AN ENERGY EFFICIENT CLUSTER HEAD SELECTION USING BIO INSPIRED OPTIMIZATION BASED SUPERVISED LEARNING FOR WIRELESS SENSOR NETWORKS

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Abstract- The wireless sensor network (WSN) comprises a group of micro, energy-limited sensors. Longer network lifespan is a crucial condition for several WSN applications. Various methods have also been proposed to increase energy utilization rates, such as clustering, efficient routing and data processing. In this article, we propose a novel strategy using clustering. The various clustering methods often vary in their objectives. Often Clustering suffers from more conflicting and consistency data as the location of the sensor node in a major phase does not realize which grouping it belongs to. One choice is to allocate these nodes to all clusters, which is similar to overlapping nodes and data replication. This work has proposed a new solution to address this problem and make use of the advantages of Support Vector Machine SVM along with spotted Hyena optimization algorithm and give us a more precise separation limit for each class. Numerical tests are conducted using Matlab to model sensor fields. Through comparing it with the classic clustering schemes, we have established that the SVM based optimization algorithm increases clustering performance in WSNs.

Keywords- WSN, Clustering, SVM, Optimization,Energy

1. INTRODUCTION

A group of investigators have recently been working on WSN wireless sensor networks [1]. Owing to their wide variety of uses in the area of security monitoring, firefighting, habitat control, industry, health monitoring and far more. WSN consists of a vast number of dynamically deployed sensor nodes. Sensor nodes are installed in the region concerned. WSN has at minimum one base station that acts as a bridge between the sensor nodes and the outside environment. Sensor nodes identify the phenomena transmitting the information to the base station through single or multi-hop connectivity. Users retrieve the cloud deposited at the base station.Sensor nodes provide restricted battery capacity, limited memory and limited computing capability. So the life of WSN is constrained by the on-board energy of the sensor nodes. Owing to the difficult area mounted, it is not easy to repair or refresh the battery. Lack of resources and a vast number of sensor nodes creates a massive flow of message propagation across the network. As much of the energy is absorbed during communication [2], network life has become a core concern in WSN science, and a range of research works [3] are aimed at energy usage and extending network life through various strategies such as filtering, scheduling, aggregation, and grouping.

Typically, heterogeneous network developers describe machine learning as a set of techniques and algorithms used to construct prediction models. Applied to a broad variety of WSN applications, computer vision algorithms offer immense versatility advantages. Current machine learning algorithms can be classified by the planned structural model. Many machine learning algorithms fall into the divisions of supervised, unsupervised and augmented learning [4-8]. A labeled training data set is given for machine learning algorithms in the first group.This collection is used to construct a machine model that describes the learned relationship between input, output and system parameters. Unlike supervised learning, unsupervised learning algorithms are not classified. The basic purpose of an unsupervised learning algorithm is to identify the sample sets into various categories by exploring the similarities between both the input samples. The third group involves reinforcement learning algorithms, in which the entity learns by communicating with the environment. Finally, certain machine learning algorithms do not automatically fall into this group because they combine the features of both supervised and unsupervised active learning [9-12][19-24].

Overcoming such issues, a hybrid energy efficient routing protocol which integrates the powerful SVM for the selection of zone based Cluster heads along with the bio inspired optimization algorithm for an efficient routing protocol.

2 RELATED WORKS

Kavita Jaiswal et al (2020) developed a new WSN routing scheme. The suggested model is energy efficient and ensures the increase of QoS. The proposed algorithm intended to handle heavy traffic loads. The path selection criteria is determined by the length of the connection, the reliability as well as the traffic volume of the nearby nodes. The model is designed and simulated by NS-2. The final outcome shows greater energy savings and better packet distribution ratios. The drawback of the design is a modest analysis of the delay throughout the hidden layer, which may further raise the delay in the whole network [13].

Damien et al (2019) conducted an extensive clustering analysis in broad WSN frameworks. Hierarchy is a challenge when tend to cluster the nodes in the WSN's. Smart cluster - based schemes are also required to optimize WSN structures. Most deep learning clustering methods are used to achieve greater positioning. Reasonable machine learning algorithms must be selected to produce the desired optimization. In the analysis, based on 10 varying metrics in WSN based on the operation of the network, the clustering algorithm is classified to study the average efficiency of the communication topologies. The analysis did not take into account WSN's spectrum utilization when clustering [14].

Liang Zhao et al(2018) have built a LEACH-based cluster head selection algorithm. ZigBee components are used to measure the remaining energy and IP of the node to upgrade the cluster formation calculation. This form of alteration greatly increases energy savings. The simulation has been carried out in NS-235 to verify the optimized usage of energy [15].

Prathibha et al(2018) suggested an improved mobility-conscious energy-efficient IoT routing mechanism (EMAEER) to refine routes for point-to-point connectivity. Remote nodes are often kept inside the system to help minimize energy losses.Experiment is compared to RPL, P2R RPL and ER-RPL architectures and energy consumption is reduced at a rate of 9.61 per cent to provide improved packet distribution. The design withholds only a minimum amount of mobile nodes [16].

Neetesh et al (2019) put forward the concept of energy conservation in WSN as a green routing protocol that allows the revised PSO (Particle Swarm Optimization) to improve the life skills of the network. The principle is based on the two principles of the best control data forwarding and the best cluster head that increases life of the battery.The framework also outperforms IoT WSN's strong collision. Thoughtful hardware implementation is a subtle challenge in this model [17].

Dwi et al (2019) built a new cluster head selection model using a reinforced learning framework. RC is an MC-based framework that learns the actions of clusters across the network. Cluster sorting is conducted on the basis of pre-learned concepts, and then accurate understanding is done. Again, the model discovers the compensation of the prior loop for additional data transfer in the WSN system. The system increases life and decreases the use of electricity in the WSN. The model tends to lag to transfer data owing to protracted node collision [18].

From the literary works, it is apparent that energy usage, cluster head design, routing for large WSN regions are difficult that need to be discussed as a core challenge for research in the modelling of effective WSN protocol implementations.

3 PRELIMINARY WORKS

3.1 Support Vector Machines (SVM)

SVMs are kernel-based training algorithm that is commonly used to address regression and classification tasks. It's a supervised learning model. While SVMs are commonly used classifiers, the evidence reveals that they could be useful in clarifying Clustering Problems. Unlike K-Mean algorithm, SVM is seen to be particularly advantageous for multidimensional space planes. It is very good in cases where the test data given are less than the set of measurements. SVMs have been found to be memory efficient. The SVMs are of a flexible type. To help decision-making, more than one kernel method can be implemented which improves the performance.

3.2 Spotted Hyena Optimization Scheme

Bio-inspired optimization is a concept that incorporates a broad range of numerical methods focused on the concepts of living organisms. This encourages the adaptation of physiology to challenges of computation. Biologically motivated programming and automation is a significant branch of natural computation.Hyena with spotting in their body is a carnivorous breed that lives in both irrigated and rain fed environments. This spotted hyenas are smart animals, and hyena flocks will target single wild animals such as zebra as well as other wild beast variants. The hyena community focused on a population-based partnership with 'Trust.' They are also primary party hunters.The major benefit of spotted hyena based optimization is its higher experimentation and utilization relative to other meta-heuristic strategies such as Gray Wolf Optimizer, Genetic Algorithms and even Particle Swarm and their effective time management skills [34].

4 PROPOSED METHOD

4.1 System Model

Figure 1 illustrates the Cluster Head selection model for WSN IoT Supported Networks. The nodes in this system are known to be static or dynamic, depending on the specifications of the request. The network performance area is divided into different areas, such as low distance, medium distance and long distance zones. Each zone group has sub-zones and is defined as a cluster. If the distance increases, each sub-area is powered by an increasing selection of cluster heads. Low distance and moderate distance areas have a minimal area with a minimal selection of cluster heads, while long range zones have a large areas with a large selection of cluster heads.

The main goal of the proposed framework is to train the SVM in an effective and extending so that: a) we can produce better results for the classification of the testing dataset and b) our methods can be conveniently used in the sense of the WSN where the training takes place.It has to take place through sensors. In the conventional proactive model, observations should first be sent to the base station in which all data is being processed and a conditional probability is formed which distinguishes these two groups. Even so, direct contact across each sensor and the base station in the WSN is both tedious and extremely energy-efficient due to range of factors.

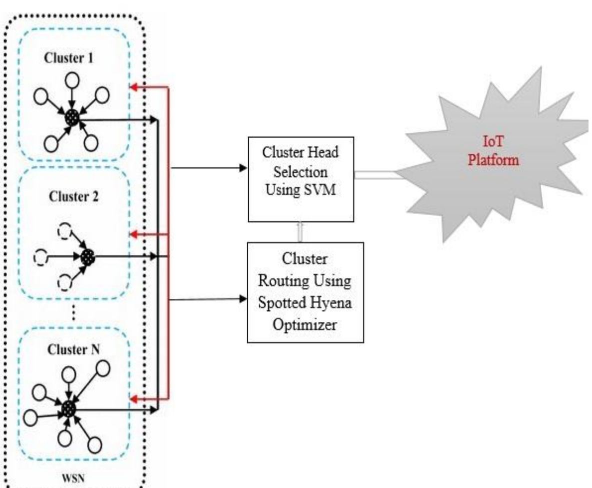

Figure 1 Cluster Head selection for WSN using proposed Framework

Sl No	Pseudo -Code for the SVM to Select the Cluster Head (Algorithm-1)
01	START
02	Assign each sensor node to the nearest Cluster Head
03	Initialize i=0
04	Compute the expected distance between the sensor node and their appropriate Cluster Head
05	When minimum distance <1, then select CH
06	Else
07	Move the Cluster Head to average position
08	i=i+1
09	If i=5; Select CH
10	End
11	Else go to step4
12	End

4.2 SVM based Cluster Head Selection

During the first step, clusters are formed in a linear input field by following the area-subdivision algorithm referred. In WSN specifications, the sensor networks are split into multiple of clusters with one cluster head for every cluster. The sensor nodes are responsible for sensing the data and sending it to their appropriate cluster head. The CH receives the results, summarizes it and sends it to the ground station. Generally, the cluster head is more inventive than the common sensor node in a network. The total energy of the system will thus be preserved to a noticeable extent.

If the configuration process has been created, the specification of the CH will be elicited by the base station running the proposed SVM based optimization algorithm. Initially, the WSN is trained in data structures with the following parameters.

The CH-Cluster head with far more residual energy will help a consistent energy loss in the grid.

Nodes that are closer to the base station and will minimize the contact gap between them and thus extend the existence of the network.

4.3 Spotted Hyenabased Routing Phase

The proposed scheme utilizes the spotted Hyena optimizing function to obtain an optimal energy efficient route. Since WSN-assisted IoT networks cover a wider area, the use of metaheuristic algorithms can lead to trap issues that may result in lower performance. This is why the proposed scheme uses spotted hyena algorithms to find an optimal energy efficient route. This algorithm actually eliminates the trapping problem and considers its suitability for wider field coverage. Multi-objective exercise feature has been developed for the best characteristics.

Spotted Hyena optimizer utilizes the kernel feature to have sufficient precision for improved performance. The key benefits of the optimization scheme are a small error in preparation and a stronger estimation. Since the proposed approach uses the automated tuning of weighted biases and non-zero learning rate, it finds applications in supervised learning values. The method is used to pick the Energy and Distance Cluster Heads. The two or more cluster heads are chosen on the basis of the above features to ensure improved network life. The optimizer is equipped with a sigmoid transfer feature with a back propagation of 0.001.

The pseudo code of the suggested spotted hyena based routing protocol is presented as follows.

Algorithm 2	**Pseudocode of Spotted Hyena Optimizer for routing protocol**
Input	P_i be the spotted hyena population($i = 1,2,..n$)
Output	best search path
1	initialize the vector parameters
2	check for the fitness function of each search path
4	Search for the cluster of solution reaching close to optimal solution
5	**while** (N, No.of repetitions) **do**
6	**for** every individual search path **do**
13	update the cluster solution with respect to the new position
14	$i = i + 1$
17	**End**

5 RESULTS AND DISCUSSION

This section examines the results of the designed SVM two classification algorithm. In the first point, the efficiency metrics of the proposed SVM were evaluated and compared to other current algorithms including Naïve Bayes Algorithms (NB), K-Nearest Neighbourhood Algorithms (KNN), Artificial Neural Networks (ANN), and Reinforcement Learning Algorithms (RL).In the second-tier test, QoS aware parameters were studied and compared to other energy-efficient systems.

Tables 1 shows the comparative analysis of performance metrics for the different learning models

5.1 Algorithm Centric Evaluation

The proposed methodology has been learned from various energy, distance vectors using the sigmoid activation function with such a learning rate of 1 × 5-00710 ^(-3) learning and a moving average decay of 0.9999. It is obvious from Table I that the accuracy of the proposed algorithm for the determination of cluster heads is 92.5 per cent for 75 hidden neurons. While the precision hit its limit at 75 hidden neurons, we took an optimum value of 100 neurons to train and validate the various data vectors.

Table. 1 Comparative Analysis of Performance for Different Learning Models @area

Sl.no	**Algorithm details**	**Performance Metrics (%)**		
		Accuracy	**Recall**	**Precision**
01	NB[25]	90.5%	89.0%	88.5%
02	ANN[26]	88.5%	87.5%	86.5%
03	RF[27]	90.5%	88.5%	89%
04	Proposed SVM Optimization	92.5%	91.0%	90.5%

for the various area coverage. In all scenarios, the accuracy of the proposed algorithm has exhibited the 5% increase than Random Forest (RF), 7.25% increase than Naïve Bayes (NB), 8% increase than Artificial Neural Networks (ANN), and 5.25% increase than ReinforcementLearning (RL) respectively. Also table clearly illustrates that the proposed learning model outperforms the other existing learning models and proves its suitability in detection the different zonal cluster heads.

5.2 Energy Consumption

Total energy consumption is determined by the mathematical model below for the increasing network coverage. In order to evaluate the energy usage of the networks, 100 nodes were distributed uniformly in the various access networks referred to in this section. Complete energy consumption is estimated using the mathematical equation.

Total Energy Consumption:

$$\sum \text{rounds} \{E^{T}_{tx,rx} + E_{tx}^{Ch}\} \quad (1)$$

Where $E^{T}_{tx,rx}$ is Energy transmitted and Received by the Nodes in the Networks and $E_{tx}^{Ch}$is the transmission and reception energy for the Cluster heads.

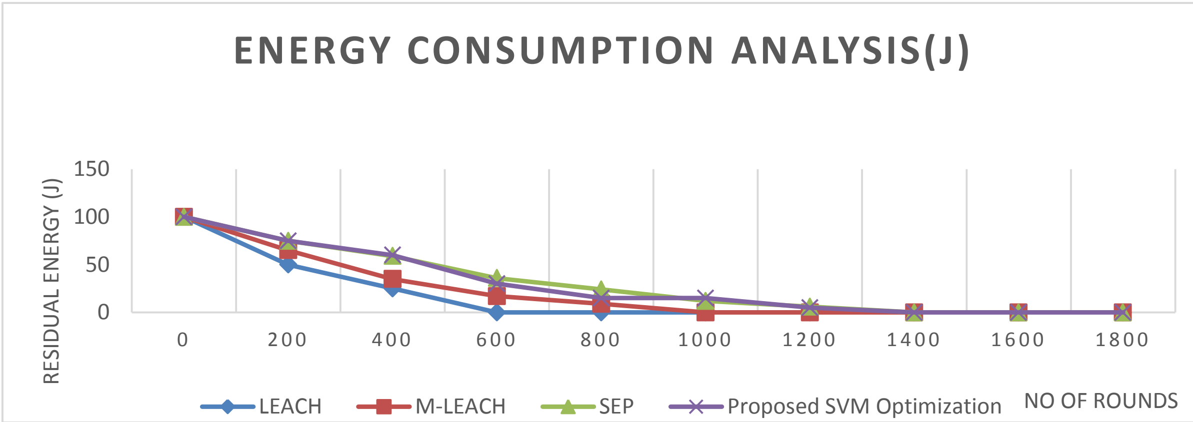

Figure 2 Energy Consumption Analysis for the various protocols at Area of Dimension 60x120 Sq. meters (7200Sq.meters)

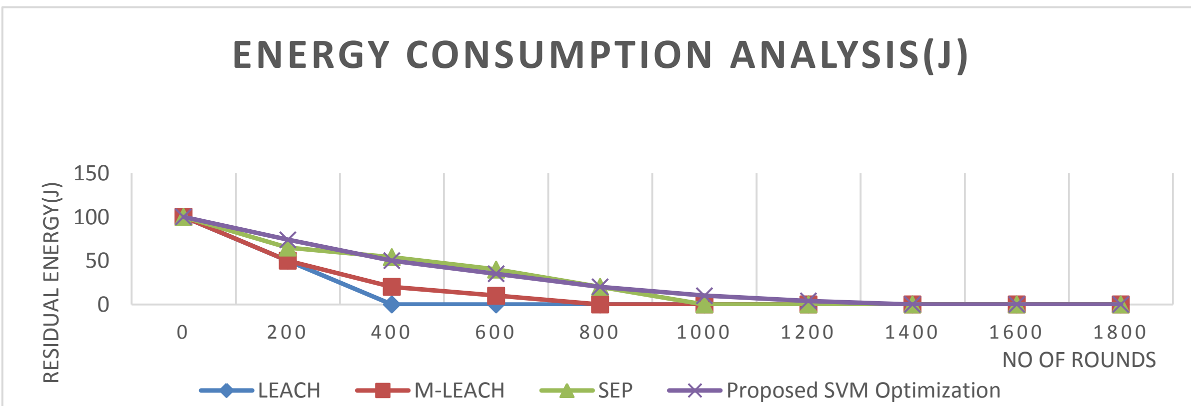

Figure 3 Energy Consumption Analysis for the various protocols at Area of Dimension 80x160 Sq.meters(12800Sq.meters)

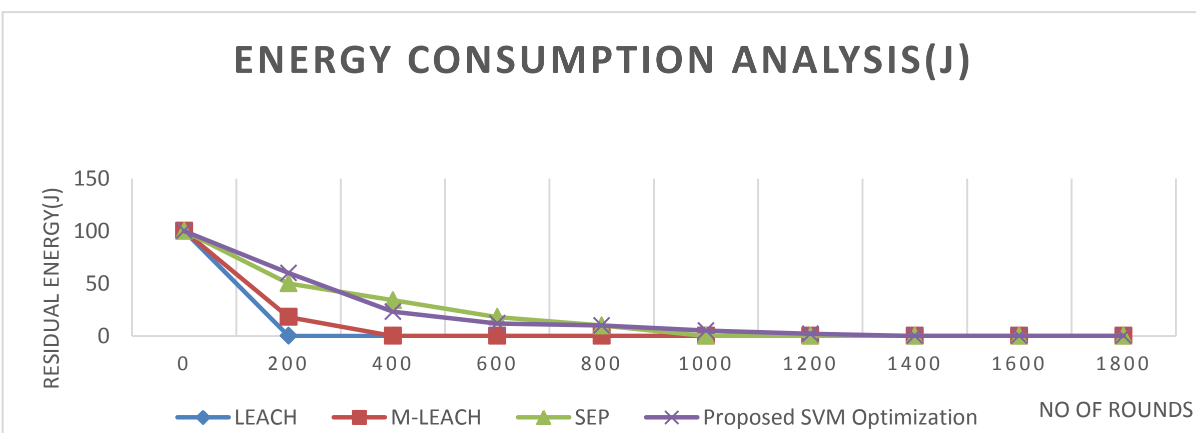

Figure 4 Energy Consumption Analysis for the various protocols at Area of Dimension 100x200 Sq.meters(20000Sq.meters)

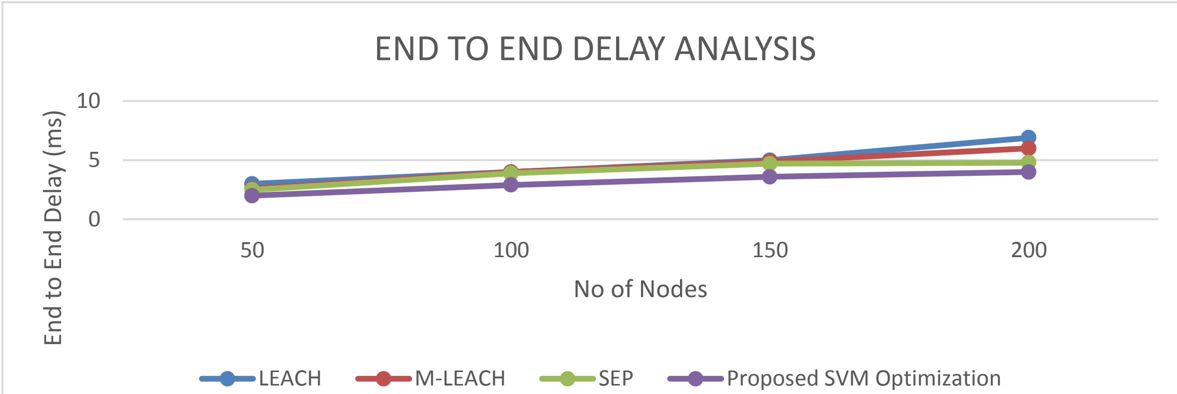

Figure 5 End to End Delay comparison between the proposed routing protocols @Area Dimension 60x120Sq.meters

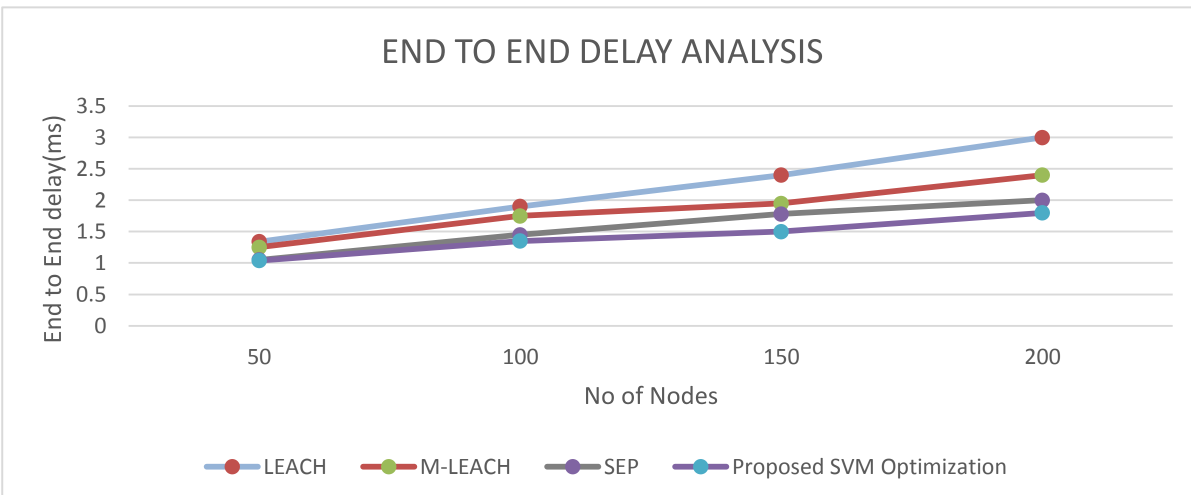

Figure 6 End to End Delay comparison between the proposed routing protocols @Area Dimension 100x120Sq.meters.

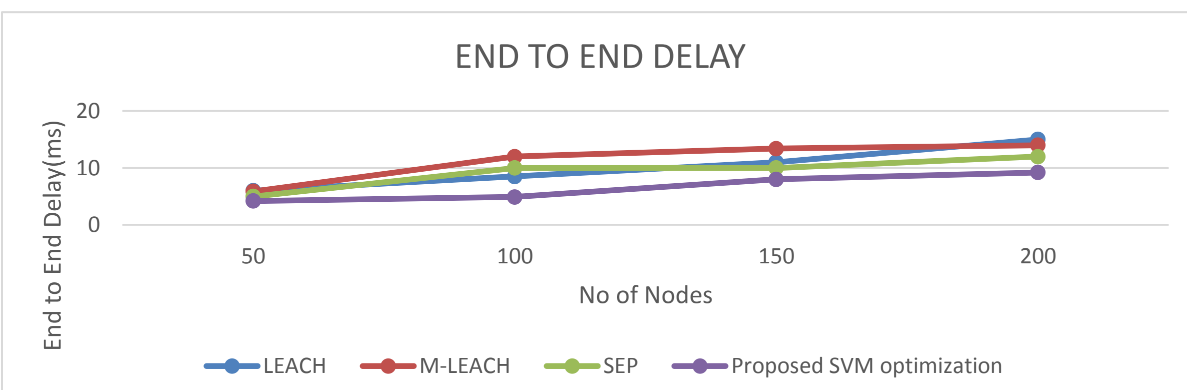

Figure 7 End to End Delay comparison between the proposed routing protocols @Area Dimension 80x160Sq.meters

Figure 2, 3 and 4 shows total energy consumption analysis of the different protocols for the area coverage of 60x120, 80x160, 100x200Sq. meters. Both LEACH and M-LEACH depletes its full energy as it reaches 600 and 1000 rounds respectively. The other algorithms such as SEP and Proposed SVM based optimization algorithm exhibits the good performance and consumes the less energy whereas the proposed algorithm maintains the same high performance.From Figures 5 to 7, due to the introduction of optimized algorithms in the proposed model decreases the latency in transmission even though the complexity of deployment has increased. It is noted that the suggested optimization of SVM exhibits improved characteristics at less coverage area, whereas the SEP architecture has decreased efficiency as the area expands. Since the optimum route for data transfer is selected, the end-to-end delay is the same as the other existing techniques and considers it ideal for extended network life in WSN-assisted wireless communication.

6 CONCLUSION

The WSN supported IoT systems are fitted with battery and thus the energy usage plays a major role in increasing the life of the network. An innovative energy-efficient networking algorithm based on the application of machine learning and bio inspired optimization with multiple stage architecture has been investigated in this work. The paper proposes a new approach to applying learning models at the base station for the accurate collection of cluster heads that depend on energy and distance. The efficiency of spotted hyena optimization helps in terms of efficient route identification of cluster heads has been studied and compared to other current algorithms.

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