IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received March 11, 2021, accepted March 25, 2021, date of publication March 29, 2021, date of current version May 4, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3069455

T2FL-PSO: Type-2 Fuzzy Logic-Based Particle Swarm Optimization Algorithm Used to Maximize the Lifetime of Internet of Things

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ABSTRACT In recent years, the Internet of Things (IoT) has evolved as a research field that transforms human lifestyle from traditional to sophisticated. In IoT, the network plays a crucial role in collecting data from sensors and moving to the sink. Increasing the network lifetime is a challenging task in IoT, which is connected to devices that are limited by resource. Clustering is one of the effective methods of increasing the network lifetime. However, improper cluster head (CH) selection easily drains the energy early in network nodes. With the aim to overcome the issue, this paper proposes the Type-2 Fuzzy Logic-based Particle Swarm Optimization (T2FL-PSO) algorithm to select the optimal CH to extend the network lifetime. The T2FL is highly useful in providing the accurate solution in uncertain network environments. Hence, T2FL is applied on the network parameters, residual energy, and the distance between sensor node and base station to determine the fitness value. Later, virtual clusters are formed on the basis of distance between sensor node and CH and between node and base station. To validate the performance of the proposed T2FL-PSO algorithm, extensive simulations are carried out using MATLAB 2019a. Furthermore, the proposed T2FL-PSO algorithm is compared with Particle Swarm Optimization Clustering (PSO-C) and Particle Swarm Optimization Wang Zhang (PSO-WZ). The result confirms that the proposed T2FL-PSO increases the network lifetime by 10%–15% and the packet transmission ratio by 10%. Compared with similar algorithms, the proposed T2FL-PSO also causes a higher increase of network lifetime.

INDEX TERMS Clustering, cluster head, fuzzy logic, Internet of Things, particle swarm optimization.

I. INTRODUCTION

In the recent era, Internet of Things (IoT) is a new field of study that draws attention of scholars, researchers, and government agencies [1], [2]. In IoT, embedded devices are connected to the Internet, which contains an IP address for identification. In addition, IoT devices can connect with other devices at anytime and anywhere [3]–[6]. The implementation of IoT technology is based on various technologies, such as cloud computing, wireless sensor networks (WSN), and embedded systems. IoT applications include smart technologies in city, grid, farming, hotel, and supply chain management. The primary aim of IoT is to provide human beings with a sophisticated life [7]–[9].

The WSN comprises fixed sensor nodes with small memory, low power, and minimal processing ability. WSNs have a weak link and short range of wireless communication. Each sensor has a memory, power and processing unit to sense the temperature and humidity. The embedded sensor devices seem to be either linearly or randomly positioned to form a wireless network for transmitting data from one location to another. In general, the Base Station (BS) is directly connected with a power supply and all the sensor nodes are connected with rechargeable batteries. In this case, extending

The associate editor coordinating the review of this manuscript and approving it for publication was Md. Abdur Razzaque.

the network lifetime plays a significant role in WSN. Routing is one of these methods [10]–[12].

Routing is a mechanism whereby data is transferred from the sender to the BS. Routing is categorized into three types, namely, flat structure-based, hierarchical structure and location-based routing protocols [13]. The multi-hop data transmission requires much energy and creates congestion during data transmission between the network nodes. Moreover, several of the applications such as temperature and environment monitoring transfers the redundant data packets to the BS. Therefore, clustering is a good option to increase the network lifetime to prevent redundant data transmission [14]–[18].

Clustering is an effective energy saving technique in a resource-constrained wireless network. This method offers the aggregation facility in the cluster, which reduces the duplicate data from the CM and only the aggregated data are passed to the BS. In a clustering protocol, the essential processes are cluster creation, cluster head (CH) selection, and route establishment between nodes and BS [19]–[27]. The CH selection plays a crucial role in increasing the network lifetime. Figure. 1 shows the cluster based IoT architecture.

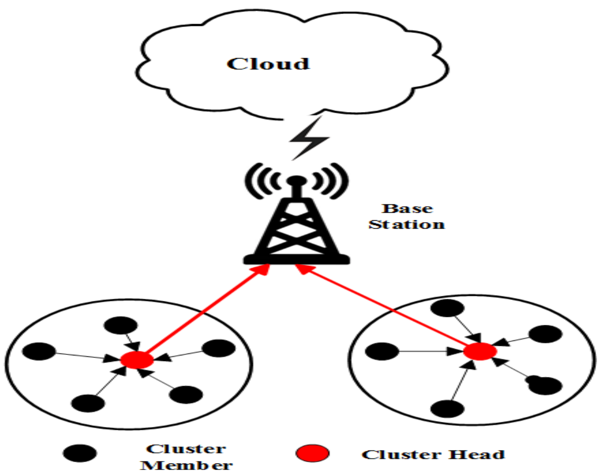

FIGURE 1. Cluster-based IoT Architecture.

CH selection uses various methods, namely, residual energy, composite metrics, probability basis, rotational basis, mathematical theories and optimization algorithm. The latter provides promising results when compared with other techniques [28], [29].

The optimization algorithm iteratively executes the procedure until the best option in the solution space is reached. Optimization algorithms include linear programming, continuous, bound-constrained, discrete, global, derivative-free and constrained optimization [30]. Linear programming is one of the most effective techniques for minimization or maximization problems to obtain the optimal solution in the solution space. The linear programming-based optimization algorithms are categorized into meta-heuristics optimization, multi-objective and multilevel optimization problems. In this, the meta-heuristics optimization is popular in finding the best solution for discrete combinatorial problems. The most popular algorithms in meta-heuristics are Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), simulated annealing, Evolutionary Algorithms (EA), Tabu Search (TS) algorithm, and Genetic Algorithm (GA) [31]–[33]. In this case, the PSO is an effective optimization algorithm for choosing the CH node within the cluster and balancing the energy depletion between nodes. Thus, PSO extends the lifetime of IoT networks batter than other meta-heuristic algorithms.

This study proposes a T2FL-PSO algorithm to select the best CH node to extend the network lifetime. The fitness value of each node is computed by exploring the fuzzy logic on the Residual Energy (RER) and BS distance. Then, virtual clusters are created based on the distance between the sensor particle and CH node and the degree of CH. Thus, the T2FL-PSO meets the network requirements and increases the overall performance.

The contributions of T2FL-PSO are stated as follows:

- In-depth analysis of CH selection based on various optimization algorithms to boost network performance in terms of network lifespan, latency, throughput and packet transmission ratio.
- Design and development of T2FL-PSO for choosing the CH in IoT to improve the network lifetime and packet transmission ratio.
- Extensive simulation is carried out using MATLAB 2019a and the performance of the proposed T2FL-PSO is compared with recent similar algorithms, namely, PSO-C and PSO-WZ.

The remainder of this paper is arranged as follows. Section 2 discusses related works. Section 3 presents the proposed system model while Section 4 presents the proposed T2FL-PSO algorithm. Section 5 discusses the result and performance comparison. Section 6 discusses the analysis. Section 7 concludes the paper with future work.

II. RELATED WORK

In this section, we use optimization algorithms to address the selection of CH in IoT. In addition, various optimization algorithm and their uses in clustering protocol are discussed. Finally, the gaps observed in related works are identified.

Zhang and Wang [34] proposed a bio-inspired CH selection in IoT. Sensor nodes are located, and the number of CH nodes is selected at random regions of the network. The cluster is created according to the division rule. Each node computes the fitness function, which is based on energy distribution and consumption. Each particle obtains the global best (gBest) and local best (pBest) based on the PSO-WZ algorithm. The particle positions are updated with respect to velocity. The velocity position is calculated from the social influence, personal influence, and inertia. The simulation is conducted, and the performance analysis is evaluated. The result confirms that the PSO-WZ algorithm increases the network lifetime by 5%–10% compared with LEACH, PSO and PSO-C.

However, the particle does not obtain the optimal value due to the consideration of parameter minimization and maximization.

Behera *et al.* [35] proposed the remaining energy-based CH selection in IoT. Choosing the right CH node plays a pivotal role in IoT load management and in optimizing network lifetime. Initially, the CH nodes are selected randomly. Later, the maximal remaining energy node acts as CH in each round. The CH node gathers data from all the cluster members (CMs) and transfers data to the BS. This type of work is suitable for smart cities, temperature monitoring and environmental monitoring. The simulation is carried out and by comparison, the proposed work increases the lifetime 8%–10% than LEACH. However, transferring data is difficult when the BS and the CH have large discrepancies.

Kulkarni and Malathi [36] proposed the penguin fuzzy logic-based ant colony optimization (PF-ACO) for CH selection in WSN. In this algorithm, the fitness value is generated by exploring the various objectives, namely, latency, remaining energy, network traffic, lifespan and node distance. The simulation is conducted, and the results show that the PF-ACO algorithm is superior to ABC, ACO and LEACH. In addition, the computational time in PF-ACO is 1.5 sec less than all other existing algorithms. However, PF-ACO takes longer to measure the fitness function.

Dohare and Singh [37] proposed the PSO-based deterministic energy-efficient clustering (PSODEC) in IoT. This algorithm selects the CH node from the cluster nodes based on maximum remaining energy. The nodes are randomly positioned within the network. The cluster is created using the K-means algorithm. Later, the PSODEC algorithm is used to select the CH node in each cluster. The simulation is conducted and the results confirm that PSODEC algorithm increases the network lifetime by 10%–15% than LEACH and DEC. However, the CH node is located far from the BS, and thus communication is difficult in certain cases.

Aziz *et al.* [38] proposed a grey wolf-based compressive algorithm (EMCA-CS) for IoT data aggregation. The EMCA-CS algorithm divides the entire network into hexagonal clusters of equal size. Selected randomly in each cluster, the CH node gathers the data from all CMs and uses compressive sensing algorithm for data aggregation. The EMCA-CS algorithm establishes the multi-hop best path between the CH nodes and BS using the grey wolf optimization (GWO) algorithm. Finally, the BS uses the GWO and reverse greedy algorithms to recover the original data sent by the CH nodes. The efficacy of EMCA-CS algorithm provides better results in terms of the network lifetime, data error rate and overall power utilization of network nodes than GWRA, CoSAMP, OMP, SP and LP.

Reddy and Babu [39] proposed the self-addictiveness whale optimization (SAWO) algorithm for CH selection in IoT. Euclidean distance is used to generate the number of clusters in the networks, and SAWO is used to select the CH in the cluster. In addition, the fitness function is calculated by utilizing the parameters, namely, latency, energy and distance. The efficacy of SAWO algorithm is compared with ABC, GA, PSO, AGSA, GSA and WOA. Compared with the latter, SAWO algorithm increases the network lifespan by 8%. However, the CH election is not optimal in several cases.

Sindhuja and Selvamani [40] proposed Ant Lion Optimization (ALOP) algorithm for CH selection in IoT to extend the network lifetime. The focus is mainly on the sink node coverage problem in the network. Energy decreases while the security increases. The experimental analysis is carried out by simulation and the result shows that the proposed ALOP extends the network lifetime by 80% relative to ABC, ABC-DB and FF. Thus, the ALOP algorithm improves security during data transmission. However, security may remain insufficient despite the energy efficiency during the transfer of data.

John and Rodrigues [41] proposed a Multi-objective Taylor Crow Optimization (MOTCO) algorithm to select CH in WSN. MOTCO constructs the network cluster based on distance between the BS and network nodes. For CH selection, the Crow search algorithm and Taylor series is applied. The objective function (OF) explores transmission delay, distance, energy and network traffic in each cluster, and then decides the optimal node as CH in each round. Finally, the CH nodes gather the information and transfers data to the BS. The proposed MOTCO algorithm improves the network lifetime by 10% compared with LEACH, PSO, ABC and FABC. However, the CH selection increases throughput and decreases the end-to-end delay.

Daniel and Rao [42] proposed a mutation chemical reaction optimization algorithm based on energy aware clustering (MCRO-ECR) for selecting the best CH in WSN. The chemical reaction and remaining energy are adopted for CH selection and cluster creation in the network. The utilization of energy in each node is computed from the following parameters, namely, sink distance, nodes distance in the cluster, node transmission energy and CH node degree. The CH node is selected in each round of the network based on energy consumption. The simulation is conducted extensively, and the result confirms that the proposed MCRP-ECR algorithm increases the network lifetime by 10% compared with all other algorithms, namely, LDC, PSO-C and CRO-ECA. However, the MCRP-ECR creates an additional concurrent problem while selecting the CH node.

Famila *et al.* [43] proposed an improved artificial bee colony optimization (IABCOCT) algorithm in WSN. The cluster creation considers the ABC algorithm and addition, which incorporates the parameters such as Cauchy operator and grenade explosion method. The CH is selected using onlooker bee and scout bee behaviour, which is considered the degree of exploitation and of exploration, respectively. Finally, the CH node passes the data directly to the BS. The IABCOCT algorithm increases the network lifetime by 10%–25% compared with HCCHE and CCT. However, IABCOCT takes more convergence.

Karthick and Palanisamy [44] proposed a CH selection using krill herd algorithm to prolong the WSN network lifetime. The major limitations are network lifetime, data redundancy in aggregation and network coverage issues. To overcome these issues, the authors proposed a krill herd (KH) optimization algorithm to select the best CH in the network. The algorithm enhances the network lifetime by 10% and raises the packet transmission ratio by 7% compared with the LEACH and GE algorithms.

Sert *et al.* [45] proposed a two-tier distributed fuzzy logic-based protocol (TTDFP) to improve the efficiency of data aggregation operations in multi-hop WSNs. Hotspots are addressed using the TTDEP, a routing protocol that adopts fuzzy logic to transfer the data from CMs to BS. The proposed TTDFP protocol is compared with similar cluster-based routing protocols. TTDFP improved the packet delivery ratio and extended the network lifetime but neglect the energy hole problem to a certain extent.

Sert *et al.* [46] proposed a multi-objective fuzzy clustering algorithm (MOFCA) for WSNs to extend the network lifetime. Problems of early energy drain in the network nodes and hotspots nearer the sink are addressed. Compared with Low Energy Adaptive Clustering Hierarchy (LEACH), Energy-Efficient Uneven Clustering (EEUC) and Energy Aware Unequal Clustering Fuzzy (EAUCF), MOFCA increased the lifespan by 8%–11%. However, MOFCA did not consider the LND metric for CH selection.

From the review of related works, various optimization algorithms for CH selection protocols in WSN-based IoT are proposed. The limitations are as follows: difficulties to reach the optimal position due to the minimization and maximization of parameters in the fitness function, several optimization algorithms take longer to measure the fitness function, lack of security while transferring the data and additional concurrency problem during the CH selection in the network. To overcome this issue, this paper proposes the T2FL-PSO algorithm to select the optimal CH to extend the network lifetime. The T2FL is highly useful to provide the accurate solution in uncertain network environments. Hence, T2FL is applied on the network parameters, residual energy and the distance between sensor node and base station to determine the fitness value. Later, virtual clusters are formed based on the distance between sensor node and CH and between node and BS. Thus, T2FL-PSO shortens the issues listed above and increases the network lifetime.

III. SYSTEM MODEL

A. NETWORK MODEL

The network comprises 'N' nodes that are randomly deployed. The DODAG root is mounted at the top of the network. Basically, the nodes should have equal energy. T2FL-PSO comprises virtual cluster formation, CH selection and route establishment. Euclidean distance is used to form the virtual clusters in the network, and the algorithm is used to find the best CH node. The route is calculated on the basis of the route metrics of the queue usage and the estimated transmission count. Above Figure. 2 show the T2FL-PSO network model.

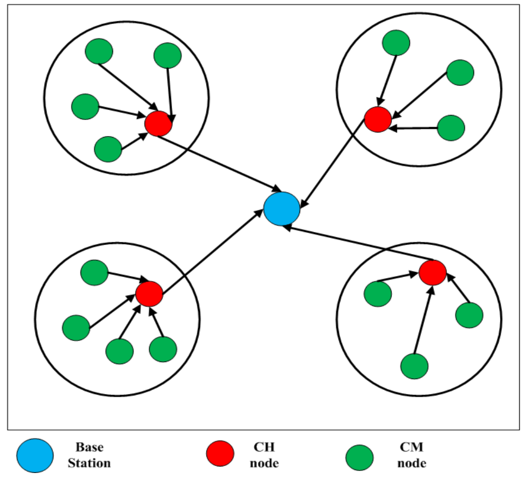

FIGURE 2. T2FL-PSO Network Model.

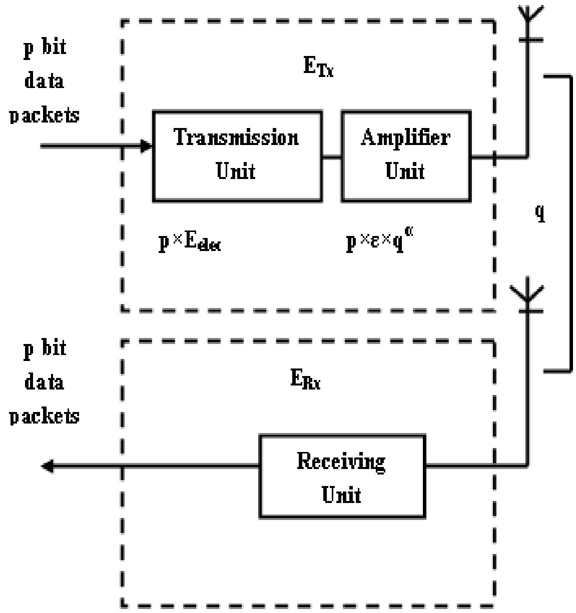

FIGURE 3. T2FL-PSO Energy Model.

B. ENERGY MODEL

The T2FL-PSO uses the model of the first order channel to consume the node energy. The node's distance within the threshold follows the free space energy model (t2 power loss) or the fading channel model (t4 power loss). Figure. 3 shows the T2FL-PSO energy model.

The energy consumption of node *x* transmits *p* bits of data to node *y* in relation to the distance *p(x,y)* [47], [48] and its measurement is given in (1).

$$\begin{aligned} E_{TX}\,(p,t) &= pE_{elec} + m\varepsilon t(x,y)^{\alpha} \\ &= \begin{cases} pE_{elec} + p \in_{fs} q(x,y)^2 & where q\,(x,y) < q_0 \\ pE_{elec} + p \in_{mp} q(x,y)^4 & where q(x,y) \geq q_0 \end{cases} \end{aligned} \tag{1}$$

where $\varepsilon_{fs} q(x,y)^2$ or $q(x,y)^4$ is energy consumption of the amplifier unit.

TABLE 1. Nomenclature of T2FL-PSO.

Notation	Definition
SP_i	Various sensor particles
D	Solution dimension space
BS	Base Station
RER	Residual Energy
T1FL	Type 1 Fuzzy Logic
T2FL	Type 2 Fuzzy Logic
IMF	Inferior Membership Function
SMF	Superior Membership Function
FOU	Foot of Uncertainty
PSO	Particle Swarm Optimization
CoG	Centre of gravity
w	Aggregated membership function
$\mu_c(w)$	Output of the defuzzifier
P_{best}	Personal best position
G_{best}	Global best position
Vel	Velocity value
c_1, c_2	Accelerate factors
CH	Cluster Head
CM	Cluster Member
w_1, w_2	Weight value

The threshold value $q0$ is calculated in (2).

$$Q_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{2}$$

The node consumes the energy for receiving p bits of data and its calculation is given in (3).

$$E_{RX}\left(q\right) = qE_{elec} \tag{3}$$

IV. PROPOSED TYPE-2 FUZZY LOGIC BASED PARTICLE SWARM OPTIMIZATION (T2FL-PSO)

The proposed T2FL-PSO has two phases, namely, CH selection and virtual cluster creation. Firstly, the CH is selected on the basis of RER and the distance between the BS and nodes. In addition, the BS executes the T2FL-PSO algorithm in the BS to select the CH in the network. Secondly, the virtual cluster is created based on the distance between node and CH an CH node degree. Each CH gathers and aggregates the data from all CMs to transfer to the BS. Table 1 presents the nomenclature of T2FL-PSO.

A. CH SELECTION PHASE

The ultimate goal of the T2FL-PSO is to select the best CH to extend the network lifetime. In this study, the metrics used are RER and distance between the BS and nodes. The T2FL-PSO has four steps, namely, particle initialization, fitness function computation, velocity and particle position update and fitness function evaluation.

1) PARTICLE INITIALIZATION

The T2FL-PSO contains a swarm of sensor particlesN_{sp}. The sensor particle is represented asSP_i, where $1 \leq i \leq N_{sp}$. Each sensor particle has various solutions or positions in the dimension space D [49]. The i^{th} sensor particle SP_i various position or solution is represented in (4).

$$SP_i = [POS_{i,1}, POS_{i,2} \ldots\ldots\ldots POS_{i,D}] \tag{4}$$

Each solution or position of the sensor particle $POS_{i,1}$ has the coordinate ($x_{i,1,}y_{i,1,}$) in the network space and its representation is given in (5).

$$\mathrm{SP_i}= [(\mathrm{x_{i,1,}}\boldsymbol{y_{i,1,}}), (\boldsymbol{x_{i,2,}y_{i,2}}) \ldots\ldots\ldots (x_{i,D,}y_{i,D,})] \tag{5}$$

where i denotes the number of sensor particles and D denotes the solution dimension space.

2) Fitness Function Computation

This function indicates the quality of the sensor particles and calculates using RER and BS distance. The former is a maximization property, and the latter is a minimization property. For weight distribution, the average weighted method cannot be applied and therefore the type-2 fuzzy logic is applied on the two parameters.

a. BS Distance

This parameter indicates the average distance between the BS and the sensor particle. The calculation is given in (6).

$$BS_{distance}\left(SP_i\right) = \sum\nolimits_{i=1}^{N_{SP}} dist(SP_i, BS) \tag{6}$$

where SP_i indicates the ith value of sensor particle and BS indicates the BS.

2) RESIDUAL ENERGY

RER is the ratio between the amounts of energy depleted and total energy in the sensor particle SP_i. The calculation is given in (7).

$$RER\left(SP_i\right) = \frac{E_{depleted}}{E_{initial}} \tag{7}$$

3) FUZZY INFERENCE SYSTEM

This method is a type of mapping between the input and output functions. Compared with T1FL, the main characteristic of T2FL is the more efficient handling of the uncertainties because of a larger number of parameters and more freedom degrees. This comprises the fuzzifier, defuzzifier, inference engine and rule base [50]. Figure. 4 displays the diagram of T2FL inference system.

The T1FLmodel is suitable to handle the unknown environment to a certain extent. To strengthen the decision making, we propose T2FL, which effectively handles uncertain environment [51]. T2FL computes the efficient fitness function to reach the G_{best} position and effectively selects the CH node. In T2FL, the membership functions comprise the low Inferior Membership Function (IMF) and high Superior Membership Function (SMF). Both IMF and SMF can be represented using T1FL membership function, and their distance is called Foot of Uncertainty (FOU) [52]–[54], with value range 0–1. The T2FL is represented in (8).

$$T2FL = SMF\left(T1FL\right) + FOU \tag{8}$$

The T2FL process is explained below.

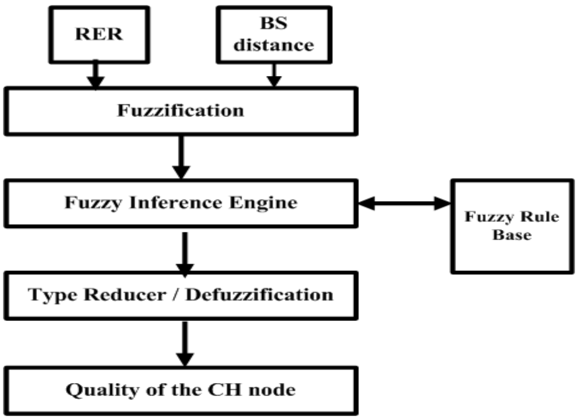

FIGURE 4. T2FL-PSO inference system.

- *Fuzzifier*

Fuzzifier is a process by which an exact value is transformed into a fuzzy value. Residual energy and BS distance are the fuzzy inputs. In a fuzzy set, the linguistic variable and membership function are important to represent the exact value in a particular context. The linguistic variable in Fuzzy set contains words or sentences instead of numbers. In T2FL-PSO, this study considers the triangular and trapezoidal membership function, which evaluates the linguistic variable in the fuzzy set. Trapezoidal and triangular membership functions are suitable for real-time operations and their computations are not complex [55], and thus are applied to the fuzzy input and output variables in this study.

The general representation of the triangular membership function is given in (9).

$$\mu_{C1}(w) = \begin{cases} 0 & w \leq d1 \\ \dfrac{w-d1}{e1-d1} & d1 \leq w \leq e1 \\ \dfrac{f1-w}{f1-e1} & e1 \leq w \leq f1 \\ 0 & f1 \leq w \end{cases} \tag{9}$$

The general representation of the trapezoidal membership function is given in (10).

$$\mu_{C2}(w) = \begin{cases} 0 & w \leq d2 \\ \dfrac{w-d2}{e2-d2} & e2 \leq w \leq f2 \\ 1 & e2 \leq w \leq f2 \\ \dfrac{f2-w}{f2-e2} & f2 \leq w \leq g2 \\ 0 & g2 \leq w \end{cases} \tag{10}$$

Figure. 5 shows the membership function of residual energy. Low, high and medium are linguistic variables, with the first two as trapezoidal and the last is a triangular membership function [56], [51]. In this context, the values of the linguistic variable set is as follows: The Low variable is 0–.1 while the High is 0.9–1. Finally, the Medium variable is 0.5. The FOU is 0.2.

The variables close, medium and far are linguistic with triangular membership with value μ of 0–1. [51]. Figure. 6

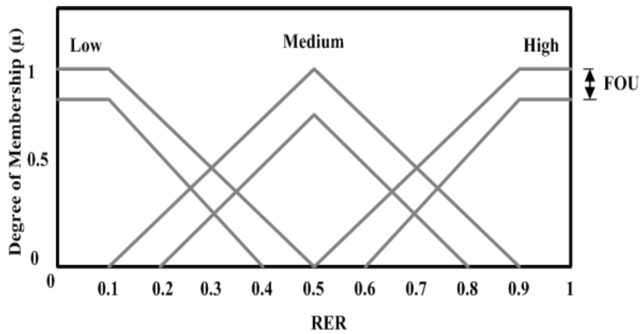

FIGURE 5. RER membership function.

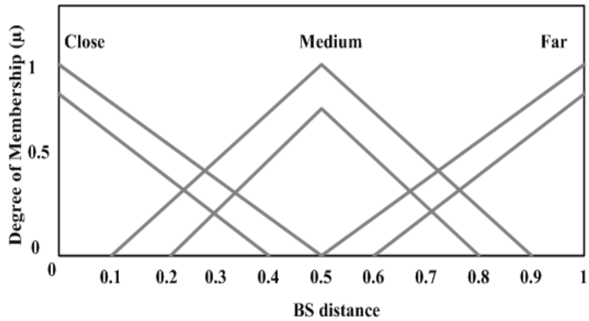

FIGURE 6. BS distance membership function.

shows the BS distance membership function. The Low variable value is 0–.1 while the High is 0.9–1. The Medium variable is 0.5. The FOU is 0.2.

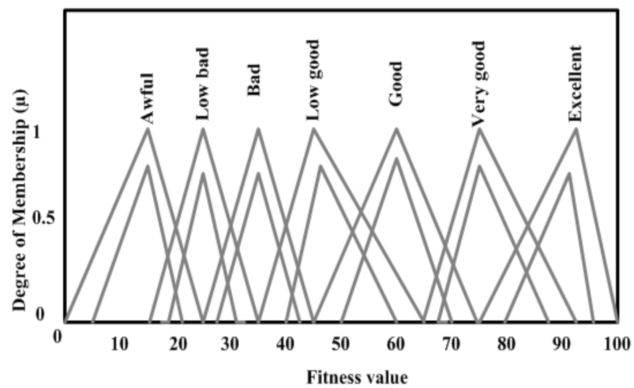

FIGURE 7. Fitness value membership function.

Figure.7 shows the membership of fitness value. The linguistic variables are Excellent, Awful, Low Good, Bad, Very good, Low bad and Good. The membership value μ is between 0–1. For all linguistic variables, the triangular membership functions are used [51], [57].

- *Fuzzy Rule Base*

This study considers the input and output parameters, namely RER, BS distance and fitness value to compute the fuzzy rules. The number of fuzzy rules is determined by the number of inputs and linguistic variables. Nine total number of rules are generated from three linguistic variables and two input fuzzy parameters. The fitness value range is 0–100. The fuzzy rules are generated using IF-THEN rules and then examined

TABLE 2. T2FL-PSO fuzzy rules.

S.No	BS distance	RER	Fitness value
1	Close	Low	Good
2	Medium	Low	Bad
3	Far	Low	Awful
4	Close	Medium	Very good
5	Medium	Medium	Good
6	Far	Medium	Bad
7	Close	High	Excellent
8	Medium	High	Very good
9	Far	High	Good

using the Mamdani model [58], [59]. Table 2 presents the fuzzy rules.

- Defuzzifier

One of the steps to transform the fuzzy output into exact value is by defuzzifier. The centre of gravity (CoG) is a method used in defuzzification, as represented in (11).

$$CoG\,(w) = \frac{\int \mu_c(w)wdw}{\int \mu_c(w)dw} \tag{11}$$

where w indicates the defuzzifier output and $\mu_c(w)$ indicates the aggregated membership function.

4) VELOCITY AND PRACTICE POSITION UPDATE

In each iteration t, the sensor particles SP_i reach their own positions, namely, P_{best} and G_{best}. Each sensor particle attempts to reach the G_{best}, which is obtained by updating the SP_i velocity $Vel_{i,d}$ and positions $POS_{i,d}$ in each iteration. The velocity $Vel_{i,d}$ calculation is given in (12).

$$\begin{aligned} Vel_{i,d}\,(t) &= w \times Vel_{i,d}\,(t-1) + c_1 \times rand_1 \\ &\quad \times (POS_{Pbest_{i,d}} - POS_{i,d}\,(t-1) + c_2 \times rand_2 \\ &\quad \times (POS_{Gbest} - POS_{i,d}\,(t-1)) \end{aligned} \tag{12}$$

where c_1 *and* c_2 indicate the accelerate factor, such as constant value, w indicates the inertial weight and $rand_1$ and $rand_2$ indicate the random values between 0 and 1.

The update of SP_i is given in (13).

$$POS_{i,d}\,(t) = POS_{i,d}\,(t-1) + Vel_{i,d}\,(t-1) \tag{13}$$

5) FITNESS FUNCTION EVALUATION

After each iteration, the sensor particles reach the new positions and the fitness function verifies that the particle reaches the G_{best}. The fitness function evaluation formulas are given in (14) and (15).

$$P_{best_i} = \begin{cases} SP_i & if\ \left(Fitness\,(SP_i) < Fitness\left(P_{best_i}\right)\right) \\ P_{best_i} & Otherwise \end{cases} \tag{14}$$

$$G_{best} = \begin{cases} SP_i & if\ (Fitness\,(SP_i) < Fitness\,(G_{best})) \\ G_{best} & Otherwise \end{cases} \tag{15}$$

The particular sensor particle SP_i that reaches G_{best} acts as a CH for a particular round. The CH selection is given in Algorithm 1.

Algorithm 1 CH Selection

Input: Set of sensor particles 'N'
Output: Optimal number CH node
1: Initialize the number of sensor particles SP
2: Compute the fitness function by applying the fuzzy logic
3: Perform fuzzification using RER and BS distance
4: Perform defuzzification using COG

$$COG\,(w) = \frac{\int \mu_c(w)wdw}{\int \mu_c(w)dw}$$

5: Update the particle velocity and its positions.
6: Evaluate the fitness function.

$$P_{best_i} = \begin{cases} SP_i & if\,(Fitness\,(SP_i) < Fitness\left(P_{best_i}\right)) \\ P_{best_i} & Otherwise \end{cases}$$

$$G_{best} = \begin{cases} SP_i & if\,(Fitness\,(SP_i) < Fitness\,(G_{best})) \\ G_{best} & Otherwise \end{cases}$$

7: If SP position reaches the G_{best}, then
8: Stop the iteration.
9: Otherwise
10: Go back to step 2

B. VIRTUAL CLUSTER FORMATION

The virtual clusters are created on the basis of distances between the node and BS and between the node and CH.

1) NETWORK PARAMETERS

a: DISTANCE BETWEEN SENSOR NODE AND CH NODE

The consumption of node energy is related to the sensor distances [56]. Therefore, the distance between sensor SP_i and CH node CH_i is calculated using Euclidean distance, which is given in (16).

$$dist\,(SP_i, CH_i) = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \tag{16}$$

where (x_i, y_i) and (x_j, y_j) indicate the sensor SP_i coordinates and CH node coordinates, respectively.

b: DISTANCE BETWEEN NODES AND BS

This parameter is measured on the basis of Euclidean distance [55]. The distance estimation is given in Eq. (17).

$$dist\,(SP_i, BS) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{17}$$

where (x_i, y_i) and (x_j, y_j) indicate the coordinates for sensor SP_i and BS, respectively.

2) OBJECTIVE FUNCTION

The Objective Function (OF) helps to find a maximization or minimization solution. In T2FL-PSO, the parameters, distance between SP and CH and distance between SP and BS are considered as minimization property. Therefore, the average weighted method can be used for both parameters in the OF for creating the virtual cluster. The simulation is carried out several times. Weight values range from 0–1. The performance of T2FL-PSO obtains better results than PSO-C and PSO-WZ, where w_1 and w_2 are 0.7 and 0.3, respectively. The objective function is given in (18).

$$OF\left(dist\left(SP_i, CH_i\right), dist\left(SP_i, BS\right)\right) = w_1 \times dist\left(SP_i, CH_i\right) + w_2 \times dist\left(SP_i, BS\right) \quad (18)$$

where w_1 and w_2 are weight values for the parameters.

The virtual cluster formation is given in Algorithm 2.

Algorithm 2 Virtual Cluster Formation

Input: Number of CH nodes

Output: Create a virtual cluster

1: Consider the network parameters

$$dist\left(SP_i, CH_i\right) and dist\left(SP_i, BS\right)$$

2: Compute the distance between sensor particles and CH node

$$dist\left(SP_i, CH_i\right) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

3: Compute distance between sensor particles and BS

$$dist\left(SP_i, BS\right) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

4: Calculate the objective function

$$OF\left(dist\left(SP_i, CH_i\right), dist\left(SP_i, BS\right)\right) OF\left(dist\left(SP_i, CH_i\right),\right. = \left. dist\left(SP_i, BS\right)\right) w_1 \times dist\left(SP_i, CH_i\right) + w_2 \times dist\left(SP_i, BS\right)$$

5. Return number of clusters

The time complexity of the PSO algorithm is O(n^2) to select the optimal CH in the network nodes. For T2fL, the time complexity is O(n^4). Therefore, the time complexity of the proposed T2FL-PSO is O($n^2 + n^4$) $\approx$ O(n^4). Figure. 8 shows the overall workflow of the T2FL-PSO protocol.

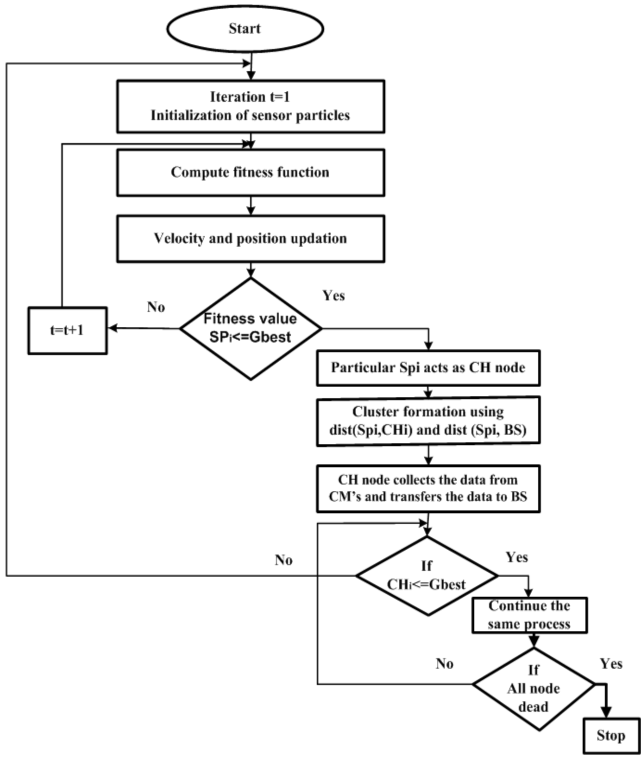

FIGURE 8. T2Fl-PSO workflow.

V. RESULT AND DISCUSSIONS

The efficiency of the T2FL-PSO is compared with those of the PSO-C and PSO-WZ algorithms using the same parameters [34]. The simulation is carried out in MATLAB 2019a [51], [56]–[61] taking 100 random nodes in the network. In the simulation, the initial energy of all nodes is set to 0.8 J over the network area of (100 $\times$ 100) m^2. The CH number is set to 5. In addition, BS is found in three different locations, such as (50, 50), (0, 50) and (50,155). Table 3 depicts the simulation parameters and values.

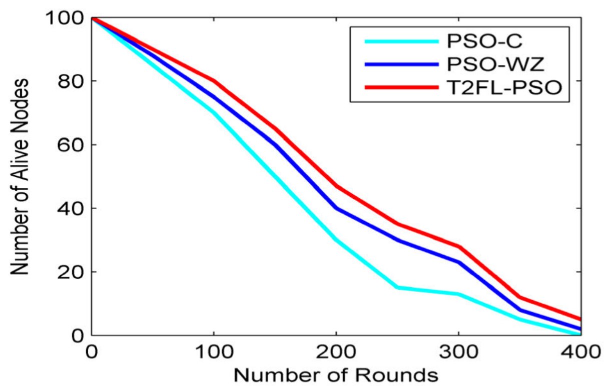

FIGURE 9. Number of live nodes related to number of rounds [BS position at (50, 50)].

A. NETWORK LIFETIME

The network lifetime indicates how long the nodes are live and can perform transmission and reception operations. The simulation is performed nearly 100 times and the average number of live nodes over time is observed. The simulation is carried out in three scenarios with respect to the BS location. The efficiency of T2FL-PSO is compared with those of PSO-WZ and PSO-C. Figure. 9 shows the number of live

TABLE 3. Simulation Setting and Parameters.

Simulation Parameter	Value
Simulation tool	MATLAB 2019a
Network area	(100 ×100) m^2
CH count	5
Number of nodes	100
Energy range	0.8 J
BS location	(0,50), (50,50), (50,155)
C_1	1.4495
C_2	1.4495
Initial Weight w	0.4 to 0.9
Velocity V	–20 to 20
Amplifier coefficient ε_{fs} ($q<q_0$)	10pj/bit/m^3
Amplifier coefficient ε_{fs} ($q \geq q_0$)	0.0013pj/bit/m^4
Energy for data aggregation E_{DA}	5nj/bit/ m^4

nodes related to the number of network rounds. In Scenario-1, the BS is located at (50, 50). Initially, all nodes in the network are live. As the network round increases, the number of live nodes gradually decreases.

For the 400th round, the number of live nodes in PSO-C, PSO-WZ and T2FL-PSO are 0, 2 and 5, respectively. In addition, the number of live nodes is high. The result confirms that the proposed T2FL-PSO extends the network lifetime more than PSO-C and PSO-WZ due to the consideration of fuzzy logic applied in calculating the fitness function.

TABLE 4. Number of live nodes with BS at (50, 50).

Rounds	PSO-C	PSO-WZ	T2FL-PSO
0	100	100	100
50	85	88	90
100	70	75	80
150	50	60	65
200	30	40	47
250	15	30	35
300	13	23	28
350	5	8	12
400	0	2	5

Table 4 indicates the number of live nodes in PSO-C, PSO-WZ and T2FL-PSO at varying numbers of rounds. The BS is located at (50 m, 50 m). The proposed T2FL-PSO increases the lifetime more than the other protocols, mainly due to the BS located at the centre of the network.

Figure.10 depicts the number of live nodes related to the number of rounds. In Scenario 2, the BS is located at (0, 50). As the number of rounds increases, the number of live nodes gradually decreases. For the 350th round, all the nodes are dying in PSO-WZ and PSO-C but not in T2FL-PSO, with live nodes of 0, 0 and 5, respectively. For each round, the number of live nodes in T2FL-PSO is higher than in the other algorithms. The result confirms that the proposed T2FL-PSO extends the network lifetime more than PSO-C and PSO-WZ. Thus, T2FL-PSO provides better network stability during data transmission.

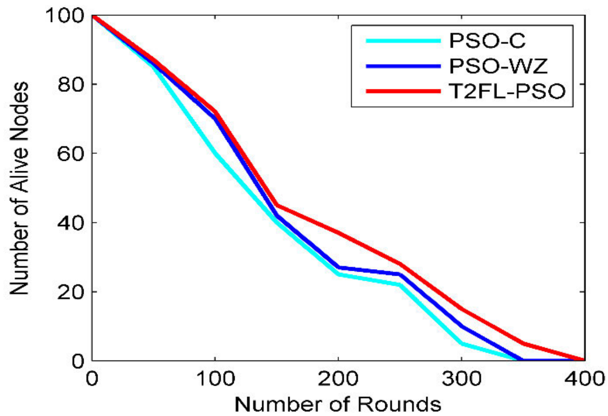

FIGURE 10. Number of live nodes related to number of rounds [BS position at (0, 50)].

TABLE 5. Number of live nodes with BS at (0, 50).

Rounds	PSO-C	PSO-WZ	T2FL-PSO
0	100	100	100
50	85	86	87
100	60	70	72
150	40	42	45
200	25	27	37
250	22	25	28
300	5	10	15
350	0	0	5
400	0	0	0

Table 5 indicates the number of live nodes in PSO-C, PSO-WZ and T2FL-PSO at varying number of rounds. The BS is located at (0 m, 50 m). The proposed T2FL-PSO increases the lifetime more than the other protocols.

Figure.11 depicts the number of live nodes related to the number of rounds. In Scenario 3, the BS is located at (50, 155). As the number of rounds increases, the number of live nodes gradually decreases. For the 300th round, all the nodes are dying in PSO-WZ and PSO-C but not in T2FL-PSO, with live nodes of 0, 0 and 10, respectively. For each round, the number of live nodes in T2FL-PSO is higher than in the other algorithms. The result confirms that the proposed T2FL-PSO extends the network lifetime more than PSO-C and PSO-WZ. Thus, T2FL-PSO provides better network stability during data transmission.

Table 6 indicates the number of live nodes in PSO-C, PSO-WZ and T2FL-PSO at varying number of rounds.

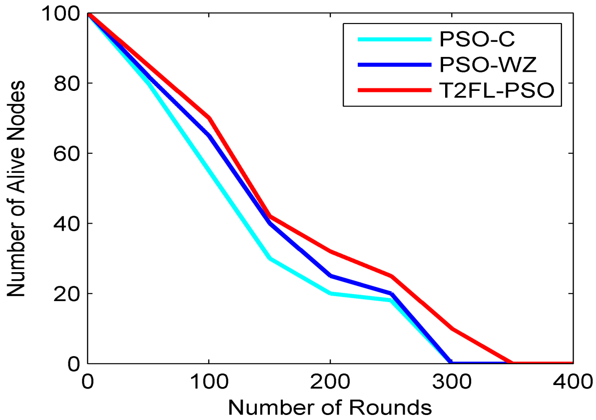

FIGURE 11. Number of live nodes related to number of rounds [BS position at (50, 155)].

TABLE 6. Number of live nodes with BS at (50, 155).

Rounds	PSO-C	PSO-WZ	T2FL-PSO
0	100	100	100
50	80	82	85
100	55	65	70
150	30	40	42
200	20	25	35
250	18	20	25
300	0	0	10
350	0	0	0
400	0	0	0

The BS is located at (50 m, 155 m). The proposed T2FL-PSO extends the lifetime more than the other protocols. However, the nodes deplete their energy early at this BS location.

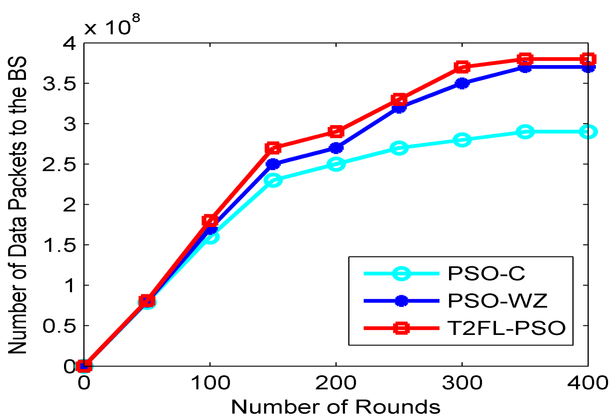

FIGURE 12. Number of packets received at BS vs. number of rounds [BS location at (50,50)].

B. NUMBER OF DATA PACKETS RECEIVED AT BS

Figure. 12 illustrates the number of packets obtained by BS located at (50, 50) from the sensor nodes in relation to the number of network rounds. Until the 50th round in Scenario 1, PSO-WZ, T2FL-PSO and PSO-C collect an equal number of data packets at BS.

The number of live nodes in all three algorithms has a small deviation from the number of network rounds. However, the number of packets received at BS shows major variations in all three algorithms. Note that for the 400th round, the number of packets received at BS in PSO-C, PSO-WZ and T2FL-PSO are 2.9×10^8, 3.7×10^8 and 3.8×10^8, respectively. The result confirms that the proposed T2FL-PSO algorithm increases the packet delivery when the number of network rounds increases due to the fuzzy concept appropriately applied on the weight values in the parameters RER and BS distance.

TABLE 7. Number of live nodes with BS at (50, 50).

Rounds	PSO-C ($\times 10^8$)	PSO-WZ ($\times 10^8$)	T2FL-PSO ($\times 10^8$)
0	0	0	0
50	0.8	0.8	0.8
100	1.7	1.8	1.8
150	2.3	2.5	2.7
200	2.5	2.7	2.9
250	2.7	3.2	3.3
300	2.8	3.5	3.7
350	2.9	3.7	3.8
400	2.9	3.7	3.8

Table 7 shows the number of data packets that BS receives using PSO-C, PSO-WZ and T2FL-PSO for varying number of rounds. In scenario1, the BS is located at (50 m, 50 m). Note that the proposed T2FL-PSO protocol transmits more packets than PSO-C and PSO-WZ. The reason is that the BS is located at the centre of the network.

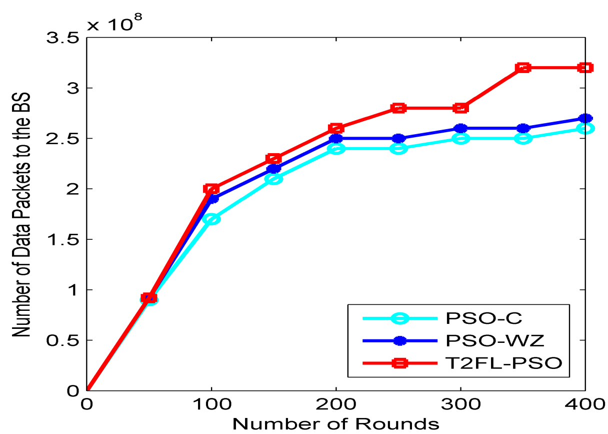

FIGURE 13. Number of packets received at BS vs. number of rounds [BS location at (0,50)].

Figure. 13 illustrates the number of packets obtained by BS at (0, 50) from the sensor nodes in relation to the number of network rounds.

In Scenario 2, the number of live nodes in all three algorithms is a minor deviation from the number of rounds. However, the number of packets received at BS shows major variations in all three algorithms. For the 400th round, the number of packets received at BS in PSO-C, PSO-WZ and T2FL-PSO are 2.6×10^8, 2.7×10^8 and 3.2×10^8, respectively. The result confirms that the proposed T2FL-PSO algorithm increases the packet delivery as the number of network rounds increases. Scenario 2 receives less number of packets at BS, which is at the centre of the network, compared with Scenario 1. Hence, the nodes die in the earlier rounds.

TABLE 8. Number of packets received by BS at (0, 50).

Rounds	PSO-C ($\times 10^8$)	PSO-WZ ($\times 10^8$)	T2FL-PSO ($\times 10^8$)
0	0	0	0
50	0.9	0.92	0.92
100	1.7	1.9	2.0
150	2.1	2.2	2.3
200	2.4	2.5	2.6
250	2.4	2.5	2.8
300	2.5	2.6	2.8
350	2.5	2.6	3.2
400	2.6	2.7	3.2

Table 8 shows the number of data packets that BS receives using PSO-C, PSO-WZ and T2FL-PSO at varyin number of rounds. The BS is located at (0 m, 50 m). Note that the proposed T2FL-PSO protocol transmits more packets than PSO-C and PSO-WZ.

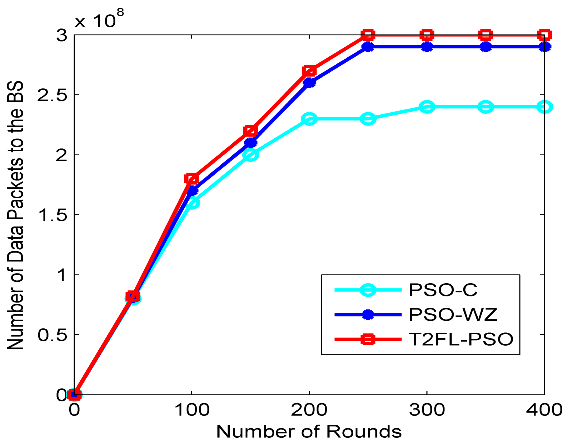

FIGURE 14. Number of packets received at BS vs. number of rounds [BS location at (50,155)].

Figure. 14 represents the number of packets received by BS in relation to the number of network rounds. In scenario 3, the BS is located at (50,150) in Scenario 2. The number of live nodes in all three algorithms is a slight deviation from the number of rounds. However, the number of packets received at BS shows major variations in all three algorithms. For the 400th round, the number of packets received at BS in PSO-C, PSO-WZ and T2FL-PSO are 2.4×10^8, 2.9×10^8 and 3.0×10^8, respectively. The experiment result confirms that the proposed T2FL-PSO algorithm increases the packet delivery as the number of network round increases. Scenario 3 receives less number of packets at BS compared with Scenarios 1 and 2 due to the positioning of the BS outside the network. Hence, majority of the nodes dies in the earlier rounds.

TABLE 9. Number of packets received the BS at (50, 155).

Rounds	PSO-C ($\times 10^8$)	PSO-WZ ($\times 10^8$)	T2FL-PSO ($\times 10^8$)
0	0	0	0
50	0.8	0.81	0.82
100	1.6	1.7	1.8
150	2	2.1	2.2
200	2.3	2.6	2.7
250	2.3	2.9	3.0
300	2.4	2.9	3.0
350	2.4	2.9	3.0
400	2.4	2.9	3.0

Table 9 shows that BS receives the number of data packets using PSO-C, PSO-WZ and T2FL-PSO for varying the number of rounds. In Scenario 3, the BS is located at (50 m, 155 m). Note that the proposed T2FL-PSO protocol transmits a greater number of packets compared with PSO-C and PSO-WZ.

VI. ANALYSIS AND DISCUSSION

From the simulation results, the data analysis shows that the proposed T2FL-PSO is more efficient in terms of network lifetime and packet transmission ratio. The simulation is carried out in different scenarios. In this case, the BS is placed in different locations, such as (0, 50), (50, 50) (50, 155). The BS placement plays a significant role in data collection and network performances. From these scenarios, the BS located at the centre point of the network is more effective in terms of the number of live nodes and the number of packets received. Furthermore, the T2FL-PSO algorithm is executed in BS and plays a crucial role in finding the optimal CH between network nodes. As a result, the T2FL-PSO algorithm improves the network efficiency, that is, the network lifetime and packet transmission ratio.

VII. CONCLUSION AND FUTURE WORK

Energy conservation is a difficult challenge in IoT given its connection to resource limited devices. Clustering is one of the popular methods of saving the network lifetime. However, improper CH selection easily drains the energy in the network nodes. Thus, this paper proposes a T2FL-PSO algorithm to determine the best CH to maximize the network lifetime. T2FL is applied on the network parameters, RER and distance between sensor and BS, to determine the fitness value. Later, virtual clusters are created on the basis of distance between the node and BS and between node and CH. The simulation is carried out in MATLAB 2019a. The T2FL-PSO algorithm is simulated extensively in different network scenarios. with BS located in different locations, such as (0, 50), (50, 50) (50, 155). Among the three scenarios, BS that is located at the centre point of the network is more effective in terms of the number of live nodes and of packets received at BS. The result confirms that the proposed T2FL-PSO increases the network lifetime by 10%–15% and the packet transmission ratio by 10%. Therefore, the proposed T2FL-PSO increases the overall network performance.

In future work, we hope to extend the T2FL-PSO in terms of security, enhance the network lifetime and real-time implementation. Security is a major concern to defend against all kinds of attacks, such as denial of service, wormhole, black hole and gray hole. In addition, PSO can be combined with another algorithm to achieve rapid convergence to increase the network lifetime. In addition, plans to implement and test the T2FL-PSO algorithm in real scenarios are underway.

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