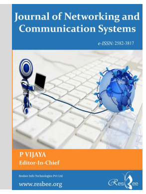
Vol.4 No.1 Jan 2021

Journal of Networking and Communication Systems

Received 11 September, Revised 20 November, Accepted 2 January



Cluster Head Selection in IoT using a Novel Hybrid Self-Adaptive Heuristic Algorithm

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Abstract: In current years, Internet of Things (IoT) applications has been an enormous outpouring. In the IoT network, the sensor nodes produce data uninterruptedly which directly affects the network longevity. Although the IoT applications probable are enormous, there are abundant challenges such as privacy, security, storage, load balancing, devices heterogeneity, as well as energy optimization that needs to be identified. Of those, the utilization of energy for the network is important which needs to be optimized. Numerous factors namely remaining energy, temperature, number of alive nodes, a load of Cluster Head (CH), and cost function affects energy utilization of sensor nodes. In this work, a hybrid self-adaptive Particle Swarm Optimization (PSO) – Differential Evolution (DE) algorithm is modeled to choose the optimal CH that in order to optimize aforesaid factors. Finally, the developed method performance is calculated with conventional methods regarding the energy-specific factors. The outcomes attained demonstrate that the developed technique performs better than the conventional algorithms.

Keywords: IoT network; cluster head; load; temperature; optimization algorithm

Nomenclature

Abbreviation	Description
PSO	Particle Swarm Optimization
SDN	Software Defined Networking
TC	Topology Control
WSN	Wireless Sensor Network
DE	Differential Evolution
cIoT	cellular IoT
SPSO	Self-adaptive PSO
MQTT	MQ Telemetry Transport
SN	Sensor Nodes
ABC	Artificial Bee Colony
BS	Base Station
CNN	Convolutional Neural Network
GA	Genetic Algorithm
SCPTM	Single-Cell Point-to-Multipoint

1. Introduction

WSN is a conservative amount of computational nodes that are equipped utilizing sensors as well as embedded computing devices with network signal transmitter as well as receiver [1]. IoT is positioned by numerous WSN nodes with measuring unit, device controller, as well as application control. In WSN, Sensors are demanded to recuperate values to measurements. IoT communication is unicast, every node necessity to be clustered address in WSN [1].

The IoT is a device's network, an extensive diversity of devices by complex designs as well as diverse functionalities, like wireless sensors in vehicles, home electronic appliances, personal mobile devices which comprises of electronic processing, sensors as well as actuators, as well as connectivity [2]. Although smartphone's right to use to smart IoT devices turns out to be erudite and further remote cloud servers are intricate, an additional recognition and fortification of IoT devices turn out to be inspiring.

https://doi.org/10.46253/jnacs.v4i1.a1

Conventional IoT networks possess three layers: Sensor, network, and the cloud. The sensor layer comprises IoT devices as well as base stations. The base stations combined the data packets produced by the IoT devices and forward them to the network layer that comprises a group of gateways [3] [4]. From the sensor layer, the data packets need to travel all way to the cloud from the sensor layer that might not be appropriate for serious applications namely haptics, autonomous driving, and so forth [15] [17]. Fog Computing (FC) has been formulated to overcome the aforesaid challenge, whereas computational resources are fetched nearer to the sensor layer to abate latency [2].

The foremost problems about IoT networks are their heterogeneous representative, to optimize the system's operation as diverse applications [16] have precise network requirements. In smart vehicles applications, the IoT characteristic such as the information conversation need nearly,'0' latency; in industrial sensor networks, also minimum latency, a negligible packet loss need obligatory; in mobile video surveillance network, latency and loss of packet are not serious, nonetheless would need higher bandwidth. These exact network needs are unsuited with the conventional networking model that has restrictions concerning scalability, mobility as well as quantity of traffic. Hence, conventional networks are incompetent to gratify the novel needs of IoT environments [7].

The foremost objectives of this article are explained as below:

・A hybrid optimization method is used for selecting an optimal cluster head.

・To optimize the IoT network's performance the contributing variables such as distance, delay, load, temperature, energy utilization is minimized.

2. Literature Review

In 2020, Tanguy Godquin et al [1], developed a technique for positioning security services in an IoT network consistent with devices' abilities. The proposed technique represents an IoT network as a weighted graph exploiting device abilities. To recognize the utmost appropriate position for a security service utilizing the latter by controlling sets as well as the graph weights. The overall outcomes specify a complete rise in network security using nominal effect on information flow when maintaining minimized deployment costs.

In 2020, John Yoon [2], presented an IoT-enabled network infrastructure that was a complimentary service to legacy network infrastructure. Here, attack models were presented in IoT devices. The main objective of this work was the IoT attacks characterization, to train IoT attack models neural network nodes were constructed, as well as to examine real-time network-streaming data the trained models were embedded.

In 2020, M. Swarna and T. Godhavari [3], presented a novel method to forecast congestion control with the optimal possible method. A progressive congestion control model exploits numerous margins instigated exploiting CoAP to analyze. Network congestion information was emerging through enormous, constrained communication devices. The developed paper implementation outcomes were exhibits that were improved in comparison to the real terms such as packet transmission, latency minimization, and surge in the transmission response time and lessening in power utilization.

In 2020, Olga Vikhrova et al [4], addressed the disadvantages of the present SCPTM solution for unplanned critical traffic delivery in cIoT networks. Multicast, and paging methods for a profligate distribution of serious updates, was developed later. The proposed SC-PTM framework was energy effectual and assurances minimum service latency, and it was shown both systematically as well as experimentations.

In 2020, K.E. Srinivasa Desikan et al [5] developed a comprehensive set of TC methods for modeling and management a large-scale smart city IoT network. The problematic of TC in two states such as the Maintenance stage as well as the Construction stage. A cost-effective IoT network comprising of fog gateways was developed in the construction stage.

In 2020, Marcos V.O. de Assis et al [6], proposed a near real-time SDN security system. It averts DDoS attacks in the source-end network. It defends sources SDN controller over traffic mutilation. Hence, a CNN was applied and tested for DDoS recognition. The performance results were carried out in two test cases, as well as the outcomes states that the developed SDN security system was propitious over subsequent-generation DDoS attacks.

3. System Model for Cluster Head Selection in WSN

Fig 1 illustrates the architecture model of IoT. Several nodes are included in the IoT network. These nodes have a restricted number of storages, processing ability, and a lifetime of the battery [8][9]. In the network, by the networks' sensor nodes the data is unceasingly sensed and redirected to the BS. Because of the aforesaid goal, there is an augmented prospect of the Base Station being overloaded which causes the SN failure in IoT network, data redundancy, temperature augment. To overwhelm these issues, numerous clusters are modeled from nodes in the IoT network and an optimal node is selected as a CH for each cluster.

On basis of the numerous parameters namely nodes energy as well as nodes temperature, network load, nodes delay being passed to the Base Station, the distance among BS and CH, so forth CHs are selected. The optimal CH chosen will initiate enhancement of the lifetime of IoT networks. Fig 2 illustrates the architecture model of the proposed method.

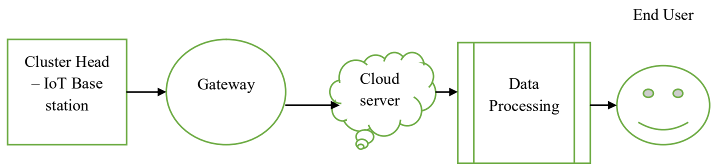

Fig. 1. *Architecture model of IoT*

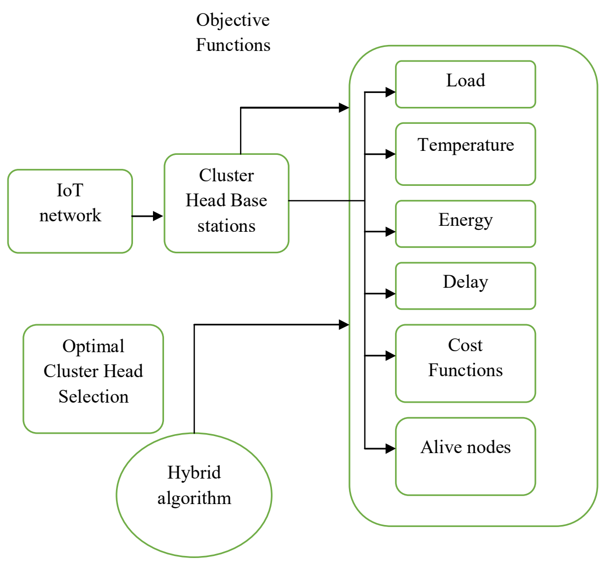

Fig. 2. *Architecture model of the proposed method*

3.1 Objective Model

The parameters such as delay, distance, energy decide CH is existing WSN. Nevertheless, in IoT, network load and the temperature is included in selecting CH separately from parameters stated earlier. Henceforth a node with the least delay, load, delay, proximity with BS, maximum energy, a lesser amount of temperature is selected as a CH for the performance of the network's optimization. Eq. (1) shows the best fitness function that improves stability as well as competence of network.

$$O_i = u * O_{temp} + \phi * O_{Load} + \chi O_{energy} + \psi(1 - O_{Dis}) + \omega(1 - O_{Delay}) \tag{1}$$

In eq. (1) u, ϕ, χ, ψ, ω are considered to be weighted parameters, the summation of weighted parameters must be equivalent to 1.

Calculation of 5 parameters stated in this experimentation as deliberated as follow.

3.1.1 Energy Computation

The remaining energy plays a significant task in maximizing lifespan as well as network performance. The node energy must be maximum to choose the optimal CH. After transmission as well as the reception of data packets CH energies and the normal nodes are revised. Eq. (2) indicates the actual energy of an SN subsequently packets are passed to CH. The residual energy presented in CH is attained as stated in Eq. (3). The data can be transmitted to CH till the node's energy drains to 0. Eq. (4) denotes energy fitness function.

$$E_{X+1}(C_S^x) = E_X(C_S^x) - E(C_S^x) \tag{2}$$

In eq. (2), $E_{X+1}(C_S^x)$ indicates the energy in normal node subsequent to transmission of data packets to CH, $E(C_S^x)$ indicates energy dissipation of x^{th} node.

$$E_{X+1}\left(C_{CL}^{t}\right)=E_{X}\left(C_{CL}^{t}\right)-E\left(C_{CL}^{t}\right) \tag{3}$$

In eq. (3), $E_{X+1}\left(C_{CL}^{t}\right)$ indicates the energy presented in CH subsequent to data packets are attained from the normal node, $E_{X}\left(C_{CL}^{t}\right)$ indicates the energy dissipation of t^{th} CH.

$$O_{energy}=\frac{1}{A}\left\{\sum_{x=1}^{A}E_{x}\left(C_{S}^{x}\right)\right\}+\frac{1}{T_{CL}}\left\{\sum_{t=1}^{CL}E\left(E_{CL}^{t}\right)\right\} \tag{4}$$

i) Distance Computation

The objective model of distance from the SN to CH as well as CH to BS is indicated in eq. (5). If the distance from a node to BS is trivial then the optimal CH selection is performed.

$$O_{distance}=\sum_{x=1}^{\chi}\sum_{t=1}^{T_{CL}}\frac{||Dis_{S}^{2}-Dis_{CL}^{2}||+||Dis_{CL}^{2}-Dis_{BS}^{2}||}{M*M} \tag{5}$$

$||Dis_{S}^{2}-Dis_{CL}^{2}|$ indicates the distance from x^{th} SN to equivalent t^{th} CH. $||Dis_{CL}^{2}-Dis_{BS}^{2}||$ indicates the distance from t^{th} CH to the Base station, M indicates sensing area regarding meters.

ii) Delay Computation

From source to destination, the transmission of data packets in a limited amount of time raises the efficacy of the network. In transferring packets to destination measuring the delay is dependent on propagation delay (T_p) as well as transmission delay (T_t).

For measuring latency time to transmitting packets from CH to BS and Eq. (6) exhibits objective function. The numerator states transmission of data from Cluster Head to Base Station, and A states total nodes.

$$O_{Delay}=\frac{Max\sum_{t=1}^{T_{CL}}CL_{t}}{A} \tag{6}$$

iii) Computation of Load and Temperature

To choose optimal CH, the temperature and load of sensor nodes must be minimum. To monitor performance, temperature, and load data of 100 nodes are subjected to the Xively IoT platform. Xively [10] is a Google IoT platform that aids manage, connect, and engross products at speeds in milliseconds athwart millions of connections.

4. Optimized Cluster Head Selection Model using Proposed Model

4.1 PSO Algorithm

The PSO technique is considered a forthright evolutionary approach [11] that is concerned with swarm intelligence-based perceptions. In the PSO algorithm, by using as well as amending particle characteristics in the search space of the issue, every particle moves toward the best solution. Finally, the velocity as well as position of each particle is updated based on eq. (7) – (9).

$$X_{m}^{(it+1)}=X_{m}^{(it)}+V_{m}^{(it+1)},\ \forall m\in N_{pop} \tag{7}$$

$$\begin{aligned}V_{m}^{(it+1)}&=w\times V_{m}^{(it)}+c_{1}\times rand\,(1,1)\left\{P_{best,m}^{it}-X_{m}^{(it)}\right\}\\&+c_{2}\times rand\,(1,1)\left\{G_{best,m}^{it}-X_{m}^{(it)}\right\},\ \forall m\in N_{pop}\end{aligned} \tag{8}$$

$$w=w_{max}-\frac{T}{T_{max}}\times\left[w_{max}-w_{min}\right] \tag{9}$$

It is, consequently, inferable that particles' velocity is updated on the basis of the eq. (8). whereas c_1 and c_2 represents solitary as well as gregarious learning coefficients, correspondingly.

In convergence performance characteristics of approach, these 2 coefficients possess a pivotal role, many researchers tend to deliberate them as constants, that outcomes in few disadvantages like premature convergence. This is on account of the circumstance that c_1 and c_2 state the impact of $P_{best,m}^{it}$ and $G_{best,m}^{it}$, correspondingly.

During global searching, particles tend to be distant from global optima in the search space if $G_{best,m}^{it}$ is a high number; hence, velocity needs to be a high amount to gratify state that culminates in higher values; hence, learning factors needs to be lesser numbers during local searching. Thus, a forthright SPSO structure is developed in this paper to cope with the aforesaid problem. The self-adaptive amendment is mathematically rewritten as (10) and (11) in that G_{best}^{i1} and G_{best}^{it} represents values of the global best location at initial as well as it^{th} iterations, consistently.

$$\xi = \frac{1}{F\left(G_{best}^{t}\right)} \tag{10}$$

$$c_k = 1 + \frac{1}{1 + e^{it \times \left(-\xi \times F\left(G_{best}^{t}\right)\right)}} \tag{11}$$

In this linking, it must be stated that (10) and (11) is confirmed that the incessant modification. By the way, in the initial iteration (i.e., it = 1), the value is attained as said by (10). This is because of the circumstance that, afterward dismissing every iteration, the $P_{best,m}^{it}$ and $G_{best,m}^{it}$, values are attained. Subsequently, c_1 and c_2 values are computed using dynamically exploiting (11) in the course of iterations. Conversely, the c_1 and c_2 state values are exclusive in every iteration, in contradiction of maximum researches in that these 2 factors are constant. This easy scheme will absolutely enhance the PSO technique performance as well as consequence in improved best solutions consequently.

4.2 DE Approach

The DE optimization technique, corresponding to SPSO, is categorized as a population-based iterative technique [12]. In the DE approach, there are 3 important operators such as mutation, crossover, as well as selection operators. A short-term explanation of this technique, with its vital parts, is itemized hereunder.

• Every control variable in conformism with its permissible bounds is allocated to numeral, which is exhibit as follows.

$$X_d^m = X_d^{min} + UD_d \times \left(X_d^{max} - X_d^{min}\right),\ \forall m \in N_p, \forall d \in D \tag{12}$$

• The mutation operator is developed to generate the experimental vectors that mutant vectors are produced based on (13).

$$X_{d,mut}^{m}(g+1) = X_u(g) + CP\left(X_v(g) - X_w(g)\right),\ \forall m, w \in N_p, u \neq v \neq w \tag{13}$$

• Crossover operator is developed to generate a variety of generated mutant vectors.

$$X_{d,trail}^{m}(g+1) = \begin{cases} X_{d,mut}^{m}(g+1) UD_d \leq C_{CO} \\ X_{d,}^{m}(g) UD_d > C_{CO} \end{cases} \tag{14}$$

• In the DE technique, the selection operator has a basis, that is used to select the optimal experimental vector for the subsequent generation as eq. (15) to upgrade population.

$$X_d^m(g+1) = \begin{cases} X_{d,trial}^{m}(g+1) F\left(X_{d,trail}^{m}(g+1)\right) \leq F\left(X_d^m(g)\right) \\ X_d^m(g) F\left(X_{d,trail}^{m}(g+1)\right) > F\left(X_d^m(g)\right) \end{cases} \tag{15}$$

4.3 Hybrid SPSO and DE Algorithm

Similar to the other optimization techniques, both SPSO, as well as DE techniques, possess a tendency to take few counterpoints, 2 visible ones that are expounded upon hereunder.

a) Rapidly imminent and ultimately converging to a locally best solution instead of a global one.

b) Perpetual convergence to global optima that is computationally incompetent. By the way, a forthright hybrid technique is developed as follows to identify the aforesaid problems in that the DE approach with a sturdy circumstantial in expanding the population is intermixed with the SPSO technique by using 6 vital steps to have a hybrid configuration. Consequently, the below steps must be performed to do so.

Step a): Incidentally generate an undeveloped population, as well as initialize their locations and velocities.

Step b): Estimate fitness function for the emerging swarm.

Step c): $\forall m \in N_{pop}$, select $P_{best,m}^{it}$ and $G_{best,m}^{it}$, in each iteration.

Step d): Put on significant operators of DE technique mentioned as aforesaid consecutively to generate a diversity of the updated population.

Step e): Both learning coefficients, such as solitary as well as gregarious learning coefficients, are computed on the basis of self-adaptive technique, as well as locations and velocities values, are updated subsequently.

Step f): For new as well as updated population compute the objective functions.

Step g): Comparation the attained outcomes; hence, if the newly attained outcomes are superior to the preceding ones, they are outdated by the novel outcomes, and in other compliments.

Step h): Termination criteria are analyzed.

Hence, if the technique attains the utmost iteration number, the technique halts; or else, it goes to step d. Notably, g and G_{max} are the generation and the utmost number of generations, correspondingly

5. Results and Discussions

5.1 Experimental Procedure

In this paper, the hybrid algorithm was used to maximize the lifetime of the network, and CH selection was performed based on the performance metrics such as residual energy, number of live nodes, as well as cost function. The aforementioned metrics was evaluated with conventional methods namely PSO [11], ABC [13], DE [12], and GA [14].

5.2 Performance Analysis

Fig.3 demonstrates the performance analysis of the developed and existing techniques regarding the delay. The proposed model exhibits the delay is minimum while comparing with the conventional models. Fig.4 illustrates that the graphical representation of the performance analysis of the developed and existing techniques regarding energy. Here, the proposed model exhibits the energy is high when comparing with the conventional models. Fig.5 depicts the performance analysis of the developed and existing techniques regarding the alive nodes. To improve the lifetime of the network, the number of alive nodes plays an important role. Here, the proposed model exhibits the energy is high when comparing with the conventional models.

Fig 6 exhibits performance analysis of convergence ratio of the cost function at diverse iterations for developed method and conventional techniques. From Fig.6, it is evident in the developed method, the cost function is converged using optimal fitness value, while other conventional techniques cost function is converged at later iterations with minimum fitness value.

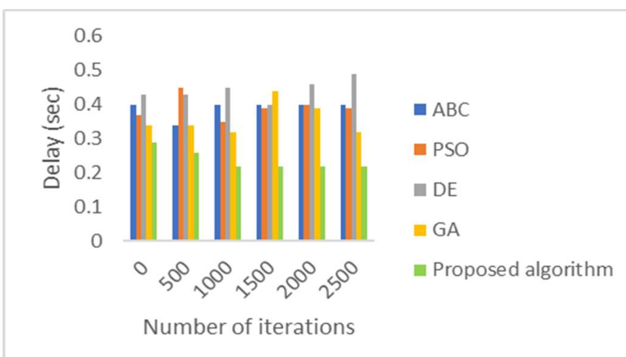

Fig. 3. *Graphical representation regarding delay*

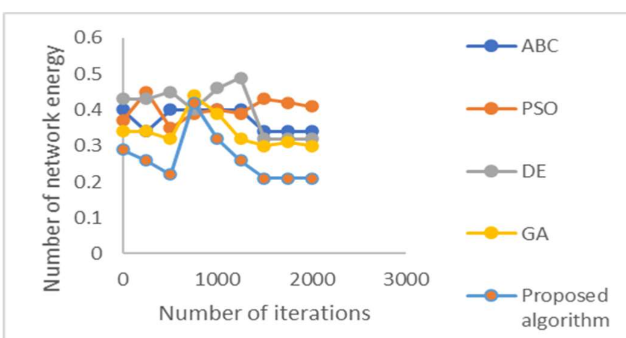

Fig. 4. *Graphical representation regarding delay*

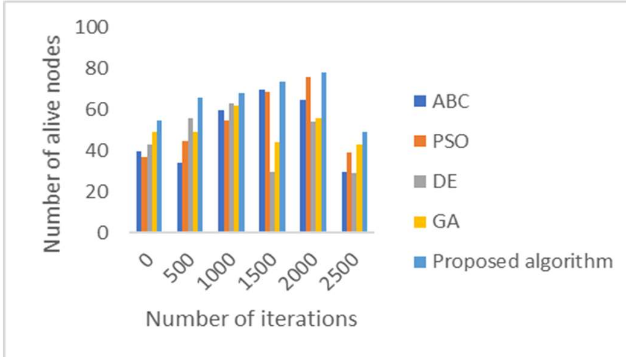

Fig. 5. *Graphical representation regarding number of alive nodes*

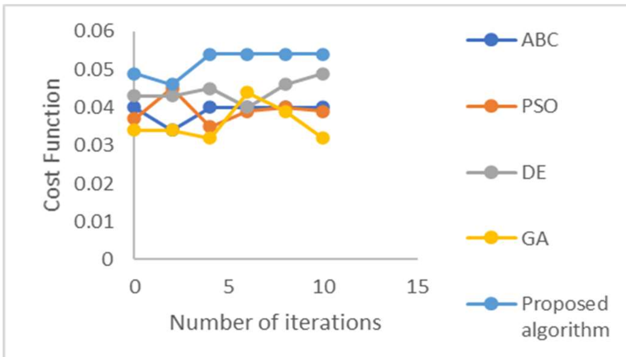

Fig. 6. *Graphical representation regarding cost function*

6. Conclusion

The IoT network's durability was chiefly based on the optimal energy utilization of sensor nodes. The utilization of energy was optimum while temperature produced by IoT nodes was fewer, the load was balanced consistently, the number of alive nodes was high, convergence rate because of the cost function was high, as well as there subsists more remaining energy. In this work, the main contribution was to select the optimal Cluster Head by developing a hybrid self-adaptive PSO–DE method that optimizes the factors as aforesaid. The performance of the developed method was evaluated with the widespread conventional techniques. The outcomes attained in the research exhibit that the developed method was better against the conventional techniques regarding all the factors such as load, temperature, the total number of alive nodes, delay, energy, and cost function.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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