Multi-Population Ensemble Particle Swarm Optimizer based Energy Efficient Clustering Algorithms for IOT Applications

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Abstract: With the growth of wireless sensor networks (WSN), new technologies like the Internet-of-Things (IoT) are being created. There may be challenges that come because when implementing these application areas in practice. The primary issue is energy utilization while data transmission between these resource restricted sensors. In this work, we present a cluster-based routing protocol for IoT to anticipate energy utilization. Furthermore, for cluster head selection and cluster updation, we presented a multi-population ensemble particle swarm optimizer. The simulation was carried out using the MATLAB platform and demonstrates its superiority over different approaches.

Keywords: Internet of Things (IoT), Wireless Sensor Network, Optimization, Energy Efficiency.

I. INTRODUCTION

The Internet of Things (IoT) is a new set of services and apps that link and provide access to all kinds of tangible gadgets. One of the fundamental infrastructures supporting the IoT paradigm is wireless sensor networks (WSNs). They are made up of a network of small electronic devices known as nodes that share and gather data about their environments. The widespread adoption of wireless sensor networks in the form of technology and applications in areas such as industrial applications, security and military surveillance, home automation, and others has increased the demand for machine-to-machine connectivity and data or information availability at all times and in all places [1]. This demand has resulted in the creation of new technologies in the shape of the Internet of Things (IoT). The Internet of Things (IoT) allows devices to communicate with one another and allows data or information to be collected at any time from any location. There are a slew of IoT applications emerging, each utilizing a distinct technology [2].

IoT also offers novel services in a variety of areas, including smart homes, smart cities, smart lifestyles, smart retail, smart agricultural, smart industries, smart emergency, smart health care, smart environment, smart transportation, and many others [3, 4]. The popularity of these applications has widened the scope of study and development in this field [2, 5]. The majority of the above IoT applications need detecting and observing the surroundings, as well as data acquisition from various IP-enabled sensors and systems. Battery-operated and energy-constrained sensor devices are used for sensing and monitoring. This indicates that energy and power usage are important considerations. IP-based communications consumes significantly more energy, causing these low-power gadgets to rapidly drain. In order to do a certain work or task, these massive numbers of devices communicate and collaborate with one another. This necessitates optimized connectivity and communication amongst various devices, which is a difficult process. In this situation, a solution that guarantees maximum connectivity with minimal communication is required. Collaboration among devices or sensors to complete activities for a given application is the most efficient way to meet these needs. One method to do this is to arrange the gadgets in the most energy-efficient and computationally complicated way possible.

For any Internet – of – things app, sensing devices must be used to collect data, which will then be processed using various algorithms. After that, processed data can be viewed from anywhere and at any time via the Internet. Clustering refers to the arrangement of electronic devices or sensors in a single area. By using clustering, it is possible to efficiently gather information while using fewer network communications [6]. This information can then be disseminated for further handling. Clustering also aids in extending the life of a network and an IoT-based application used for a certain purpose.

A two-tier architectural structure is used to do this, with the upper layer being IP-enabled IoT devices and the lower layer being sensor-only gadgets. Using clustering
methods, the devices can be grouped together. There are nodes in the network that communicate with each other by way of a node serving as a cluster head, which is used in clustering. Multihop communication is required when two network nodes are far apart. Multihop communication can be avoided to some extent when communicating through a cluster head. In addition, the cluster head aids in the aggregation of data obtained from various network nodes. As previously stated, the sensor layer and the IoT layer make up the two-layer architecture of an Internet of Things (IoT) network. These devices can be grouped in two ways: from the sensor layer to the IoT layer, or the other way around.

The advantages of clustering are numerous. It aids in network expansion. Reduce the routing overhead by making routing decisions within a cluster and handling them through the cluster head. This reduces the amount of bandwidth needed to exchange data between nodes by ensuring that communication between Cluster heads (CH) is working properly. The cost of network topology maintenance can be considerably lowered by stabilizing the network at the cluster level. Changing the inter-CH tier has no impact on the end devices because they are only concerned with connecting to their own CHs. A significantly simpler topology, with fewer nodes, means less overhead and less flooding and collision on the backbone network. A CH reduces the amount of packets transmitted by aggregating data collected by sensors within its cluster. A CH increases the lifespan of a network’s battery by applying advanced management procedures [7]. When a node is not in use, a CH can use various scheduling techniques to keep it running in a low-power state to save battery life. Collisions are avoided and redundancy is minimized by establishing transmission and reception timeslots for nodes participating in round-robin fashion.

II. LITERATURE REVIEW

Iterations or rounds of cluster formation are required because the clustering protocol elects a new cluster head after each iteration or round. Due to routing overhead, this could result in high energy consumption in mobile devices, especially in IoT devices, which may not be acceptable. As a result, an energy-efficient CH replacement mechanism is needed to prevent using additional energy during cluster formation and propagation of promotional messages to member nodes. For Internet of Things (IoT) applications with dynamic node counts and mobile nodes, an unequal clustering routing technique is required. Reduced network energy usage and increased network stability are the results of this. Here are a few examples of researchers’ contributions:

Extreme learning machine (ELM)-based data aggregation was proposed by Ullah et al. [1], which effectively minimizes redundant and incorrect data by clustering nodes. An ELM projection stage is used to alleviate training process instability using Mahalanobis distance-based radial basis function (MDRBF). The data is filtered at each sensor node using a Kalman filter before being sent to the cluster members.

The updated clustering methodology is provided by Radhika et al. [2] reduces the cost in clustering and message exchanges, allowing the clustering process to be more effectively scheduled. The sensor nodes’ remaining energy determines how dense the network will be. Cluster head nodes and ancillary nodes are determined by energy-based criteria, and member nodes are linked to them. The functions of the cluster’s head nodes alter according to the states of the nodes. The update cycle is calculated using a fuzzy inference approach to achieve minimum energy consumption by clustering nodes.

When it comes to energy efficiency, Manzoor et al. [3] concentrated on making the Two-Level Hierarchy for Low Energy Adaptive Clustering Hierarchy (TL-LEACH) protocol as resilient as feasible while also reducing communication overhead. The research has concentrated on two significant limitations of the TL-LEACH protocol, which are mostly connected to deploying the guidelines for wide WSN and making communication between nodes reliable. To increase the energy efficiency of the TL-LEACH, a new cluster-head selection process was added, and the new version was dubbed Extended TL-LEACH (ETL-LEACH).

According to the satisfaction list, Madhumathy et al. [4] devised an agent cluster-based routing technique that divides the cluster into autonomous subgroups. Each of the autonomous subgroups has its own agent node that really can interact with the member nodes. The suggested agent cluster-based routing algorithm was developed with the goal of reducing energy usage while sending information from station to cluster head. The satisfaction list is used to choose the agent node, which reduces the risk of agent component failures and so boosts reliability of the network and lifespan.

By incorporating a threshold limit for cluster head selection while simultaneously adjusting the power level amongst the nodes, Behera et al. [5] changed the previous low-energy adaptive clustering hierarchy (LEACH) clustering technique. The suggested improved LEACH protocol beats the conventional LEACH protocol with a 67 percent increase in throughput and a 1750 round increase in the number of living nodes, which can be leveraged to prolong the WSN lifespan. In several situations of area, energy, and node density, the suggested algorithm outperforms current energy efficient protocols in terms of stability period and network lifetime.

A K-means clustering-based navigation mechanism has been suggested by Razzaq et al. [6] that takes into account an ideal fixed packet size based on the transceiver’s radio characteristics and channel circumstances. This method can reduce individual node energy usage while also extending the network lifetime.

III. METHODOLOGY

Clustering has proved to be among the more potent strategies for enhancing system capacity and creating an energy-efficient WSN routing algorithm. Furthermore, as previously stated, model-based WSN management has
significant disadvantages. The routing method is intended to adhere to different QoS requirements in order to improve efficiency and extend the lifetime of WSN challenges and issues evaluated by the network. As a result, this segment discusses several optimization techniques that assist to WSN energy efficiency and give implementation guarantee for Quality of Service (QoS).

A. Network Diagram

The design assumption used in this investigation is as follows:

- N sensors are typically distributed over the sensing zone, which is A= N*N in size. When both sensors and the base stations are randomly placed.
- Each network device has an unique Registration identification as well as identical starting energies. The nodes have a finite quantity of energy, whereas the Base Station has an infinite supply.
- The link is symmetrical. The node can determine the distance between the transmitter and itself based on the collected signal intensity.
- Each node needs just one timeslot to link up with its parent node, and each node may only take or transmit single data packet and corresponding control packet within that period. The node’s transmit power may be changed dependent on the contact range.

B. Prototype of Energy Usage

The quantity of energy used by sensor nodes is spent by exchanging data. In this study, we just examine the energy use price of information transmission and combining. The energy consumption of sending and receiving is codified in the following computations in equation (4.1):

\[
E_{\text{TX}}(M,S) = \begin{cases} 
    ME_{\text{selects}} + M\varepsilon_{\text{fs}}S^2, & S < S_0 \\
    ME_{\text{selects}} + M\varepsilon_{\text{amp}}S^4, & S \geq S_0 
\end{cases} 
\]

(i)

\[
E_{\text{RX}}(M) = ME_{\text{selects}} 
\]

(ii)

Here M is the length of the data.
S denotes the length or duration of data transfer.
E_{\text{selects}} = the amount of energy used through transmission and reception of unit length data.
\varepsilon_{\text{fs}} and \varepsilon_{\text{amp}} = amplifier energy use in the free space model and the multiple path attenuation model, respectively.

Whenever the range S between the transmitting and reception nodes is less than the energy use model threshold S0, the free space model is used, and the transmit power is attenuated as S2. The multi-path attenuation architecture could be used instead, with S4 as the transmission power. The energy required by nodes to combine M-length data is determined as follows:

\[
E_u(M) = ME_{\text{da}} 
\]

Here Eda is the amount of energy needed to combine a unit quantity of data.

A. Multi-population Ensemble Particle Swarm Optimizer (MEPSO)

MEPSO’s core idea is to combine PSO exploring methods with diverse characteristics into a single algorithm and flexibly assign particles to the best-performing exploring approach. As a result, the favoured PSO searching method might employ additional computing resources to boost the effectiveness of the suggested algorithm. MEPSO particles are categorized into three indicative sub-populations and one reward sub-population. Every indicative sub-population does have the same tiny amount of particles, and particles in various indicator sub-populations modify their velocities in various manner. Particles in the three indicative sub-populations modify their velocities using the LDWPSO, UPSO, and CLPSO strategies, respectively, in this study. A learning period is specified as a set number of rounds. So at end of a learning period, the effectiveness of each indicative sub-population is assessed to determine the best-performing exploring approach, and then the reward sub-population is assigned to the associated strategic approach.In the suggested method, Figure 1 depicts a multi-population of twenty-five particles. Each indication subpopulation contains five particles, while the reward sub-population has ten particles. The reward sub-population particles are instantaneously assigned to the best-performing indicative sub-population.

Proposed Algorithm MEPSO

MEPSO contains single reward sub-population POPr and three indicator sub-populations represented by POPh, wherein H \in 1,2,3 is the PSO exploring technique indexing that correlates to the LDWPSO, UPSO, and CLPSO. The percentage of POPh in the population is denoted by h. The number of particles in the indicative sub-populations is determined by the amount of h.

The indication sub-population N_H population size is calculated using the following formula:

\[
N_h = [N * \lambda_h] 
\]

(vi)

Strategy H updates the velocities of the particles in POPh. Consequently, the quantity of particles in the reward sub-population Nr may be calculated as follows:

\[
N_r = N - \sum_{H=1,2,3} N_H 
\]

(vii)

The strategy enhancement \Delta F_H will be documented as:

\[
\Delta F_H = \Delta F_{H_i} + f(\text{best}_i) - f(x_i), \quad i \in POP_h 
\]

The method that performs the best will be chosen and listed by K:

\[
K = \arg \max_{H=1,2,3} \left( \frac{\Delta F_H}{N_r + N_H} \right) 
\]

(viii)

POP_r represents the reward population. Particles in POP_r will be assigned to POP_k and their velocities will be updated using the best-performing method k. The suitable PSO exploring technique will have much more particles to discover a better alternative by flexibly assigning the
reward subgroup to a good performing method at a particular learning period. As a result, MPEPSO's performance is projected to improve. Throughout the calculation process, the learning time is utilized to fine-tune the learning pace.

Algorithm 1

Multi-population Ensemble PSO
Initialize values of MPEPSO, consisting LP, N, \( \lambda \), \( H \)
Here, \( H \in 1, 2, 3 \)
Initialize the sub-population for LDWPSO, UPSO, and CLPSO
Set the function evaluations, \( N_H, N_r \)
Initialize positions \( x \)
Initialize velocities
Calculate function values \( F_E \)
While (termination condition is not satisfied) do
i = i + 1
Randomly allocate the values of \( N_H, N_r \)
If mod (gen, LP) == 0
Set the values of \( K, F_H \) as described in above equations
\( POP_K = POP_K \cup POP_r \)
Modify the values of \( POP_1, POP_2, POP_3 \) by LDWPSO, UPSO & CLPSO
For i = 1:N; if \( x_{min} < x < x_{max} \)
Again calculate function evaluations
If \( F(x_i) < F(p_{best}) \)
Evaluate \( \Delta F_H \) from eqn 11
If, \( F(p_{best}) = F(x_i) \)
Similarly if \( F(g_{best}) = F(x_i) \)
end if
end if
end for
end while

IV. RESULT ANALYSIS

The simulation is performed on the MATLAB platform beneath various situations and with varied settings to evaluate the effectiveness of the suggested model. These variables are addressed more below.

Throughput: It is also an essential statistic that is determined regarding the successful transmission of packets of data to the sink node at a specific time. IoT routing methods are designed to enhance throughput.

Network Longevity: Because sensor nodes are battery-powered, network endurance is the most significant metric in IoT routing protocol. This is determined by counting the number of alive and dead nodes after each round sometimes after a set length of time.

Simulation Scenario is presented in table 1.

Table 1. Simulation scenario

| Simulation Scenario | Values |
|---------------------|--------|
| Area                | 100m*100m |
| WBAN sensor nodes   | 50-100  |
| Initial energy of network | 50 J     |
| Energy Dissipation while transmitting bits | 16.7 nJ/bits |
| Energy Dissipation while receiving bits | 36.1 nJ/bits |
| Energy Dissipation during amplification of power | 1.98 nJ/bits |
| Packet size         | 2000,3000,4000 |

Figure 1 represents the simulation result of number of packets transmitted to base station and similarly, figure 2 represents the simulation result for energy utilization by all nodes in the network. Table 2 represents the comparative result analysis of the proposed methodology with existing works.

V. CONCLUSION

One of the key challenges in the adoption of IoT and its applications is the energy efficiency of sensor nodes. One of most essential elements in dealing with the situation is selecting the data forwarding node to sink node. In this article, we treated it as an optimization issue. The paper also included a comparison of results for characteristics such as network lifespan and remaining energy. Detailed
analysis of the results is discussed, it is shows that the proposed algorithm-based routing protocol proves its efficacy over existing works.

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