

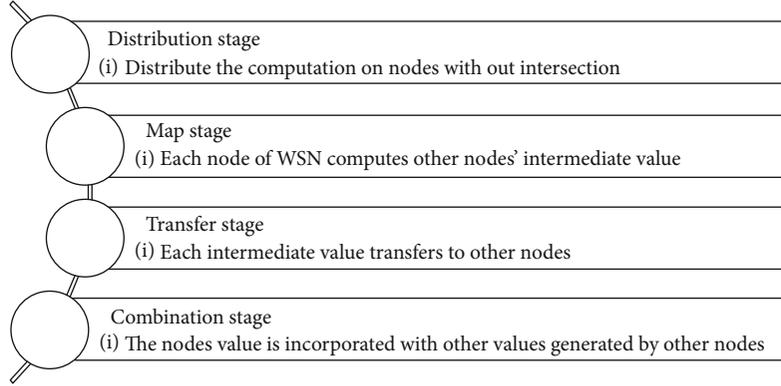


FIGURE 1: The flow chart of the presented distribution method.

### 3. Methods and Materials

**3.1. The Fog Computing.** The devices in fog computing are known as nodes. Each device with a network connection, computing, and storage can be a node that can be placed anywhere with a network connection. A variety of devices, from controllers to switches, routers, and cameras, can act as a fog in WSN. These nodes can be used in target areas such as the office or a vehicle. Each node in WSN is designated as a fog node and computed the primary services.

**3.2. Architecture and Working.** The conceptual diagram of the proposed fog computing for WSN is illustrated in Figures 1 and 2. In the presented fog computing, WSN is related to four stages of computation. Before starting the computation, data should be distributed to each node without any intersection (distribution stage). Then, in the second stage, each node of WSN computes other nodes' intermediate value from data received from the access point (map stage). In the third stage, each value transfers to other nodes (transfer stage). The node's value is incorporated with other values generated by other nodes in the combination stage. In the presented diagram, red arrow shows the first stage of the computation. At this level, data is divided into node computation memory. The nodes now act as fog computation systems. Then, each node calculated all other nodes' intermediate values at the same time. This stage (map) is depicted in green, blue, and yellow colors. Now each value should be exchanged by other node-related results. In order to achieve this goal, data is exchanged among nodes by the access point (transfer stage). In the final stage of combination, the values of the nodes are combined to reach their exact value.

The presented method with the main four steps is called Distribution-Map-Transfer-Combination (DMTC) method. The presented techniques are based on fog computing, and the main aim is to decrease the computational complexity and dead nodes as well as increase energy efficiency.

There are several reasons or objectives for using fog computing in WSN. These reasons ultimately increase organizational productivity. First is the reduction of latency in the WSN. One of the most significant benefits of fog computing is reducing latency. It is no longer necessary to send data for processing to cloud data centers or base stations, and elimi-

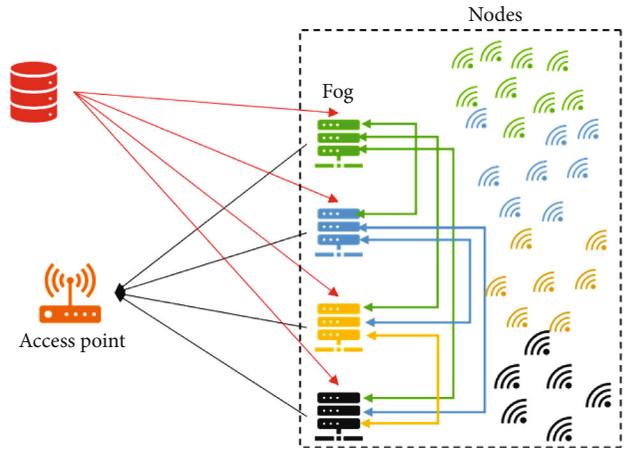


FIGURE 2: The conceptual diagram of the proposed model.

nating this problem makes data analysis and processing much better and more efficient [46]. The second is increasing performance. Not sending data to cloud computing data centers and saving time can also reduce the amount of bandwidth required to do so. In contrast, this amount of bandwidth can be used to communicate with sensors and data centers or base stations [47]. Third is extensive geographical distribution. The use of fog computing with the network's decentralization allows for wider geographical distribution than traditional networking or cloud computing. It will lead to better quality service for the end user [48–51]. Fourth is analysis instantaneously. In many environments, the ability to analyze data immediately is essential. Eliminating inefficiencies and delays in cloud services means that the user can have an accurate and instantaneous data analysis [49, 52].

**3.3. Governing Formulation.** In this paper, linear mathematical programming is used to optimize energy consumption in the presented DMTC system. The objective function for computing is presented as Eq. (1):

$$M = E_m + E_t + E_c, \tag{1}$$

where  $E_m$ ,  $E_t$ , and  $E_c$  are energy consumption for mapping, transfer, and combination stages, respectively. Also,  $n$

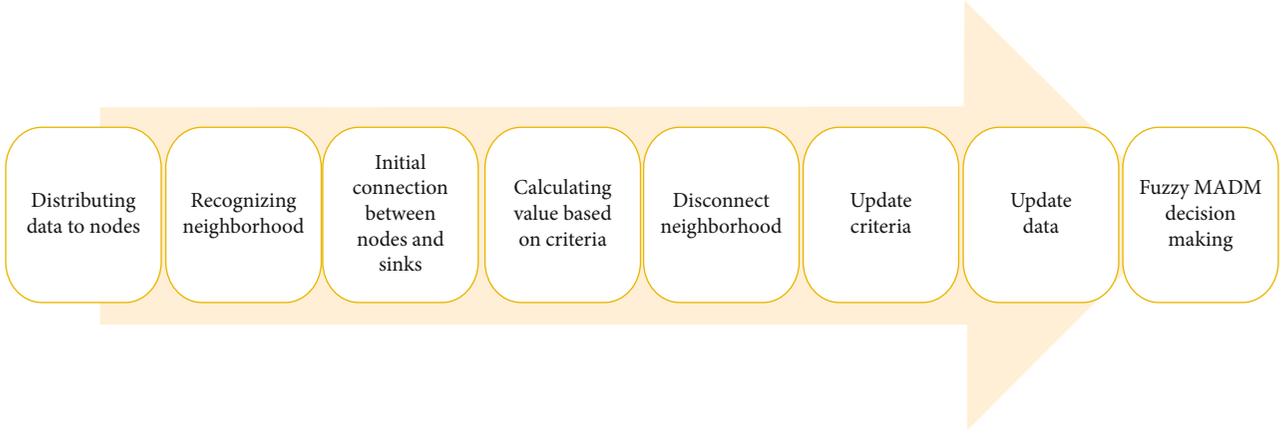


FIGURE 3: The flowchart of CH detection for routing.

is the node number. Energy consumed in mapping level is defined as follows:

$$E_m = C_n P_n (ND + l_n), \quad (2)$$

such that  $C_n$  is the number of CPU cores for processing single bit and  $P_n$  is the energy required for the process. Therefore,  $C_n P_n$  is the amount of energy for processing a single node.  $N$  is the number of nodes,  $D$  is distributed data, and  $l_n$  is the size of the distributed file.

Moreover, in transfer level, the energy consumption is equal by Eq. (3).

$$E_t = C_n P_n. \quad (3)$$

In this equation,  $T$  is the number of bits for computation.  $E_s$  shows shuffle level energy consumption is the WSN. It equals by Eq. (4):

$$E_c = \frac{p_n (N-1) T l_n}{LB \cdot \log_2(1 + p_n |h_n|^2 / T \sigma^2)}, \quad (4)$$

where  $p_n$ ,  $h_n$ ,  $B$ ,  $\Gamma$ , and  $\sigma^2$  are the power of radiofrequency of node  $n$ , wireless channel, bandwidth, SNP gap, and noise power, respectively. The following constraints are exerted to the computation:

$$\sum_{n=1}^N l_n = L, l_n \geq 0, N \geq 1, T \geq 0, \quad B \geq 1, L \geq 1, \quad (5)$$

$$\frac{l_n C_n}{F_n} + \frac{E_t}{p_n} \leq \tau_n,$$

where  $F_n$  is the number of CPU process per second in node  $n$  and  $\tau_n$  is defined as the latency of node  $n$ . According to mathematical programming, we should obtain the minimum value of energy consumption in the WSN system.

**3.4. Clustering and Routing Protocol.** In WSN routing, only a small number of nodes must be connected to the base station to increase network lifespan and decrease energy consump-

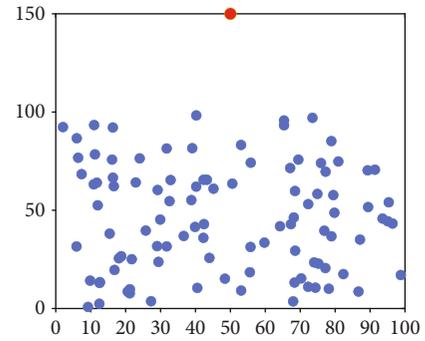


FIGURE 4: Initial wireless sensor network for the involving problem with 100 nodes and an access point.

tion. These nodes are cluster heads (CHs). Because the nodes are dynamic, the most appropriate nodes should be selected as the CHs. In this section of the study, the Fuzzy Multiple Attribute Decision-Making (MADM) method was used to select the CHs. The Fuzzy MADM method uses three criteria: concentration, the energy level in each node, and the node's centrality. The properties of the network are as follows:

- (i) The base station must be away from the sensor nodes and immobile
- (ii) All network nodes are heterogeneous and have energy limitations
- (iii) Nodes have spatial information sent to the base station with the corresponding energy level in the phase adjustment phase
- (iv) Nodes are dynamic

In this research, however, routing is based on clustering. However, the choice of CHs based on a method depends on multiple parameters. Therefore, in this study, unlike previous methods where the selection of CHs was mainly based on one criterion or a one-sided approach, in the proposed method of selection protocols, the CHs are chosen based on multicriteria.

According to the flowchart of Figure 3, first, the data is randomly distributed between the nodes. Then, the initial

TABLE 2: Parameter's value used in the presented DMTC algorithm.

Parameter	Letter	Range	Unit
Energy free space	$E_{fs}$	10	pJ/bit/m <sup>2</sup>
Energy of multipath fading	$E_{mp}$	0.0013	pJ/bit/m <sup>2</sup>
Energy dissipated per bit	$E_{elec}$	5.5	nJ/bit
Energy consumed in aggregating one-bit data	$E_{DA}$	5.5	nJ/bit
Number of CPU	$C$	500-1500	Cycle/bit
Wireless channel	$h$	$10^{-3}$	-
CPU process per second	$F$	0.1-1	GHz
Bandwidth	$B$	15	kHz
Power of process	$P$	10-200	pJ/cycle
Noise power	$\sigma^2$	1	nW
SNP gap	1	-	-

connection between the nodes and the sinks is established to load the data of each node in the system. The criteria should be identified using the existing constraints, and the values based on them should be calculated. In the next step, in order to update the data, the connection between the user and the sink is disconnected, and the criteria will be updated and measured in the new phase so that the final selection can be made based on the Fuzzy MADM method by modifying the existing data and taken from the nodes. In general, the space considered in the flowchart can be described in the following sections.

- (i) In the first stage, the establishment of nodes in the field begins so that the mechanism of neighbor detection to discover the general network and create an initial routing tree begins
- (ii) In the second stage, the best route from the relay node to the sink is identified
- (iii) The final step involves the operation stage, these criteria are monitored, and the value is dynamically changed in response to changes in the status of the network

This method optimizes the lifespan and reduces the error in the network by presenting new constraints and different assumptions. Adding node power consumption as a new constraint can have different challenges in the simulation of the proposed model.

## 4. Results and Discussion

**4.1. Architectural Properties of the WSN.** As shown in Figure 4, the first sensor network is a square network with dimensions of  $100 \times 100$  m, with the base station (BS) placed away from the sensors. In addition, all sensor nodes are provided 0.1 J of starting energy. As a result, the network's total starting energy is 10 J. The energy parameters  $E_{fs}$  and  $E_{mp}$  are 10 pJ/bit/m<sup>2</sup> and 0.0013 pJ/bit/m<sup>2</sup>, respectively.  $E_{elec}$  and  $E_{DA}$  parameters have values of 5.5 nJ/bit and 5.5 nJ/bit,

```

Forall(nodes)
  Find(neighborhood);
  Connect (nodes and Access point);
  Distribute (data);
  Em=Eq.(2)
Forall (node i:N)
  I_i=Calculate (int_value(i,...,N))
  Et=Eq.(3)
  For (node i:N)
    I_i=I_i1+I_i2+...I_iN
    Ec=Eq.(4)
    E=Eq.(1)
  For all (nodes)
    Calculating (Concentration, Centricity, Energy level)
    Disconnect (neighborhoods)
    Update (criteria)
    Update (data)
    Fuzzy MADM decision making
    Find (CHs)
    Calculate (energy, death node, pack size)
End

```

ALGORITHM 1: Pseudocode of the presented approach.

respectively. Simulation tests for 100 WSN installations were conducted to guarantee the correctness of the results. To offer a comparative description of the procedures, the average of the collected findings was employed. Experiment has numerous  $N$  clusters ranging from ten to twenty to find the ideal value of a cluster. For each value of  $N$ , the average energy consumption per cycle is determined. Moreover, the efficiency of optimum computing is studied through mathematical operations. The presented DMTC computing system includes regularly sharing  $w$  among the  $N$  nodes, without considering the nodes' computing capacities and the power of channel to access point. The used parameters for the simulation are illustrated in Table 2.

**4.2. Results of Presented Distribution Analysis.** Regarding Figure 4, the presented problem in the initial condition

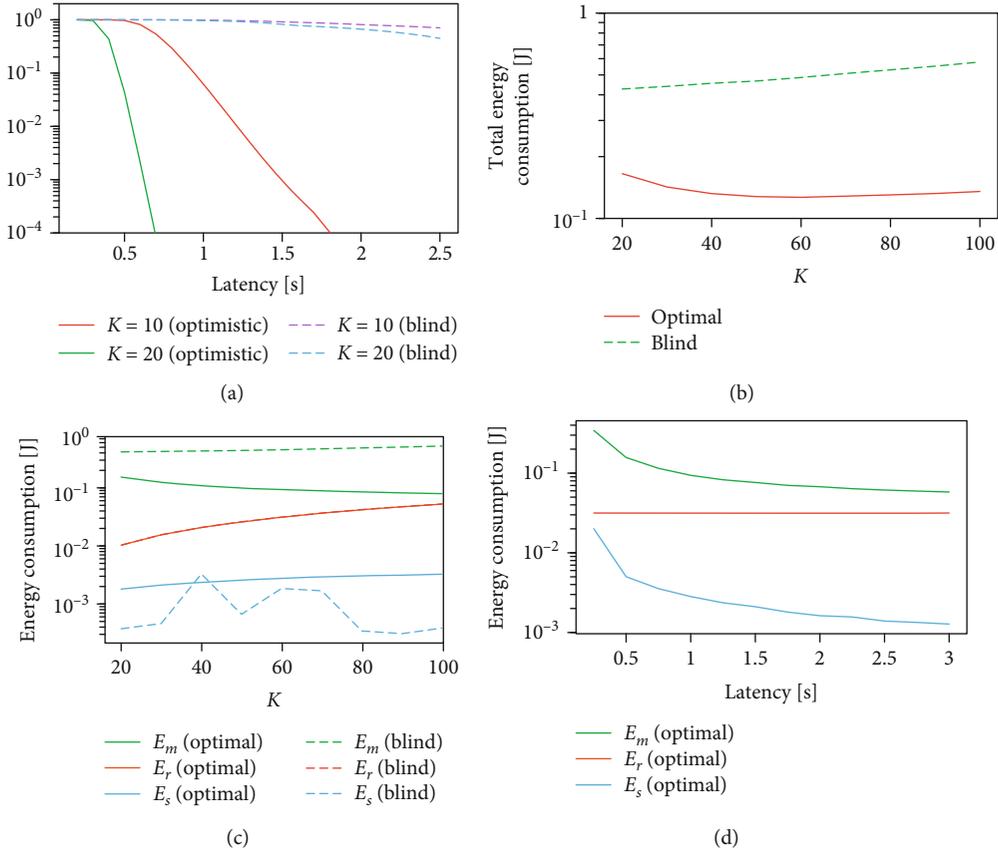


FIGURE 5: Results of the presented DMTC distributed computing method. (a) Interruption probability vs. latency, (b) total energy of fog nodes vs. number of nodes, (c) disruption of energy consumption vs. number of nodes, and (d) energy consumption vs. latency.

consists of 100 dynamic nodes of fogs with an access point. The solution area is 100 × 100 m the access point is located 50 m upper than the problem area. Before processing the network, the process is equally divided by each node based on the architecture of Figure 1. The presented method is implemented on the different number of nodes  $N$ . Two methods of computing are considered as optimistic and blind schemes.

The highest point of computational load for both of the schemes is calculated as the following equation.

$$L_{\text{optimistic}} = \tau_1 \frac{F_1}{C_1} + \dots + \tau_K \frac{F_N}{C_N}, \quad (6)$$

$$L_{\text{blind}} = N \min \left\{ \tau_1 \frac{F_1}{C_1}, \dots, \tau_K \frac{F_N}{C_N} \right\}. \quad (7)$$

If we consider each node's capacity as random values, computational load also is random. In this condition, interruption probability is shown in Figure 5(a) in different latency values in 10 and 20 nodes. Findings show that the optimistic distribution among nodes has a lower interruption in comparison with the blind model. In the optimistic method, the computing load is calculated as the sum of the process of each node. However, in the blind method, the load value is equal to  $N$  times the minimum value of the nodes

process. The results of the distribution method in Figure 5(a) show that the rising number of the total system interruption is decreased that is one of the advantages of this method. Another advantage is the remarkably low energy consumption of the optimistic approach shown in Figure 5(b) compared to the blind one. The process is done for 100 number nodes with one-second latency.

Regarding Eq. (1), total energy consumption in the presented system is constructed by three  $E_m$ ,  $E_r$ , and  $E_c$  as energy consumption for mapping, transfer, and combination stages, respectively. The results of total energy decomposition on the three factors of Figure 5(b) are depicted in Figure 5(c). Based on the results, high percentage of energy belongs to  $E_m$  and  $E_c$  for mapping and composition, respectively. With an increasing number of nodes, mapping energy decreased. Regarding Figure 5(d), with rising latency, energy consumption for mapping stage is reduced. Another advantage of the presented method is that a slower process leads to reduced energy used. We used the Fuzzy MADM method for routing the wireless sensor network based on the presented distribution algorithm in the other parts of the paper.

**4.3. Results of the Clustering Process.** Regarding Figure 4, the initial network consists of 100 fog nodes and one access point for connection. The computing load is randomly distributed between nodes based on the methods mentioned above.

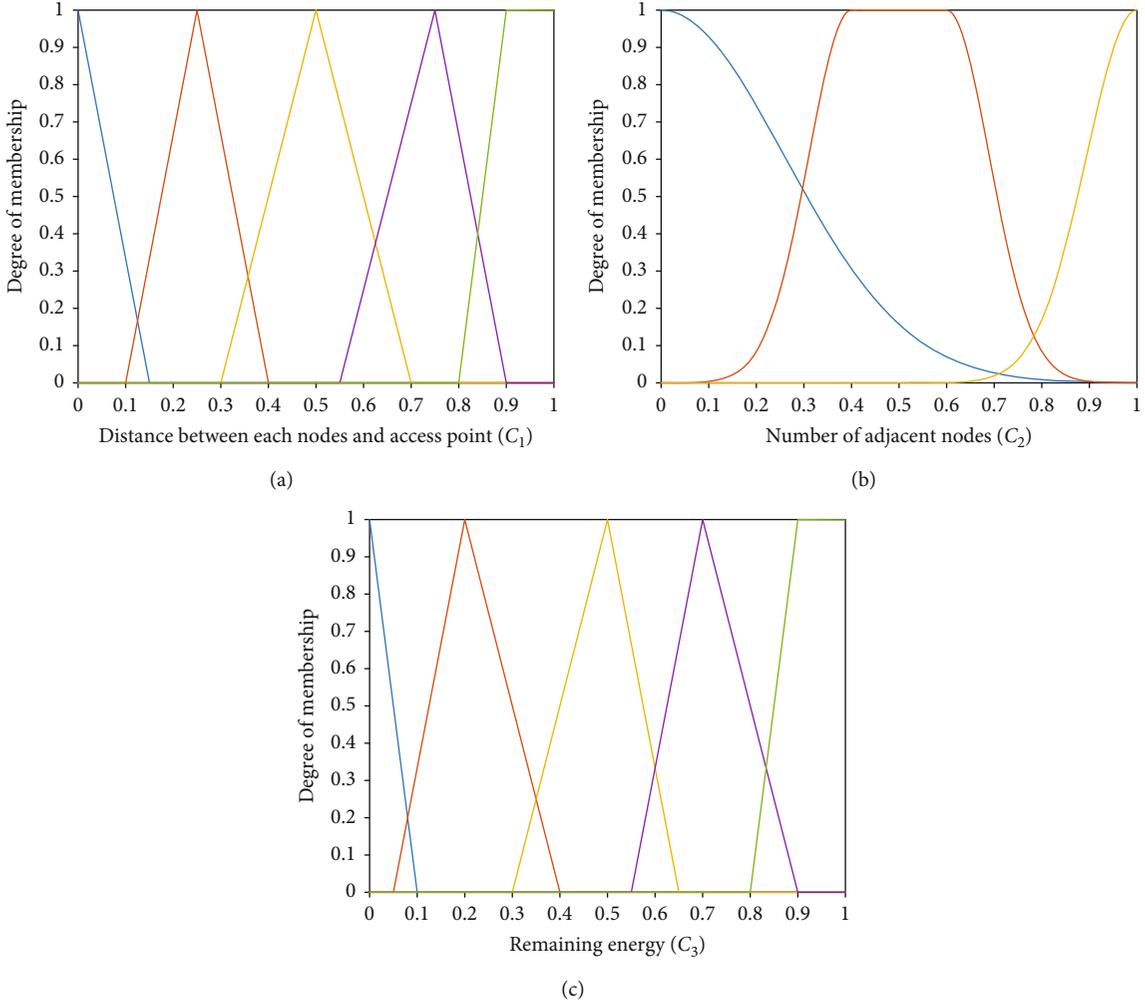


FIGURE 6: Plots of membership functions for the three components of the Fuzzy MADM method.

These processes are performed in any iteration of the presented routing method.

- (i) Checking the equipment remaining energy and determining to inactivate equipment due to the depletion of energy
- (ii) Determining cluster heads (CHs) based on the Fuzzy MADM methods
- (iii) Clustering of the remaining nodes (except CHs) according to the shortest distance to one of the CHs
- (iv) Transfer of information from nodes to CHs and then to access points based on radio transmission relationships that lead to energy consumption in nodes
- (v) If termination is not done, return the mentioned loop, i.e., check the remaining energy in the nodes and determine the inactive nodes

For determining CHs based on Fuzzy MADM, first, a decision matrix is constructed. The number of rows of the matrix is the number of nodes  $N$ , and columns are equal to three numerical criteria of decision as follows:

$C_1$ : distance between each node and access point.

$C_2$ : number of nodes in the adjacency of nodes.

$C_3$ : remaining energy of each node.

In the next step, the matrix is standardized to be ranged between 0 and 1. We used five values of very low, low, media, high, and very high for fuzzification of the matrix based on the adaptive Neuro fuzzy system. The fuzzified standardized criteria of  $C_1$ ,  $C_3$  using triangular and  $C_2$  using second-order Gaussian function are depicted in Figure 6. The equations for the energy required to transmit information on WSNs comply with wireless communication laws as follows:

$$E_{TX} = \begin{cases} K(E_{elec} + d^2 E_{fs})d \leq d_0, \\ K(E_{elec} + d^4 E_{mp})d \geq d_0. \end{cases} \quad (8)$$

The last steps are determining the CHs, calculating the energy consumption to send information from nodes to CHs and from the CHs to the access point, and implementing the node allocation to the clusters based on the minimum node's distance to the CHs. Total energy consumption is calculated as the amount of energy consumed in data

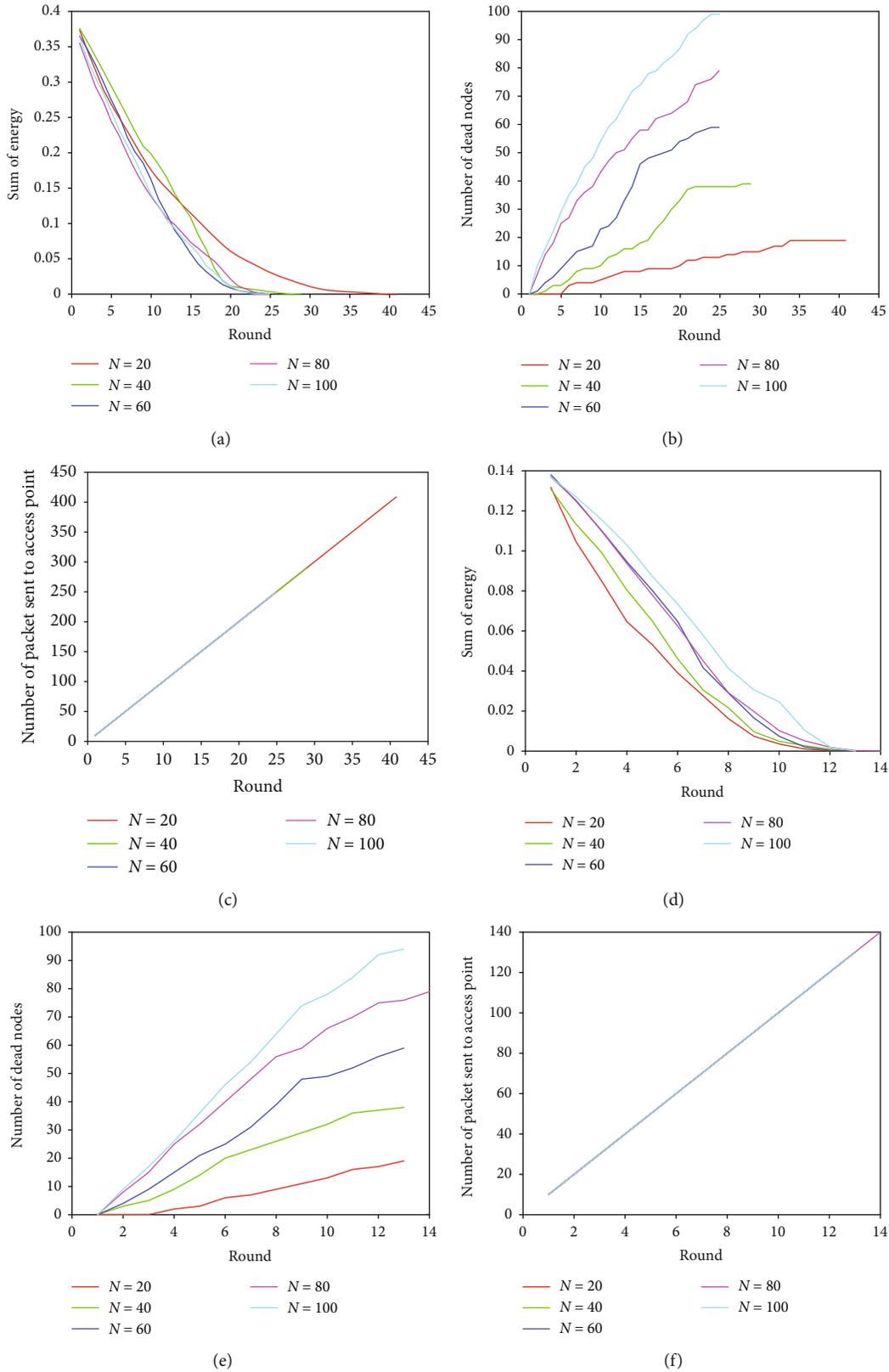


FIGURE 7: Results of routing for the presented method with Fuzzy MADM approach. (a) Energy consumption vs. round for optimistic model, (b) number of dead nodes vs. round for optimistic model, (c) number of the packet sent to the access point vs. round for optimistic model, (d) energy consumption vs. round for blind model, (e) number of dead nodes vs. round for blind model, and (f) number of the packet sent to the access point vs. round for blind model.

TABLE 3: The comparison between used protocol and literature review.

Protocol	Network size	Nodes	Death rate 1%	Death rate 50%	Death rate 100%	Computational complexity (s)
SPIN	100 × 100	100	251	283	379	630
OCM-FCM	100 × 100	100	400	980	1000	593
FD-LEACH	100 × 100	100	500	960	1000	591
PEGASIS	100 × 100	100	762	1216	1270	690
MH-EECDA	100 × 100	100	630	650	980	503
M-GEAR	100 × 100	100	951	998	1015	610
Fuzzy MADM (opt)	100 × 100	100	960	1200	1400	453
Fuzzy MADM (blind)	100 × 100	100	530	630	700	330

transmission, mapping, and composition by each node with network execution.

The routing is done using two methods of optimistic and blind, and the results are illustrated in Figure 7. Figure 7(a) shows total energy consumption for the network with the optimistic scheme for computational load distribution for the number of nodes  $N = 20, 40, 60, 80,$  and  $100$ . For all the process of optimistic scheme, computational load  $L_{\text{optimistic}}$  (see Eq. (6)) is identical. Energy consumption until all the nodes are dead shows that a network with many nodes is lower energy consumption. However, a network with 20 nodes used a higher value of energy.

Due to the optimal formation of clusters using fuzzy logic and selection of fuzzy CHs, long-distance transmission in the network is further reduced, which CHs show low energy consumption in each sensor node. It is one of the advantages of the optimistic method that has been aforementioned in the previous process. When the remaining energy of a sensor node in a network hits zero, it is called dead. The operational capacity of the network diminishes as the number of dead nodes in the network grows. As a result, sensor node mortality has a direct impact on network operation. Therefore, optimistic method endurance is reduced with the increasing number of nodes based on Figure 7(b). While 40, 60, 80, and 100 nodes are dead, only 20% of the node of 20 cases is dead. Also, the number of packed sent to access point is decreased Figure 7(c) with the increasing number of nodes. On the other hand, in the blind method, according to Figure 7(d), the increasing number of node energy consumption also has risen. Moreover, maximum energy consumption is belonging to the 100 node cases.

In this case, nodes' death is completed in almost the same round and with an identical percentage. Also, sent packages are the same approximately. The comparison between previous research is shown in Table 3. Based on the results, the mortality rate of the Fuzzy MADM method is higher than the other methods, which means that the percentage of death has lately occurred. It shows the reliability of networks based on the high lifespan of the network between the presented distributions. The optimistic scheme enhanced network endurance and led it to be competitive with other protocols. Based on the results of complexity analysis, the presented method is processed in a lower time than the other methods.

Considering the SPIN method as a baseline, the presented optimal method and blind methods were 28% and 48%, respectively.

## 5. Conclusion

Practical engineering in data distribution between nodes in a wireless sensor network can meet the time lost in the irregular information channel. These wireless sensor systems can be made inside the structure of figuring appropriating the computational fog between a few nodes successfully. This investigation is aimed at working in the field of a computational system of fog with a lot of inhomogeneous wireless nodes. The goal is to give a computational distribution strategy that outcomes in diminished energy utilization in the network and fulfills the constraints of the edge latency. The nodes are dynamic and can both look at nodes and measure their correspondence joins. In this paper, we presented the DMTC distribution method for a dynamic wireless sensor network. In this system, one access point plays the base station roles in the system, and nodes are considered fog computing subsystems. The computational load is divided by fog nodes with two optimistic and blind models in the distribution methods. In the optimistic scheme, the computing load is distributed randomly on each node, and the total load is the sum of each node process. On the other hand, in the blind model, the load value equals  $N$  times the minimum value of fog node computation. Findings show that the optimistic distribution among nodes has a lower interruption in comparison with the blind model. Also, with the number of nodes, the total system interruption is dropped, which is one of the benefits of the presented approach. Another efficiency is the low energy consumption of the optimistic method. In addition, the high contribution of energy belongs to the mapping and composition stages of energy. Also, with the rising of fog nodes, mapping energy reduced. Moreover, with the growth of latency, energy consumption for the mapping stage is dropped and a slower process consumes a low value of energy. In the next step, the distribution system was implemented on a routing and clustering technique using Fuzzy MADM. Choosing suitable cluster heads can also significantly reduce energy consumption and increase the lifespan of the WSN. The implementation of the routing

method on optimistic and blind schemes revealed that large networks consume lower energy in an optimistic approach than small ones. Also, energy consumption is dropped with clustering and choosing cluster heads. Because nodes' mortality rate influences WSN efficiency, increasing nodes' number network endurance is decremented; however, in the blind method, the efficiency of the network with an increasing number of nodes reduced. To be concluded, the optimistic scheme is proper for an extensive network. However, the blind method is better for a small network.

Fog node resources may be virtualized and distributed to several users. Multitenant support in fog resources and scheduling compute jobs based on their QoS needs have not been thoroughly addressed in the available literature. Future study can be directed toward addressing this gap in the literature. The development of a real-world testbed for testing the operation of fog-based rules is typically quite highly priced and not scalable in many circumstances. As a result, many academics are looking for an effective toolbox for fog simulation to conduct preliminary evaluations of fog computing systems. Nevertheless, there are just a few fog simulators on the market right now. Future research might include the construction of a more efficient simulator for fog computing.

### Data Availability

In this paper, a random dataset is used. And the parameters' values are extracted from articles.

### Disclosure

The funding sources had no involvement in the study design, collection, analysis, or interpretation of data, writing of the manuscript, or in the decision to submit the manuscript for publication.

### Conflicts of Interest

We declare no conflict of interest.

### References

- [1] N. Jeyakkannan and B. Nagaraj, "Online monitoring of geological methane storage and leakage based on wireless sensor networks," *Asian Journal of Chemistry*, vol. 26, Supplement 2, pp. S23–S26, 2014.
- [2] P. Saini and A. K. Sharma, "E-DEEC - enhanced distributed energy efficient clustering scheme for heterogeneous WSN," in *2010 1st International Conference on Parallel, Distributed and Grid Computing, PDGC-2010*, pp. 205–210, Solan, India, 2010.
- [3] S. H. Thimmaiah and G. Mahadevan, "Analysis of improved DV-distance algorithm for distributed localization in Wsns," *International Journal of Engineering Research and Development*, vol. 14, no. 2, pp. 16–20, 2018.
- [4] A. Gallegos, T. Noguchi, T. Izumi, and Y. Nakatani, "Zone-based energy aware data collection protocol for WSNs," *IEICE Transactions on Communications*, vol. E101.B, no. 3, pp. 750–762, 2018.
- [5] A. Petitti, D. di Paola, A. Milella et al., "A network of stationary sensors and mobile robots for distributed ambient intelligence," *IEEE Intelligent Systems*, vol. 31, no. 6, pp. 28–34, 2016.
- [6] E. Pietrosemoli, "Long-distance, low-cost wireless data transmission," *URSI Radio Science Bulletin*, vol. 339, no. 339, pp. 23–31, 2011.
- [7] B. Song, W. Xiao, and Z. Zhang, "Multi-step sensor scheduling for energy-efficient high-accuracy collaborative target tracking in wireless sensor networks," in *Proceedings-2013 IEEE International Conference on Green Computing and Communications and IEEE Internet of Things and IEEE Cyber, Physical and Social Computing, GreenCom-iThings-CPSCom 2013*, pp. 1341–1345, Beijing, China, 2013.
- [8] G. P. Sunitha, S. M. D. Kumar, and B. P. V. Kumar, "Energy efficient hierarchical multipath routing protocol to alleviate congestion in WSN," *International Journal of Ad Hoc and Ubiquitous Computing*, vol. 32, no. 1, pp. 59–73, 2019.
- [9] M. Azharuddin and P. K. Jana, "PSO-based approach for energy-efficient and energy-balanced routing and clustering in wireless sensor networks," *Soft Computing*, vol. 21, no. 22, pp. 6825–6839, 2017.
- [10] L. Chan, K. Gomez Chavez, H. Rudolph, and A. Hourani, "Hierarchical routing protocols for wireless sensor network: a compressive survey," *Wireless Networks*, vol. 26, no. 5, pp. 3291–3314, 2020.
- [11] P. S. Mann and S. Singh, "Energy-efficient hierarchical routing for wireless sensor networks: a swarm intelligence approach," *Wireless Personal Communications*, vol. 92, no. 2, pp. 785–805, 2017.
- [12] M. Jamuna Rani and C. Vasanthanayaki, "Network condition based multi-level image compression and transmission in WSN," *Computer Communications*, vol. 150, pp. 317–324, 2020.
- [13] A. Lipare and D. R. Edla, "Cluster head selection and cluster construction using fuzzy logic in WSNs," in *2019 IEEE 16th India Council International Conference, INDICON 2019 - Symposium Proceedings*, pp. 1–4, Rajkot, India, 2019.
- [14] M. A. Siddiqi, A. A. Mugheri, and M. Khoso, "Analysis on security methods of wireless sensor network," *Sukkur IBA Journal of Computing and Mathematical Sciences*, vol. 2, no. 1, pp. 52–60, 2018.
- [15] G. Zhang and R. Li, "Fog computing architecture-based data acquisition for WSN applications," *China Communications*, vol. 14, no. 11, pp. 69–81, 2017.
- [16] A. Nayyar and R. Singh, "A comprehensive review of simulation tools for wireless sensor networks (WSNs)," *Journal of Wireless Networking and Communications*, vol. 5, no. 1, pp. 19–47, 2015.
- [17] A. Kaur, P. Singh, and A. Nayyar, "Fog Computing: Building a Road to IoT with Fog Analytics," in *Fog Data Analytics for IoT Applications*, pp. 59–78, Springer, 2020.
- [18] A. Mohammadi, S. H. Javadi, D. Ciunzo, V. Persico, and A. Pescapé, "Distributed detection with fuzzy censoring sensors in the presence of noise uncertainty," *Neurocomputing*, vol. 351, pp. 196–204, 2019.
- [19] S. P. Singh, R. Kumar, A. Sharma, and A. Nayyar, "Leveraging energy-efficient load balancing algorithms in fog computing," *Concurrency and Computation: Practice and Experience*, p. e5913, 2020.

- [20] P. Nayak and B. Vathasavai, "Energy efficient clustering algorithm for multi-hop wireless sensor network using type-2 fuzzy logic," *IEEE Sensors Journal*, vol. 17, no. 14, pp. 4492–4499, 2017.
- [21] H. El Alami and A. Najid, "ECH: an enhanced clustering hierarchy approach to maximize lifetime of wireless sensor networks," *IEEE Access*, vol. 7, pp. 107142–107153, 2019.
- [22] J. S. Lee and W. L. Cheng, "Fuzzy-logic-based clustering approach for wireless sensor networks using energy prediction," *IEEE Sensors Journal*, vol. 12, no. 9, pp. 2891–2897, 2012.
- [23] Y. Yang, J. Cai, H. Yang, J. Zhang, and X. Zhao, "TAD: a trajectory clustering algorithm based on spatial-temporal density analysis," *Expert Systems with Applications*, vol. 139, p. 112846, 2020.
- [24] S. Wang, Z. Bao, J. S. Culpepper, T. Sellis, and X. Qin, "Fast large-scale trajectory clustering," *Proceedings of the VLDB Endowment*, vol. 13, no. 1, pp. 29–42, 2019.
- [25] L. Campanile, M. Gribaudo, M. Iacono, and M. Mastroianni, "Performance evaluation of a fog WSN infrastructure for emergency management," *Simulation Modelling Practice and Theory*, vol. 104, article 102120, 2020.
- [26] S. Hossain and N. Nower, "Fog-based dynamic traffic light control system for improving public transport," *Public Transport*, vol. 12, no. 2, pp. 431–454, 2020.
- [27] A. Tspis, A. Papamichail, G. Koufoudakis, G. Tsoumanis, S. E. Polykalas, and K. Oikonomou, "Latency-adjustable cloud/fog computing architecture for time-sensitive environmental monitoring in olive groves," *AgriEngineering*, vol. 2, no. 1, pp. 175–205, 2020.
- [28] S. Rani and P. Saini, "Fog Computing: Applications and Secure Data Aggregation," in *Handbook of Computer Networks and Cyber Security: Principles and Paradigms*, pp. 475–492, Springer, 2019.
- [29] A. Ullah, G. Said, M. Sher, and H. Ning, "Fog-assisted secure healthcare data aggregation scheme in IoT-enabled WSN," *Peer-to-Peer Networking and Applications*, vol. 13, no. 1, pp. 163–174, 2020.
- [30] S. Sharma and H. Saini, "Fog assisted task allocation and secure deduplication using 2FBO2 and MoWo in cluster-based industrial IoT (IIoT)," *Computer Communications*, vol. 152, pp. 187–199, 2020.
- [31] E. Niewiadomska-Szynkiewicz, A. Sikora, J. Kołodziej, and P. Szynkiewicz, "Modelling and simulation of secure energy aware fog sensing systems," *Simulation Modelling Practice and Theory*, vol. 101, article 102011, 2020.
- [32] A. Mohammadi, S. H. Javadi, and D. Ciunzo, "Bayesian fuzzy hypothesis test in wireless sensor networks with noise uncertainty," *Applied Soft Computing*, vol. 77, pp. 218–224, 2019.
- [33] V. K. Menaria, S. C. Jain, N. Raju, R. Kumari, A. Nayyar, and E. Hosain, "NLFFT: a novel fault tolerance model using artificial intelligence to improve performance in wireless sensor networks," *IEEE Access*, vol. 8, pp. 149231–149254, 2020.
- [34] N. K. Giang, R. Lea, and V. C. M. Leung, "Developing applications in large scale, dynamic fog computing: a case study," *Software: Practice and Experience*, vol. 50, no. 5, pp. 519–532, 2020.
- [35] D. Zeng, L. Gu, and H. Yao, "Towards energy efficient service composition in green energy powered Cyber-Physical Fog Systems," *Future Generation Computer Systems*, vol. 105, pp. 757–765, 2020.
- [36] P. Bellavista, C. Giannelli, and D. D. P. Montenero, "A reference model and prototype implementation for SDN-based multi layer routing in fog environments," *IEEE Transactions on Network and Service Management*, vol. 17, no. 3, pp. 1460–1473, 2020.
- [37] A. Jain and A. K. Goel, "Energy efficient fuzzy routing protocol for wireless sensor networks," *Wireless Personal Communications*, vol. 110, no. 3, pp. 1459–1474, 2020.
- [38] M. Tortonesi, M. Govoni, A. Morelli, G. Riberto, C. Stefanelli, and N. Suri, "Taming the IoT data deluge: an innovative information-centric service model for fog computing applications," *Future Generation Computer Systems*, vol. 93, pp. 888–902, 2019.
- [39] Z. Sun, L. Wei, C. Xu et al., "An energy-efficient cross-layer-sensing clustering method based on intelligent fog computing in WSNs," *IEEE Access*, vol. 7, pp. 144165–144177, 2019.
- [40] A. Maatoug, G. Belalem, and S. Mahmoudi, "Fog computing framework for location-based energy management in smart buildings," *Multiagent and Grid Systems*, vol. 15, no. 1, pp. 39–56, 2019.
- [41] S. R. Sahith, S. R. Rudraraju, A. Negi, and N. K. Suryadevara, "Mesh WSN data aggregation and face identification in fog computing framework," in *Proceedings of the International Conference on Sensing Technology, ICST*, pp. 1–6, Sydney, NSW, Australia, 2019.
- [42] V. Mihai, C. E. Hanganu, G. Stamatescu, and D. Popescu, "WSN and fog computing integration for intelligent data processing," in *Proceedings of the 10th International Conference on Electronics, Computers and Artificial Intelligence, ECAI 2018*, pp. 1–4, Iasi, Romania, 2019.
- [43] K. Bhargava, S. Ivanov, C. Kulatunga, and W. Donnelly, "Fog-enabled WSN system for animal behavior analysis in precision dairy," in *2017 International Conference on Computing, Networking and Communications, ICNC 2017*, pp. 504–510, Silicon Valley, CA, USA, 2017.
- [44] H. Deng, Z. Guo, R. Lin, and H. Zou, "Fog computing architecture-based data reduction scheme for WSN," in *1st International Conference on Industrial Artificial Intelligence, IAI 2019*, pp. 1–6, Shenyang, China, 2019.
- [45] T. Wang, J. Zeng, Y. Lai et al., "Data collection from WSNs to the cloud based on mobile Fog elements," *Future Generation Computer Systems*, vol. 105, pp. 864–872, 2020.
- [46] Y. Y. Shih, W. H. Chung, A. C. Pang, T. C. Chiu, and H. Y. Wei, "Enabling low-latency applications in fog-radio access networks," *IEEE Network*, vol. 31, no. 1, pp. 52–58, 2017.
- [47] K. Bhargava and S. Ivanov, "A fog computing approach for localization in WSN," in *IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC*, pp. 1–7, Montreal, QC, Canada, 2018.
- [48] A. H. Gandomi, A. H. Alavi, A. Asghari, H. Niroomand, and A. M. Nazar, "An innovative approach for modeling of hysteretic energy demand in steel moment resisting frames," *Neural Computing and Applications*, vol. 24, no. 6, pp. 1285–1291, 2014.
- [49] A. Matin Nazar, P. Jiao, Q. Zhang, K. J. I. Egbe, and A. H. Alavi, "A new structural health monitoring approach based on smartphone measurements of magnetic field intensity," *IEEE Instrumentation & Measurement Magazine*, vol. 24, pp. 49–50, 2021.

- [50] M. H. Syed, E. B. Fernandez, and M. Ilyas, "A pattern for fog computing," in *ACM International Conference Proceeding Series*, pp. 1–10, New York, NY, USA, 2016.
- [51] A. M. Nazar, K.-J. I. Egbe, P. Jiao, and A. H. Alavi, "A novel multi-mode magnetic triboelectric nanogenerator energy harvesting system," in *Behavior and Mechanics of Multifunctional Materials XV*, 2021.
- [52] K. Intharawijitr, K. Iida, and H. Koga, "Analysis of fog model considering computing and communication latency in 5G cellular networks," in *2016 IEEE International Conference on Pervasive Computing and Communication Workshops, PerCom Workshops*, pp. 1–4, Sydney, NSW, Australia, 2016.