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Research Article

Machine Learning-Based Data Analytics for IoT-Enabled Industry Automation

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The virtual network which is regarded as a bridge between real-world applications and computerized systems is termed Internet of Things (IoT). Internet of Things can access the real-world application by considering the wireless sensor network and internet facility as its main technology. The Internet o Things (IoT) comprises a global network that connects sensors, electronic devices, and software. Fog computing requires managing services among the various fog nodes. Fog computing plays a major role in the reduction in latency and energy consumption. Traces of fog nodes help to identify the location awareness to the IoT destination. As the fog nodes are geographically distributed, they can support high availability and scalability factors in large amounts of data provided by various sensors in industries. The heterogeneity issues can be handled by the proposed cognitive fog of things system by supporting interoperability and flexibility in sensors connected to machinery. The proposed work comprises of reduction in energy efficiency and latency reduction in the industrial sector with the fault analysis from the data received from sensors in machinery. The proposed system consists of the newly developed cognitive fog of things with optimization techniques. This work determines the impact of data transmission in cloud computing with the fog computing layer to improve the energy efficiency, delay time, and throughput.

1. Introduction

The IWSN is one of the most widely used applications of the WSN, and it makes use of a large number of sensor nodes to accomplish its goals. Temperature sensors, sound sensors, vibration sensors, pressure sensors, and other sorts of sensor nodes are all used to monitor and track different forms of data [1]. When anything goes out of control, the sensor nodes give data to the control system, which then notifies the system. At this stage, the most important consideration is the passage of time. Communication delay must be decreased in an industrial setting due to the importance of the communication [2]. In order to conserve even more energy as a consequence of their limited energy capacity, the sensors' energy consumption must be reduced to an absolute minimum. The greater the amount of energy saved, the longer the life expectancy of the network. For lowering the energy consumption of data transmission, a variety of methods have been published in the literature [3]. The usage of sink nodes to improve communication is one of the most extensively utilised strategies to do this. The sink node may be either fixed or mobile, depending on the situation [4]. In accordance with [5], the immobile sink nodes remain in a certain location at all times, and as a consequence, the nodes in close proximity to the sink node drain more energy as a result of data flow [6]. It is possible to overcome this drawback by using a mobile sink, which is a device that moves around the network and collects data on the go. The energy consumption of the nodes throughout the network is reduced as a result of this approach [7]. As a result, this work installs a mobile sink node for data gathering in order to benefit from the benefits of mobile sinks [8–10]. While the mobile sink is travelling from node to node, it is doing so in order to collect information [11]. As a consequence of this, the latency and time needed to reach the sink node are both raised as well. As a result, the concept of clustering is also used in this study, resulting in all of the nodes being clustered together in a single group of nodes [12]. Every cluster is governed by a node known as the cluster head node, which is in charge of managing the activity of many member nodes [9] and is responsible for the overall health of the cluster. All of the member nodes in a cluster have the ability to interact with the cluster head node, and the cluster head node has the ability to connect with the mobile sink [10, 13]. It is possible to increase manageability while simultaneously lowering communication latency using this technique. Because of this, energy consumption is reduced, and the lifetime of the network is prolonged [13]. The primary objectives of the initiative are to lower communication latency and energy consumption in order to increase the network's lifespan [14]. This work is divided into two primary components, which are cluster formation and data accumulation by a mobile sink node [15]. Cluster formation is the first part of the study, and data accumulation is the second portion of the study. The job selection method is used to form the first cluster of nodes in the first cluster. Using the Artificial Bee Colony (ABC) algorithm [16], the data gathering by the mobile sink node is carried out by reaching out to all of the clusters, and the ideal path is built with the assistance of the mobile sink node. It is then determined how well the job performs in terms of communication throughput, latency, energy consumption, time consumption, and network longevity [17].

2. Proposed Clustered Data Accumulation Scheme Based on Mobile Sink with ABC Algorithm

This section describes the proposed data accumulation strategy, which is based on the stages of clustering and ideal route selection [18]. The clustering phase was aimed at bringing the nodes together under the control of a cluster head node, which is in charge of managing the cluster [19]. This process of clustering is accomplished with the assistance of the task selection algorithm [20], which has been developed. Figure 1 depicts an overview of the planned work's overall flow diagram.

It can be readily seen in the above-presented image that the nodes are initially grouped, and that the cluster head nodes may communicate with the mobile sink node by using the optimal route selected by the ABC algorithm to do so [21]. Periodically, the data is sent from the mobile sink to the control room. The computational complexity and time consumption for data transport are reduced as a result of this concept. The ABC algorithm is described in further detail in the next section [22].

3. ABC Algorithm

ABC is a metaheuristic algorithm that is designed to emulate the natural behaviour of honey bees. It was developed [23] and is based on his research. The food supply, the number of employed and unemployed bees, and the number of employed bees are all key components in the ABC algorithm [24]. The primary goal of this algorithm is to locate the most suitable food source.

Food Source: a food source may be designated as the best by taking numerous factors into consideration, including the distance between the food and the hive, the quality of the food, and the ease with which the energy can be absorbed [25]. A food source is determined to be the best based on the factors listed above

In their day-to-day activities, bees on the job are tasked with disseminating vital information about the food supply. Food supply location and distance from the hive are the most important pieces of information being sent [26]. In the case of a large swarm, the hired bees take care of half the bees, while the observation bees take care of the rest.

Jobless bees may be divided into two types: scout bees and observer bees. Scout bees are the most common kind of unemployed bee. The scout bees are on the lookout for a new food source in the vicinity of the beehive [27]. The spectator bees remain in the hive and use the information gleaned from the employed bees to discover the source of food for the colony [28]. The location of the food supply is often found to be the optimal answer to the optimization issue, and the amount of honey present in the food source determines the quality of the meal produced [29]. The fitness function of the algorithm is determined by the quality of the meal. Using the theme of employed bees, the algorithm determines that employed bees are concerned with the food source; observer bees remain in the beehive and determine the food source; and scout bees hunt for new food sources [30]. The following is a representation of the standard pseudocode for the ABC algorithm 1.

Scout bees are responsible for conducting the first search for food sources. As soon as this stage is completed, the spectator and the hired bees will begin to exploit the food supply [31]. The food supply becomes depleted after continuous exploitation, and the hired bees are relegated to the role of scout bee [32]. The number of employed bees is always the same as the number of food sources, since each employed bee is connected with a single food source, as a result of this relationship [33]. Generally speaking, the most fundamental ABC method is divided into three phases: initialization; employed; onlooker; and scout bees phase. After each step has been completed, the process is repeated until the maximum number of iterations has been completed within a specified time frame [34]. To begin, it is required to identify the total number of solutions that are accessible, as well as the control parameters that will be used

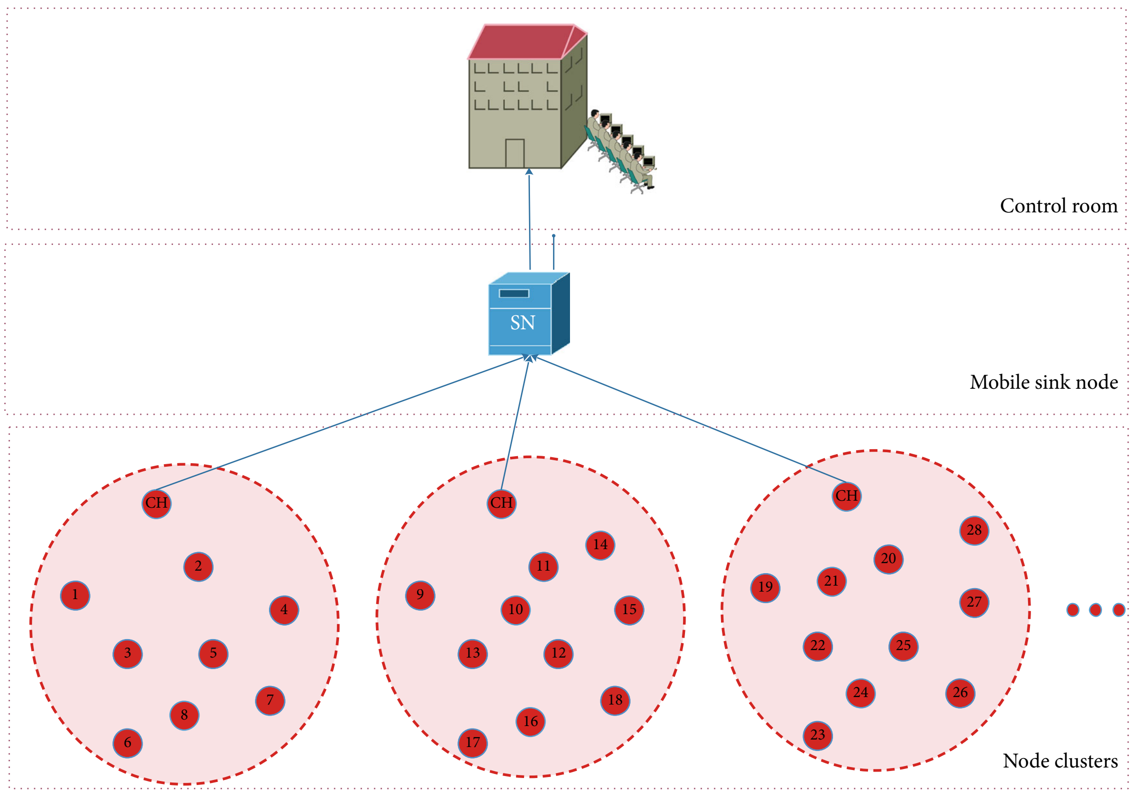

FIGURE 1: Overall flow diagram of the proposed data accumulation scheme.

1: Produce initial population $i_p = 1 to MC$
2: Calculate the fitness function of the population
3: Fix counter=1
4: Do
//Employed bees phase
5: Search for the food source;
6: Calculate the fitness function;
7: Employ greedy selection process;
8: Compute the probability for the food source;
// Onlooker bees phase
9: Select food source based on the probability values;
10: Generate new food source;
11: Calculate the fitness function;
12: Apply greedy selection process;
//Scout bees phase
13: If food source drops out then swap it with new food source;
14: Save the best food source;
15: Counter + =1;
16: While counter=MC;

ALGORITHM 1: Standard pseudocode of the ABC algorithm.

[35]. The employed bees' phase is characterised by the search for new, higher-quality food sources in the neighbourhood of the old food source in which they were previously engaged [36]. The new food source is examined for its fitness in the next stage, and the findings are then compared to the prior food source with the help of greedy selection to determine which is superior [37]. It is the observation bees that are present in the hive that spread information about the food source that has been collected [38] about the food source that has been obtained. When it comes to choosing food sources, the spectator bees use a probabilistic approach that is informed by the information supplied by the employed bees during the second phase of the decision-making process [39]. The computation of the fitness function of a food source that is located near to

Input: Clustered Nodes;
Output: Ideal Path Selection;
Begin
1: Produce initial population $i_p = 1 to MC$
2: Calculate the fitness function of the population by eqn (5.1)
3: Fix counter=1
4: Do
//Employed bees phase
5: Search for the food source;
6: Calculate the fitness function by eqn.(5.1);
7: Employ greedy selection process;
8: Compute the probability for the food source by eqn.(5.3);
// Onlooker bees phase
9: Select food source based on the probability values;
10: Generate new food source;
11: Calculate the fitness function;
12: Apply greedy selection process;
//Scout bees phase
13: If food source drops out then swap it with new food source;
14: Save the best food source;
15: Counter + =1;
16: While counter=MC;

Algorithm 2: Proposed ideal path selection algorithm.

Table 1: Simulation parameters.

Parameter	Settings
Network area	200 × 200
Initial energy of nodes	2 J
Communication radius	50 m
Energy for data transmission	50 nJ/bit
Speed of mobile sink	2 m/sec

the food source that was picked in the previous step is carried out after this phase [40]. The avaricious selection compares and contrasts the old and new food sources that are accessible to the greedy selection. The hired bees are eventually demoted to scout bees if it is not possible to make improvements to the replies within a certain number of iterations. It is the bees' decision to abandon the answers that they have identified. A fresh food source is being sought by the scout bees at this point, and any unacceptable choices have been ruled out of consideration. All three steps are repeated until the stopping point is achieved, according to [41].

3.1. Proposed Ideal Path Selection by ABC Algorithm. The mobile sink node has to handle multiple cluster head nodes for accumulating the data [42]. Let the cluster head nodes be represented by $\varphi = ,\mathrm{CH}-1.,,\mathrm{CH}-2.,,\mathrm{CH}-3.,\cdots.,\mathrm{CH}-n..$, and the traversing path of the sink node must be detected, so as to reach all the CH nodes. The choice of route is finalized by considering two parameters, which are distance between the mobile sink and the CH node and the energy cost. With these parameters, the fitness function is built as follows.

$$\mathrm{fv}(i) = ,q(\mathrm{ER}(\mathrm{PT})) - \mathrm{Di}(t, \mathrm{tts})..\qquad (1)$$

In the above equation, I is the cluster head, ER(PT) is the energy required to transmit a message, and $\mathrm{Dis}(i, \mathrm{ms})$ is the distance between the cluster head and the mobile sink node. Based on this fitness function, the proposed ABC-based path selection algorithm is presented as follows in algorithm 2.

The probability of the food source is computed by the following equation.

$$(\mathrm{FS}) = \mathrm{LN}(\mathrm{OS}) + \alpha(\mathrm{LN}(\mathrm{OS}) - \mathrm{LN}(\mathrm{NS})).\qquad (2)$$

In the above equation, LN(OS) and LN(NS) are the locations of old and new cluster heads, and α is a parameter ranges between 1 and -1.

$$\mathrm{pro}, b - i. = ,f, v - y.-, \frac{\mathrm{is}}{1} - \mathrm{fl}-.f, v - s \cdots\qquad (3)$$

In the above equation, fvi is the fitness value of the i^{th} cluster head node and n is the total number of cluster head nodes.

By this way, the ideal path is selected with the help of energy gain and distance between the mobile sink and cluster head. This idea conserves energy and reduces the communication delay [43]. The performance of the proposed work is evaluated in the following section.

4. Results and Discussion

The performance of the work is evaluated by implementing the work in NS2, on a standalone computer [44]. The parameters chosen to carry out the simulation are presented in Table 1.

The performance of the proposed work is analysed in terms of throughput, latency, energy consumption, time

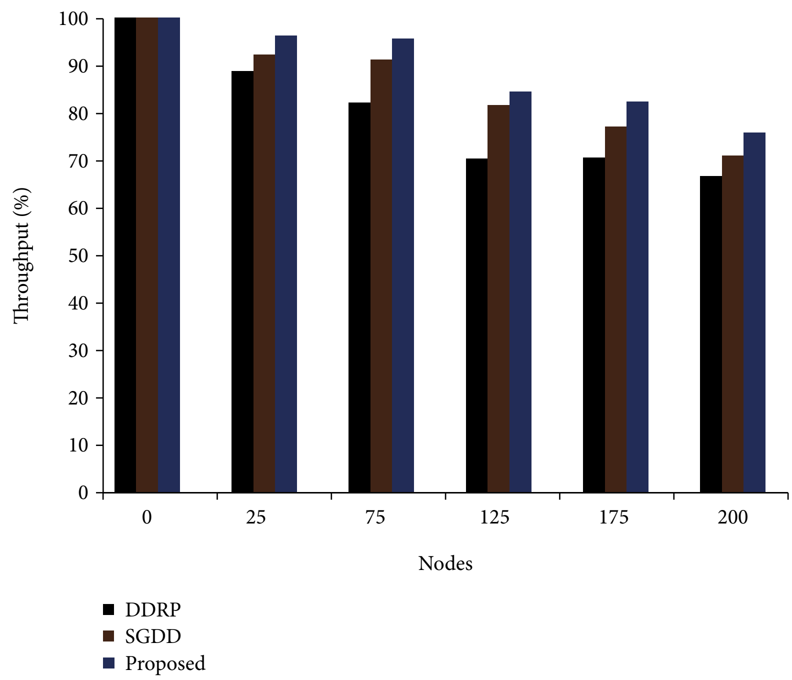

Figure 2: Throughput analysis.

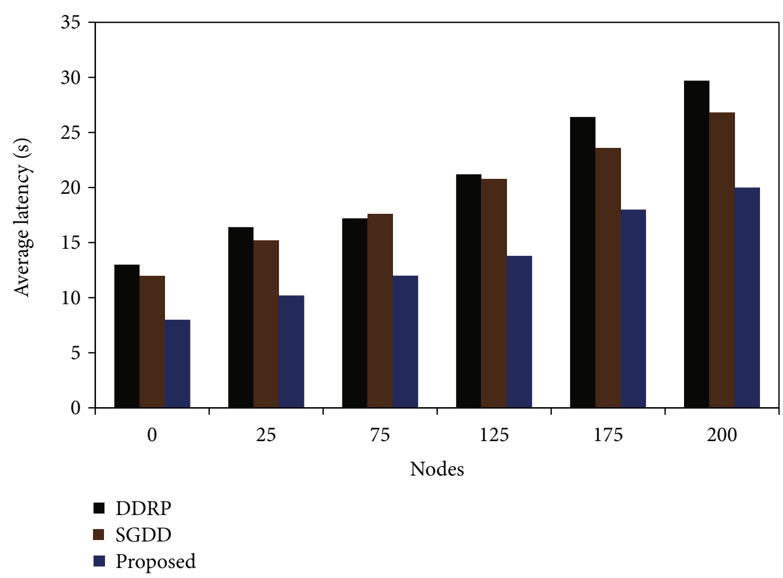

Figure 3: Average latency analysis.

consumption, and network lifetime. The results attained by the proposed work are compared with the existing approaches, such as DDRP and SGDD, respectively. The attained experimental results are presented as follows in Figure 2.

From Figures 2–5, you can see the planned work's throughput and average delay, as well as its energy consumption and network lifespan. The experimental findings demonstrate that the suggested approach results in increased throughput and network lifespan while reducing latency and energy consumption to an acceptable level. Throughput refers to the total volume of data sent over a specific period. The throughput must be as high as possible, regardless of the data transfer mechanism utilised. The latency of data transmission should be kept to a minimum in order for the data to be transferred on time. Due to the high sensitivity of industrial applications, it is essential to guarantee that data transmissions have the shortest possible latency. This study achieves low latency via the application of two concepts: the use of sink nodes and the selection of the optimal route for sink nodes to go to and from the cluster head node. The energy consumption of the suggested task is then evaluated in relation to the length of time spent in simulation. As time passes, the energy

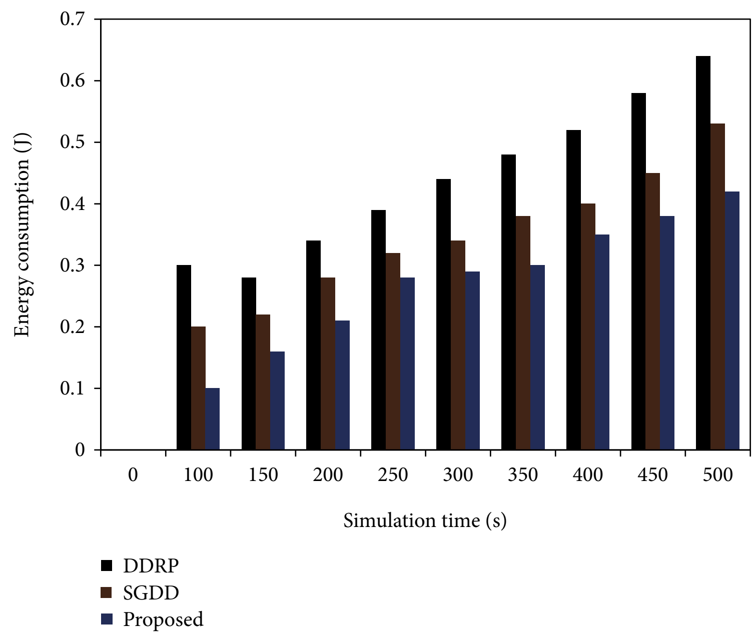

Figure 4: Energy consumption analysis.

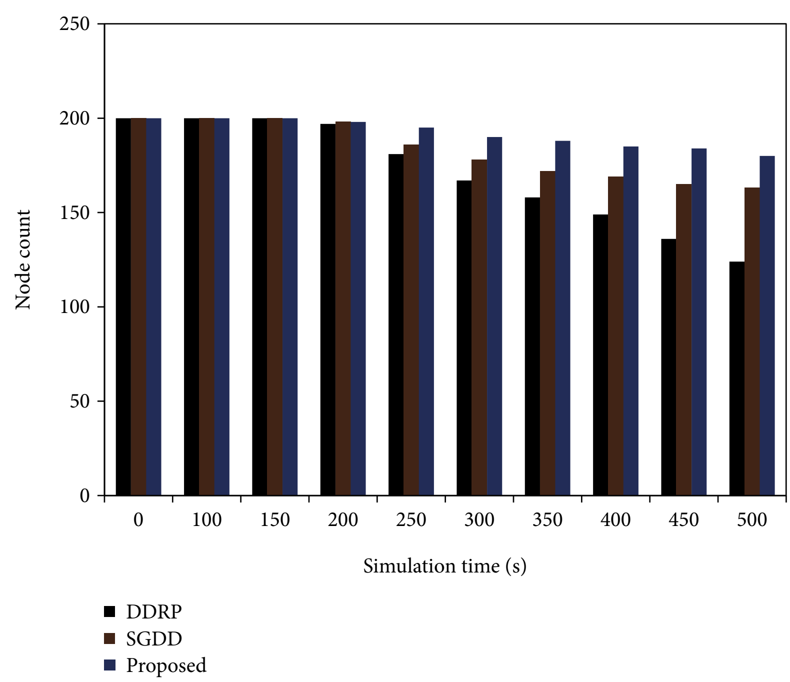

Figure 5: Network lifetime analysis.

consumption of the nodes increases [45]. If we compare the suggested technique with others that have been used before, it uses the least amount of energy, thanks to the optimal route selection that takes into account both energy gain and distance metrics. As the energy usage decreases, it becomes evident that the network's lifespan will be extended. The lifespan of a network is assessed in terms of the number of nodes that are still operational in the network. There are about 180 living nodes in the proposed work at the conclusion of the 500th second, while the rival strategies had 124 and 163 alive nodes, respectively. Time is measured and recorded in Table 2 for the time at which the final node dies.

The proposed work has lived up to 10262 seconds, whereas the competitive works show up with 6219 and 7634

Table 2: Network lifetime analysis with respect to time.

Sensor count	DDRP (s)	SGDD (s)	Proposed (s)
100	2134	2304	2473
200	2581	2864	3021
300	2867	3215	3543
400	3142	4046	4873
500	3314	4628	6043
600	4017	5537	6943
700	4324	6242	8261
800	6219	7634	10262

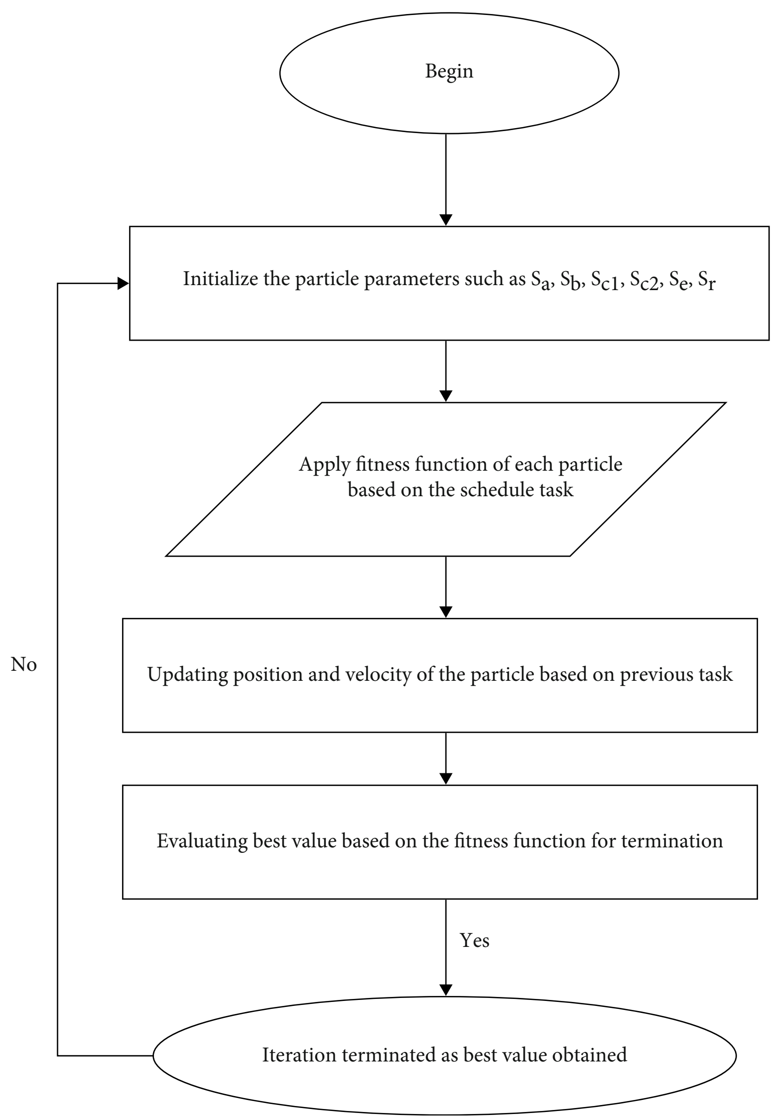

Figure 6: PSO optimization.

seconds, respectively. The complete network lifetime is measured and presented in Table 2. From the experimental results, it is proven that the proposed work has shown greater lifetime owing to the employment of mobile sink node and ideal path selection concepts.

Figure 6 represents the flow chart of PSO optimization, and Figure 7 represents the ACO optimization.

The proposed work provides a structured fog computing architecture comprised of various conceptual layers that successfully preserves the decentralisation of Internet of Things

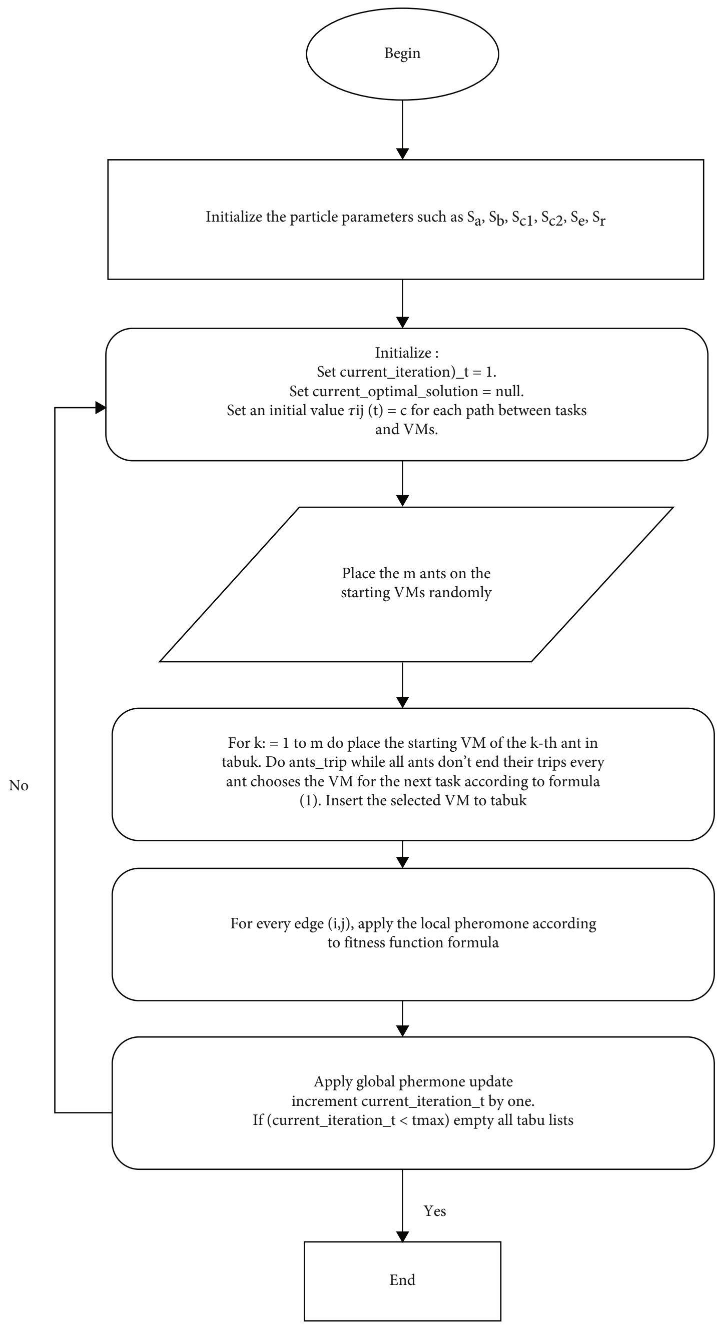

Figure 7: ACO optimization.

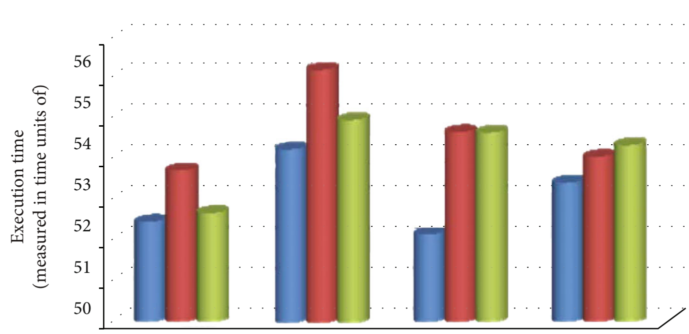

Figure 8: Job execution time after ACO, GA, and PSO scheduling.

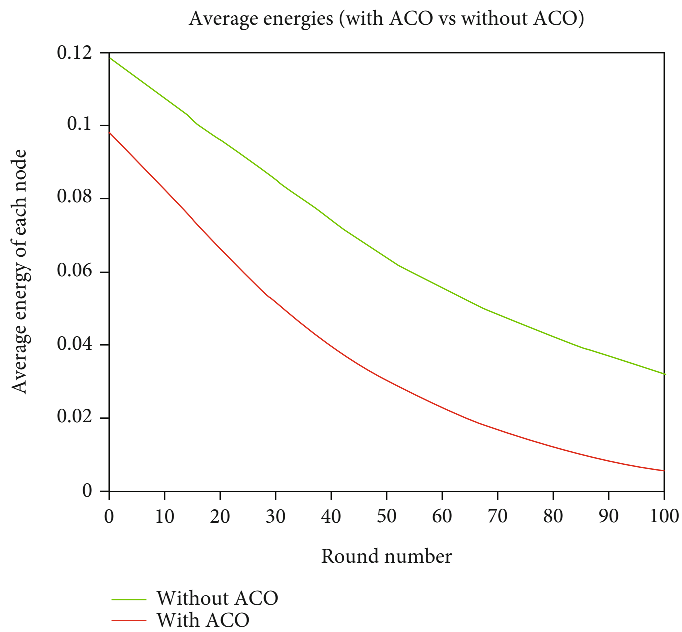

Figure 9: Average energy.

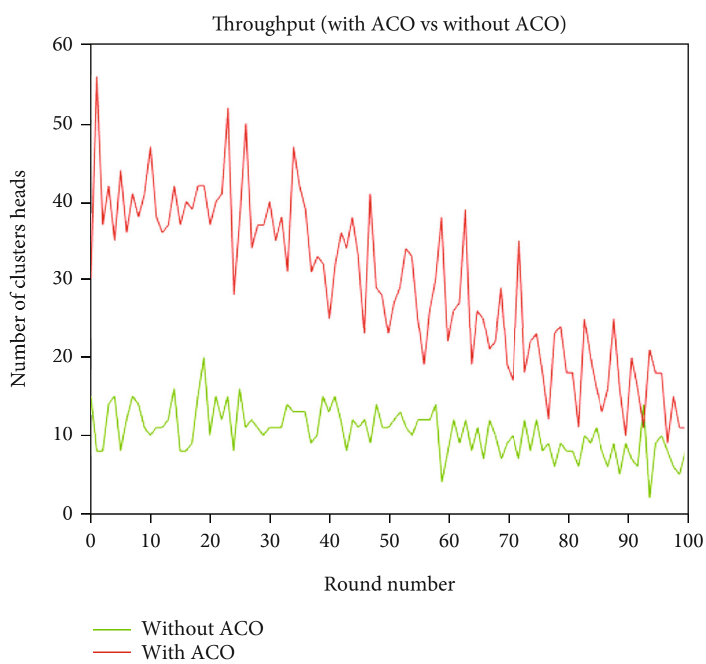

Figure 10: Throughput.

(IoT) service delivery while also reducing costs and increasing efficiency. To optimise service decentralisation on the fog computing landscape, a task (service) placement approach is developed. This approach makes use of context-aware information, such as the application's location, computation and storage capacities of fog devices, and the application's expected deadline, in order to maximise the utilisation of fog devices that are available at the network edge while minimising latency, energy consumption, and cost. For this purpose, we develop a simulation platform in the MATLAB environment, test the recommended task scheduling approach to see whether or not it is effective, and configure the fog computing system model, as well as the task scheduling model that is associated with it. In this paper, the improved particle swarm optimization algorithm and the improved ant colony optimization algorithm are introduced in order to solve the task scheduling objective function and to improve the performance of the improved particle swarm optimization algorithm and the improved ant colony optimization algorithm, respectively, for the first time. Using ACO [44], a range of simulation tests may be executed in less time, as shown in Figure 8. Comparing ACO with PSO, ACO completes all jobs in 52.42 seconds with 60 fog nodes, but PSO completes all tasks in 53.34 seconds with the same number of fog nodes.

With a reduction in power consumption, the latency and throughput of the system rise. Task scheduling employing ACO Optimization methods boosts throughput while simultaneously reducing power consumption, as seen in Figures 9 and 10, respectively.

5. Conclusion

It is described in this chapter how an IWSN data-accumulation system may be made more energy efficient by using a mobile sink to gather information. The clustering and optimum route selection techniques are used at every stage of the process. The job selection algorithm is used to group the nodes, and the ABC algorithm is used to calculate the ideal path for the mobile sink to travel in order to reach the cluster head. The ABC algorithm is implemented in Java. The performance of the job is assessed in terms of throughput, average latency, energy consumption, and network longevity, among other metrics. To solve the problems presented by the ant path, we suggest a route-oriented solution that is based on the collaborative efforts of the ant path's members. The two most fundamental acts of ACO, reproduction and the pursuit of food, are very similar to those of ants themselves. As part of our approach to solving the fog computing problem, we relied on two performance assessment criteria: CPU runtime and the total amount of memory that was accessible. Every operation set to be performed in the fog computing architecture is expected to need the use of this resource (allocated memory). In the future, it is intended to investigate the adoption of a holistic approach to work planning that will take into consideration the introduction of new applications while the other applications for fog computing are being developed.

Data Availability

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of Interest

All authors declared that they do not have any conflict of interest.

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