ENERGY AWARE TALENTED CLUSTERING WITH COMPRESSIVE SENSING (TCCS) FOR WIRELESS SENSOR NETWORKS

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ABSTRACT

Wireless sensor networks (WSNs) are networks of sensor nodes that interact wirelessly to gather information about the surrounding environment. Nodes are often low-powered and dispersed in an ad hoc, decentralized manner. Although WSNs have gained in popularity, they still have several serious shortcomings, like limited battery life and bandwidth. In this paper, the cluster head (CH) selection, the Compressive Sensing (CS) theory, the Connection-based Decentralized Clustering (CDC), the relay node selection, and the Multi Objective Genetic Algorithm (MOGA)are all taken into account The initial stage provided a theoretical revision to the concepts of network construction, compressive sensing, and MOGA, which impacted the improvement of network lifetime. In the second stage developed a novel model such as Energy Aware Talented Clustering with Compressive Sensing (TCCS) for the sensor network. This approach considers increasing longevity but also raises the network's overall quality of service (QoS). In the analysis, the TCCS model is applied to both the centralized and distributed networks and compared with the existing methods. When compared to the previous methods, the simulation results show that the proposed work performs better in terms of the calculation of maximum packet delivery ratio of 93.93 percent, minimum energy consumption of 8.04J, maximum energy efficiency of 91.04 percent, maximum network throughput of 465.51kbps, minimum packet loss of 282 packets, and minimum delay of 63.82 msec.

KEYWORDS

Wireless sensor networks, clustering, clusterhead, compressive theory, decentralized clusting, relay node.

1. INTRODUCTION

Wireless sensor network exhibits significant advantages in terms of minimal cost, tiny sensor nodes and small-scale factor. It can be employed in the dangerous and cumbersome area for region monitoring and controlling, with the automated mundane tasks for deployment. The conventional sensor units are expensive and fails to perform effective computational and communication capabilities for the present sensor nodes [1]. The present sensor node involved in data sensing, processing, storing and forwarding those are powered with the battery. The vast range of application are implemented with the wireless sensor network with minimal cost solutions for monitoring environment for different applications such as military, target detection, application tracking and civilian, precision farming, health care application. Also, WSN has been applied in residential application for the management of energy, safety and efficiency of the outer space explorations [2].

Over the period of time, Wireless sensor network are deployed over the region with motes which provides the short-range radio communication and minimal coverage area [3]. The WSN comprises of large number of nodes those involved in provision of multi-hop communication in the network and collaboration for each node to provide appropriate coverage and connectivity. Apart from the traditional concern ad-hoc environment involved in collaboration and communication with the plagued power and energy management for the battery-operated nodes [4]. Sensor nodes are non-rechargeable those are equipped with batteries therefore energy efficiency is considered as important concern for increasing the lifetime of the network. In WSN environment, energy consumption and modeling are major concern for the design and implementation of the network energy optimization. The sensor node energy consumption depends on the three factors such as sensing, signal processing and communication [5]. The communication module comprises of the signal transmission and reception which consumes more energy. Hence, majority of the research concentrated on the reduction of energy consumption to minimization communication cost of the network.

The key factor involved in management of the drained energy is effective management of the network coordinates between sensor nodes through clustering. To minimize the data transmission time and energy consumption in the network the small sensor nodes are grouped together into small groups known as clusters [6-10]. Also, the grouping of sensor nodes iscalled as clustering. Within every cluster lead node is elected act as a cluster head (CH). The CH in the sensor node exhibits higher capabilities rather than the other sensor in the network. Within the respective cluster the cluster head is selected for the sensor node where CHs are pre-assigned by the user. The clustering exhibits the advantages involved in transmission of the aggregated data in sink or base station. The process of clustering provides scalability for large nodes and reduce energy consumption. In the centralized clustering process the cluster head is fixed. Through this with failure of the cluster head the complete cluster is collapsed. Hence, it defines centralized clustering does not have adequate reliability. However, distributed clustering involved in provision of the data reliability when cluster head fails. In this case, the complete network fails when all nodes are failed. In WSN environment distributed clustering commonly engaged in provision of efficient gathering of data and reliability [25-27].

The theory of Compressive Sensing (CS) offers an efficient paradigm for WSN data gathering. The signal may be captured at a sample rate lower than the Nyquist sampling rate using CS. With the decrease in sample frequency, the CS technique may be used in the network to increase the network's lifespan. There are minimum linear measurement features required to reconstruct the sparse signal using the CS-based techniques. The l_1-norm convex optimization problem may be used to locate the signal source. CS theory is concerned with determining sample frequencies based on the features of the signal rather than the bandwidth of the signal. One of the most difficult issues in WSN design and deployment is reducing the network's WSN energy usage. The components of the network's energy consumption must be evaluated in order to solve the issues associated with WSN's energy consumption. Additionally, the development of a viable model for analyzing WSN energy usage has been aided by many suggested models, all of which are linked to the CS method.

Contributions:

- It is suggested to do energy-aware talent grouping using Compressive Sensing (CS) approaches. The developed model is regarded as a useful tool for the analysis of energy usage using the CS-based data collection approach to improve network efficiency.
- The proposed method considers the Cluster Head selection, Compressive Sensing (CS) theory, Connection-based Decentralized Clustering (CDC), Relay node selection, and Multi-Objective Genetic Algorithm (MOGA) for energy-efficient path selection.

- Cluster selection (CH) uses Euclidean distance to decrease network energy use. Connection-based Decentralized Clustering considers data transport hops and message weight..
- Through relay node selection the consumption of energy is reduced. For energy efficiency and reconstruction error, Multi Objective Genetic Algorithm (MOGA) is utilized.
- The suggested strategy enhances the network's overall Quality of Service (QoS), in addition to considering lifetime enhancement.

The present paper is organized as follows: In section 2 presented a related works for energy aware clustering along with compressive sensing technique. The network model considered for analysis is presented in section 3. The proposed CH selection and clustering in the WSN model is elaborated in Section 4. The proposed model involved in formulation of the relay node selection and multi-objective genetic algorithm. The performance of the proposed model is presented along with comparison of TCCS in section 5. The overall conclusion for the proposed model is presented in Section 6.

2. LITERATURE REVIEW

The wireless sensor node's lifetime is inversely proportional to its battery consumption. By calculating the energy consumption of the network's nodes, applications and routing protocols may make better judgments to increase the sensor network's lifespan. This section provides the existing algorithmutilized for reduced energy consumption and reliable routing scheme for the WSN. KalpnaGuleria et al.,[11] proposed an scheme for minimization of the energy consumption through Enhanced Energy Proficient Clustering (EEPC) for complete sensor for the application of field tracking. The constructed nodes are designed based on the mobile and fixed nodes. Initially, the nodes those are fixed involved in information broadcast and select mobile nodes form the cluster head with the fixed nodes. The nodes those are mobile elects the cluster head (CH) with the associated energy and placement level of nodes. With Mobile sensor nodes (SNs) data has been transmitted to the CH with the introduction of concept relay nodes, with fixed nodes. The developed EEPC algorithm selects the relay node based on the calculation of the fitness value based on location and velocity. The developed scheme involved in minimization of energy depletion to improve network lifetime. However, the proposed methods fail to evaluate the transmission delay for data transmission.

V. Seedha Devi et al., [12] proposed a Cluster-based data aggregation reduces latency and packet loss in WSN. Construction of Aggregation Tree and Slot Scheduling are aspects of the proposed strategy. Every cluster head compresses node data at first. Through the built aggregate tree sink node employs MST (MST). Based on allotted timeslots and priority, phase 2 aggregated data may minimize packet loss and latency in the network. The presented approach reduces WSN retransmission and waiting times, improving network performance. The simulations showed that the suggested technique reduces delay and overhead while increasing packet delivery rate and residual energy. However, the planned plan doesn't assess energy use.

Pakdaman Tirani, Shima & Avokh, Avid [13] constructed a Energy-aware CS-based Data aggregation and "Energy-balanced High level Data aggregation Tree" The technique improves network longevity and energy balance by considering diverse nodes. The suggested technique is compatible with mobile sinks and improves network longevity. The developed EHDT technique featured network load-balancing with weighted routing tree for data transmission and cluster head creation with sink via effective energy distribution between nodes. Numerical examination of the suggested method showed that it boosted network transmissions, energy consumption, and longevity. The designed approach has simple sink mobility. The suggested strategy doesn't optimize sink node mobility.

Senouci, Mustapha & Mellouk, Abdelhamid [14] evaluated a uncertainty aware cluster-based deployment approach for the sensor environment. The developed scheme comprises of the different factors based on consideration of the different characteristics for real-world applications in sensor measurement, sensor spatial measurements, harsh deployment model, reliability and unreliable connectivity. The developed results expressed that proposed scheme exhibits significant performance for the real-world wireless sensor network to achieve desire network performance.

Osama MohdAlia [15] developed an energy-efficient network model for dynamic reallocation of the mobile BS within cluster-based infrastructure network with the harmony search algorithm. At first, the developed model allocated information between nodes for framed optimal cluster number with formulation of the appropriate cluster. Through optimal CHs formulation in the sensor cluster order are evenly distributed among sensor with formation of CH. The infrastructure of dynamic environment is evaluated based on the consideration of the number of alive nodes and load balancing in the sensor node. Subsequently, with the optimal placement of the BS CH is determined to minimize the communication distance in the network. Finally, the data transmission and sensing placed based on placement of each sensor node with CH and aggregate the data sensed in BS. The simulation results expressed that proposed scheme exhibits improved lifetime of network, data delivery and energy consumption for static and random BS in the network models.

Anis Jari and Avid Avokh [16] constructed a plan for clustering, multilink placement, and load balancing. The suggested technique includes Multi-sink Placement and Anycast Routing (MPAR) and EMPAR. The proposed MPAR and EMPAR architecture has clustered sensors. Each sensor node communicates data to the cluster head (CH) through load-balancing tree. In upper level, the approach uses a modified particle swarm optimization technique to find the ideal sink node placement. The ant colony algorithm optimises the routing tree based on a high-level analysis. Every tree for anycast employs compressive sensing (CS) for data forwarding and aggregation. Simulations show that the suggested system improves efficiency, network longevity, energy consumption, and variation.

Lv, Cuicui& Wang, Qiang& Li, Jia. [17] constructed a framework to minimize the energy consumption in WSN. The constructed framework uses the covariance matric for sparsify the generated sensor data. The developed scheme uses the numerical sparsity to evaluate the performance of data. The constructed matrix in the network comprises of the sparse binary measurement with computation of numerical sparsity. For every measurement, the part of sensor nodes is involved in gathering of sensor data and transmit data for sink node to recover data. The experimental analysis demonstrated that the constructed sparsify exhibits real temperature data approximation. Compared with other types of constructed sparsifyingexhibits numerical temperature data those are smaller and sequential temperature performance recovery of the data. The proposed framework model exhibits minimal total energy consumption of the proposed scheme is minimal than the other compressive and data gathering algorithm. The proposed scheme exhibits limitation of the higher time complexity for the reduced energy consumption.

Zhang, Ce at al.,[18] constructed a algorithm for data gathering to minimize energy consumption and packet loss. The proposed model involved in formulation of the cluster head with Sparest random measurement matrix (SRMM) through the received data to minimize the lost node measurement and reduce the measurements. To employ between cluster spatial correlation is performed for the constructed sink with the block diagonal matrix (BDM) through reconstruction of the SRMMs for the entire network data. Additionally, with the formulation of the optimal cluster number the developed model reduces the power consumption. The proposed SR-BDM involved in estimation of the emulated data for the sensor data GreenOrbs respectively. The simulation results demonstrated that the proposed model exhibits higher precision through reliable links and packet link of 60% with minimal energy consumption.

G. Yang, M. A et al.,[19] developed a model for energy efficient communication for green communication with the hierarchical approach based on clustering to monitor health status of patients. The developed model organizes the devices in the cluster with devices in equal sizes. Within every cluster the designated cluster collect data from the member devices to broadcast information with centralized base station. The constructed model evaluates the energy consumption of the devices at different states such as idle, sleep, awake and active to perform data transmission between two different states. Through analytical modeling energy consumption of each device at different states are measured. The simulation results demonstrated that the analytical approach improves the lifetime of the network with reduced energy consumption at different states.

S. M. M. H. Daneshvar et al.,[20] constructed a new effective clustering algorithm for election of cluster head with grey wolf optimizer (GWO). The GWO is class of intelligence algorithm based on the consideration of the grey wolf's behavior with comparative examination of results. The proposed model utilizes the similar clustering with proposed protocol with the formulated consecutive rounds. The designed protocol concentrated on the energy saving those are utilized for the clustering reformation. The dual-hop routing strategy is used in the provided model to choose the CH depending on the base station's distance. The analysis of the results expressed that the proposed scheme exhibits reduced and balanced energy consumption through single-hop communication. The performance of the designed protocol expressed that the proposed scheme increases the lifetime of the network with the similar protocols.

M. A. Mazaideh and J. Levendovszky [21] constructed a model for WSN to perform efficient data transmission data nodes with the CS-based approach. The developed model uses the energy efficient optimization model with the multiple objective genetic algorithms (MOGA) to optimize the transmission range measurements with the matrix sensing scheme. The developed model aimed to strike the balance between accuracy and energy efficiency. Through the optimized values the constructed paths are evaluated based on muti hop manner. The numerical analysis and experiments stated that expressed output model exhibits MOGA to elect the appropriate combination based on the measurement number and fitting in the transmission range. The analysis stated that the developed model exhibits the effective balance between the accuracy and energy efficiency. The experimental results demonstrated that existence of the measurement matrices exhibits minimal lower coherency and improved accuracy of CS. Ghaderi, M.R et al.,[22] presented a complete model for analysis of the CS-based energy consumption in the WSN. The designed model expressed that source energy consumption is based on the CS those can be divided in to two categories such as communication and computation energy those are modeled based on the energy components. The distinct number of the data aggregation schemes are developed and presented based on CS-based in WSN are investigated and discussed comparatively. The developed model expressed that the proposed optimization scheme perform effectively in the designing of the CS-based operation in WSN.

Q. Wang, D et al.,[23] proposed a compressive sensing-based (CS-based) for the clustering strategy. The relationship between the two WSN adjacent layer are exhibited as lemmas, cluster optimal size, cluster head (CH) optimal distribution and corresponding analysis are evaluated. Additionally, the problem of the hot spot is designed with the minimization of the energy consumption resulted in the rotation of the CH role. Finally, the backup CH (BCH) exhibits the mechanism to compute the roles and functionality of the CH and BCH. Subsequently, the performance of the network is developed with the energy-efficient compressive sensing-based clustering routing (EECSR). With extensive simulation experiments energy performance are evaluated in the different aspects. Through extensive simulation analysis the evaluation and experiments are examined for energy performance. The comparative analysis is performed with the CS-based and clustering algorithm to evaluate the impact of the EECSR to increase the energy efficiency and improves the lifetime of the WSN.

In this paper the proposed scheme concentrated on the alleviating the challenges associated with the issues involved in energy consumption. Primarily, the developed theoretical model involved in evaluation of the concepts related to network construction, MOGA and compressive sensing those impacts on the network lifetime. Secondly, the proposed Energy Aware Talented Clustering scheme with the Compressive Sensing (TCCS) in WSN is evaluated. The proposed TCCS comprises of the optimal selection relay nodes to minimize the CH node energy depletion. The proposed algorithm effectively minimizes the data transmission complexity and improved network lifetime.

3. PROPOSED METHOD

Battery-powered sensor nodes have a short life expectancy and are thus very energy-reliant. Research into reducing the power consumption and the overall size of wireless sensor networks (WSNs) is critical if these networks are to be widely deployed.

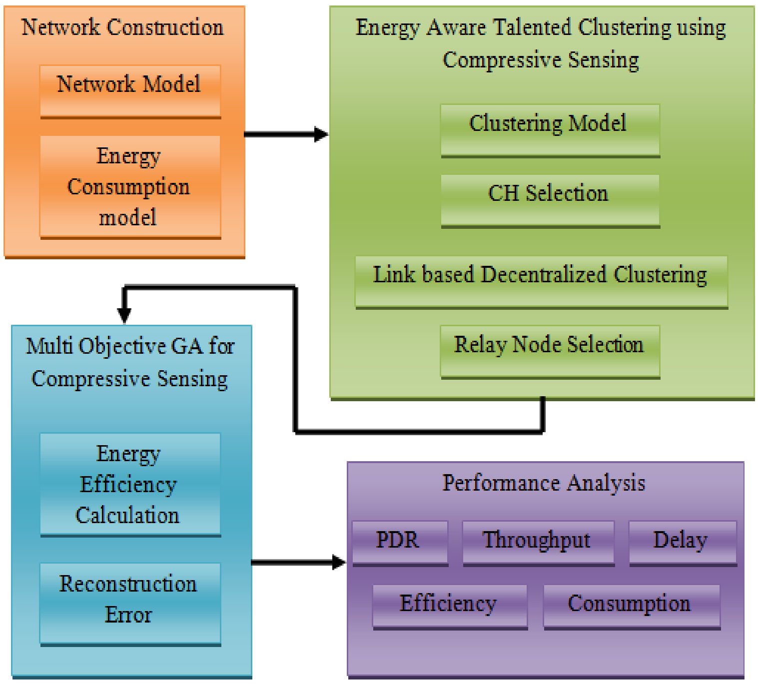

Figure 1. Architecture of the proposed method

The proposed method is sub divided into four main sections namely Network basic models, Multi objective Generic Algorithm (MOGA), Clustering Module with decentralized Structure and Relay Node Selection. Multi-objective GA consist of energy efficiency calculation and reconstruction error parameters. Finally, MOGA based Compressive Sensing with Performance analysis. The network basic model consists of network model, energy consumption model and compressive sensing. With Genetic Algorithm Multi-Objective concept is combined in MOGA. Clustering involves the construction of clusters, choosing cluster leaders, and using a decentralized method with relay node selection. The suggested technique architecture is shown in figure 1.

The Euclidean distance is calculated in this case to pick the Cluster Head, which significantly lowers the network's energy usage. The connection based decentralized clustering model give attention to the number of hops used for data transfer and the weight of the message. through relay node selection the consumption of energy is reduced. Finally, MOGA with compressive sensing consists of energy efficiency and reconstruction error. Measurements of metrics including the packet delivery ratio, energy efficiency, energy consumption, end-to-end latency, network throughput, and packet loss are used in the calculations for performance analysis. The suggested work's flow diagram is shown in Figure 2.

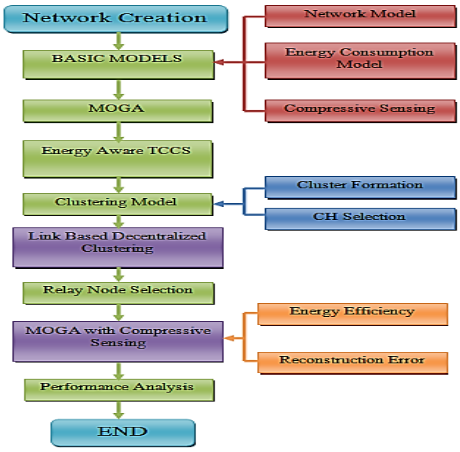

Figure 2. Workflow of the proposed TCCS methodology

The detailed explanation of the proposed work is given below.

3.1. Network Model

Consider the battery-powered nodes as N in the WSN those are deployed randomly over the deployment area size $S = a \times a$. The network topology for cluster is employed in the network with partition of the h clusters. The orthonormal basis comprises of the FFT adopted with sparse representation and reconstruction algorithm model with the orthogonal matching pursuit (OMP) method. Consider the basis sparse representation as $\boldsymbol{\Psi} = \left(\phi_{i,j}\right)_{N\times N}$ and measurement matric is denoted as $\boldsymbol{\Phi} = \left(\boldsymbol{\varphi}_{i,j}\right)_{M\times N}$. The node in the network is considered as dead when energy level are completely exhausted.

3.2. Energy Expenditure Model

In the proposed model, the energy consumption in radio with first order is defined as in equation (1) and (2)

$$E_{Tx}(L, d) = E_{elec} \times L + \epsilon_{amp} \times L \times d^2, (1)$$

$$E_{Rx}(L) = E_{elec} \times L, (2)$$

In above equation (1) and (2) transmitting energy consumption for the L-message for the distance d is represented as $E_{Tx}(L, d)$. The energy consumption for the L-bit message is denoted as $E_{Rx}(L)$. The transceiver required energy for transmission of electrical energy is denoted as $E_{elec}$and transmission amplifier for the energy consumption is denoted as ϵ_{amp}.

3.3.Compressive Sensing Background

In the compressive sensing the reading of N sensor is represented as $\boldsymbol{X} = (x_1, \cdots, x_N)^{\mathrm{T}}$and the k - sparse is denoted as $\boldsymbol{\Psi} \in \mathbb{R}^{N \times N}$: represented as in equation (3)

$$\boldsymbol{X} = \boldsymbol{\Psi\theta}, \quad (3)$$

where $\boldsymbol{\theta} \in \mathbb{R}^N$denoted the sparse basis of the vector coefficient in the sparse basis $\boldsymbol{\Psi}$. The k-sparse X is denoted as the compressive in the vector is denoted as $\boldsymbol{\theta}$with nonzero components as $k(k \leqslant N)$ and the smallest components are defined as (N- k) those can be ignored.

Assume the $\boldsymbol{\theta} \in \mathbb{R}^{MxN}$ measurement matrix those are uncorrelated with the basis $\boldsymbol{\Psi}$. Then,the CS measurement variable with X can be denoted as in equation (4)

$$\boldsymbol{Y} = \boldsymbol{\Phi X} = \boldsymbol{\Phi\Psi\theta} = \boldsymbol{\Theta\theta}, \qquad (4)$$

Where, sensing matrix is denoted as M << N, and $\Theta = \Phi\Psi$. The reconstructed original signal X can have probability of overwhelming for the measurements M for the l_1-norm minimization denoted as in equation (5)

$$\widehat{\boldsymbol{X}} = \arg min \parallel \boldsymbol{X} \parallel_1 \text{ subject to : } \boldsymbol{Y} = \boldsymbol{\Phi X} \quad (5)$$

Where, the reconstructed sparse signal X is represented as $\widehat{\boldsymbol{X}}$

The two factors considered for reconstruction of X from Y that need to be considered: 1) X is compressive at Ψ, and 2) $\boldsymbol{\Phi}$need to evaluate the RIP denoted as $M \geqslant ck\lg(N/k)$. In other words, the condition for k-sparse X is expressed as conditions in equation (6)

$$(1-\varepsilon) \parallel \boldsymbol{\theta} \parallel_2^2 \leqslant \parallel \boldsymbol{\Phi\theta} \parallel_2^2 \leqslant (1+\varepsilon) \parallel \boldsymbol{\theta} \parallel_2^2 \quad (6)$$

Where $c, \varepsilon \in (0,1)$ while $\boldsymbol{\Phi}$ sto withstand the RIP parameter ε.

3.4. Multi Objective Genetic Algorithm

To perform optimization of the different parameters multiple objective genetic algorithms (MOGAs). The metaheuristics algorithm uses the MOGA those are applied in the WSN to achieve optimal contradictory objectives. The set of restriction are adjusted based on the simultaneous objectives. Those objectives are adjusted based on the simultaneous restriction's subjects. With multi-objective optimization for optimal solution specific definition are presented instead of yielding single solution through conventional genetic algorithm (GA). The set of MOGA non-dominated solutions are accepted to derive the best solution with subjective those need to be formulated.

MOGA involved in formulation of vector fitness function denoted as F(x) = [*f1(x), f2(x),* · · ·, *fn(x)*]T to derive the decision variable to compute the inequality and equality constraints, through those constraints the viable domain are defined to derive acceptable solutions.

The pareto-Optimality in the MOGA involved in computation of the vector fitness function to derive the Parento-Optimal solution. The vector in the multi-objective optimization with Pareto-Optimal solution vector is defined as X = [x1, x2, · · ·, xn] ^{T} those engaged in provision of the feasible solutions to minimize the least one objective to increases the characteristics of other objectives. The vector solution of Pareto-optimal set or Pareto-front $\widehat{\mathbf{X}} = [\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_n]^T$ those are not dominated for any other solution space where Xˆ are dominated for the value X if and only if as presented in equation (7) and (8)

$$\forall i \in i = 1,2,\cdots,n, f_i(x) \leq f_i(\hat{x}) \qquad (7)$$

And

$$\exists i \in i = 1,2,\cdots,n, f_i(x) < f_i(\hat{x}) \qquad (8)$$

4. Energy Aware Talented Clustering Approach Using Compressive Sensing (TCCS)

In energy saving scheme the transmission count is reduced but it is not sufficient enough. According to first-order radio model for the energy consumption for transmission of the L-bit messages based on the computation of the distance leis between the nodes. The figure 3 presented that the comparative examination of the aggregation trees with the 7 nodes in which the near link is computed based on the link Euclidean length. In figure Figs. 3-a and 3-b presented the total transmitted packets involved in transmission. In example of both case node 0 involved in transmission of packets 5 to the sink node. However, the computation of the links between Fig. 3-b is less than the Fig. 3-a for computation of the energy consumption. The main objective of the network to maximize the lifetime of the network, in this paper both transmission and remaining network energy are considered. At the end, the proposed scheme involved in resolving cluster-based routing problem, CS theory, sink placement and load balancing [24-26].The data aggregation is constructed based on the trees with round by round.

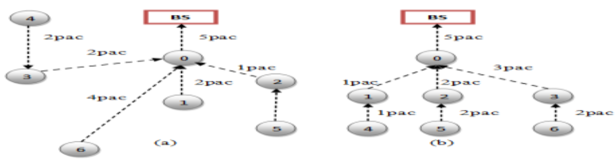

Figure 3. Process for aggregating data using TCCS

A cycle that involves calculating the amount of time needed to transport the aggregated data to the sink and gather data using sensor nodes. Each round in the developed model comprises of the three phases: At first phase, the sensor node effectively forms the clusters. In second phase, remaining energy is determined based on the CHs energy and position based on the previous round. In third phase, every node transmits the data with the corresponding CH through formulation of the shortest path tree. With the CS scheme the data collected is compressed. Further, the projection of every CH generates the forwarded information towards sink by sink with the routing tree in high-level scenario. Based on the following constraints different phases are proposed for TCCS those are explained as follows:

4.1. Clustering Model

As stated above, the sensor nodes are partitioned into C clusters with the implementation of the significant strategy modifications. The proposed scheme uses the random set of the CHs election.

The nodes those are near to the CH are connected and formulate the cluster. In each cluster, the nodes those are near to the CH are elected [27-29]. In every cluster, a CH selects in such a manner to summarize the hop counts in the cluster nodes to minimize the CH. The similar process is continued till no changes are observed in the CHs. At first round, the random CH is stated compatibility with the derived energy consumption model based on the Euclidean metric distance with hop count. The better CHs involved in minimization of the energy consumption. The objective to perform effective network load-balancing with consideration of the CH. With the typical node Euclidean distance calculation typical node are minimal than the CH distance, the sink cluster member are computed for the node values. This involved in minimization of the transmission number and improves the load balancing for the sink node.

Thus, the steps involved in processing are presented as follows:

1) The distance of Euclidean between CH and other nodes are computed. Every sensor nodes become the cluster member based on the Euclidean distance estimation for the minimized CH.
2) In each cluster, the selected CH is based on the summation of the Euclidean distance between nodes and CH in minimized manner.
3) The above process continues until the no changes are observed in CHs.

4.2. CH Selection

The constructed traffic model of the sensor node computes the data measured based on round by round. The CHs involved in utilization of the more energy than the other sensors, these impacts on the lifetime of the network. Thus, the proposed model involved in computation of the different node energy distribution. This leads to uniform loss of energy with increased First Node Dies (FND). In first round, the CHs determined the strategy that explained in phase 1. In next round, based on the first metrices, the hop between 1-hop or 2-hop distance are involved in computation of the present CH, the candidate node computes the more energy required for the CH as explained in equation (9)

$$\mathrm{CH}_1(j) = \arg \max_{i \in \cos \text{ didate nodes } (j)} \mathrm{Er}(i) \tag{9}$$

Where, in above equation (9)$\mathrm{CH}_1(j)$denoted the *j*th cluster CH based on the considered first metrics and $\mathrm{Er}(i)$ illustrate dthe remaining energy in the ith node those need to be randomly broken. Based on this, the factor considered are remaining energy and distance are presented in equation (10)

$$\mathrm{CH}_2(j) = \arg \max_{i \in C \text{ tuster nodes(j)}} \left(\frac{\mathrm{Er}(i)}{d_{min}(i, CH_{FR}(j))} \right) \tag{10}$$

Where $\mathrm{CH}_2(j)$, $CH_{FR}(j)$,and $d_{min}(i, CH_{FR}(j))$demonstrate the *j*th cluster head in the *j*th cluster of the second metric, *j*th cluster of CH is computed in first round and minimal hop count is computed for nodes I and $CH_{FR}(j)$, respectively.

Based on the second metric, the nodes those are closer to center are having more chance to select as CH. The reduced energy consumption and transmission number is based on the remaining node energy, different node energy consumption.

Energy, distance, and delay are factors that are taken into consideration while choosing a cluster head.

The energy consumption between the two nodes is given in below equation (11)

$$f^{\text{energy}} = \frac{f^{\text{energy}}(q)}{f^{\text{energy}}(p)} \qquad (11)$$

$f^{\text{energy}}(q) = \sum_{j=1}^{M} uEN(j)$

$$u\text{EN}(j) = \sum_{\substack{i=1 \\ i\in j}}^{L} \left(1 - \text{EN}(D_i) * \text{EN}(CH_j)\right); 1 \leqslant j < M$$

$$f^{\text{energy}}(p) = M * \text{Max}_{i=1}^{L}\left(EN(D_i)\right) * \text{Max}_{j=1}^{M}\left(EN(CH_j)\right)$$

where $EN(D_i)$ and $EN(\text{CH}_j)$implies the energy of i^{th} the normal node as well as the energy of j^{th} the CH, respectively. $f^{\text{energy}}(q)$, refers to the energy between the CH and the normal node and between the CH and the BS of the network.

Distance is indicated in mathematical Eq. (12). The value of $f^{\text{dist}}(q)$should fall within the category of[0,1].

$$f^{\text{dist}} = \frac{f^{\text{dist}}(q)}{f^{dist}(p)}$$
$$f^{dist}(q) = \sum_{i=1}^{L} \sum_{j=1}^{M} \|D_i - CH_j\| + \|CH_j - B_s\| \qquad (12)$$

where $f^{\text{dist}}(q)$ shows the distance between the CH and the network's BS, as well as the distance between the CH and the normal node.

In Eq. (13), the nodes' data transmission delay is described, and the delay value is required to fall within [0, 1]. As the number of nodes in a cluster decreases, the latency also becomes significantly decreased.

$$f\text{delay} = \frac{\text{Max}(\text{CH}_j)}{L=1} \qquad (13)$$

4.3. Link based Decentralized Clustering (LDC) Approach

In this section, the algorithm for the LDC scheme is developed and pseudocode is presented for analysis. The developed algorithm is stated with the initiating messages based on the originator's node using clustering. The initiated nodes are denoted as O = {O_1,O_2, . . ., O_Q}. The started node involved in message circulation process with transmission of message to all nearby nodes. Every message cluster of the tuple comprises of the five fields those are presented as follows:

- Originator ID (OID): The originator node field are provided with the unique identity.
- Message ID (MID): The constructed field classifies all messages form the all messages through the originators.
- Message Weight (MWeight): The message carried weights for data transmission
- Source ID (SourceID): The message visited by the recent node are indicated in this field.
- Time to Live (TTL): The maximal hop count those need to be recirculated based on the number of hops.

The constructed fields SourceID, the MID, and the OID self-explanatory in the tuple. The weighted function is estimated based on the probability to reach the destination node from the source node. The initialized originator node O_l message weights are denoted as $sg.MWeight = \frac{1}{Degree\ (O_l)}$.

The field of TTL comprises of the small value integer those only constraints the originator node those uses similar TTL value. Every V_i node compute the value set denoted as TotalWeight(V_i,O_l). The defined values stated that the all-message weights are generated from the $O_l$and reaches the destination node as V_i. Upon reception of the message Msg the recipient updates the V_i as TotalWeight function for the originator message. Every V_i evaluate the TTl message those are higher than 0. If $V_i$perform data forwarding of messages between nodes. The recirculation is evaluated based on the recipient MWeight update in the TTL. The weight messages are classified based on the TTL degree as V_i those are decremented by the value 1. The message circulation halts are denoted as V_i in TTL as 0 or MWeight those are significantly minimal. Every node in the network receives multiple messages from the different data nodes. The computation performs the function of TotalWeight in the originators with the received messages. The nodes those receives the last message need to wait for few times to ensure high messages for processing. Then the node involved in the formulation of the originator for the value of maximal TotalWeight. To construct a particular cluster the messages are originator with the informing decision based on the node-ID. In case if all nodes lie below TotalWeight values than the node remains the outlier. The node those are joined in the cluster are decided and remain in the discover outlier at any point instances. It involved in accumulated weights form the different originator messages. In those cases, the nodes already in cluster are within the group the originator cluster make decision about the cluster. It involved in transmission of new messages in the originator to notify the decision about the cluster.

Algorithm 1: Algorithm Executed by Message Originator O_l
Create a New Message Msg
$Msg.OID \leftarrow O_l, Msg.MWeight \leftarrow \frac{1}{\text{Degree } (O_l)}$
$Msg.SourceID \leftarrow O_l, Msg.TTL \leftarrow$ InitialTT L
$Msg.MID \leftarrow$ Current System Time { A unique value }
for Each node $V_i \in Nbr(O_l)$ **do**
Send Msg to V_i
end for

Algorithm 2: Algorithm Executed by Node V_i on Receiving Msg
{Check whether I have received messages from $Msg.OID$}
if I have seen messages from $Msg.OID$ before **then**
{Check if the $LastMsgId(O_l) == Msg \cdot MID$}
if $LastMsgID(O_l) == Msg \cdot MID$ then
$TotalWeight(V_i, O_l) \leftarrow TotalWeight\ (V_i, O_l) + Msg \cdot M\ Weight$
else
$TotalWeight(V_i, O_l) \leftarrow Msg.MW\ eight$
$LastMsgID\ (O_i) \leftarrow Msg.MID$
end if
else
{This is the first message from O_l}
$TotalWeight(V_i, O_l) \leftarrow TotalWeight\ (V_i, O_l) + Msg\ M\ Weight$
$LastMsgID\ (O_l) \leftarrow Msg \cdot MID$
end if
if$TotalWeight(V_i, O_l) > MaxWeight$ *then*

MaxWeight ← *TotalWeight* (V_j, O_l)
MaxWeightID ← *Msg.OID*
end if
if $Msg.TTL > 0$ *and* $\frac{M_{sg.MWeight}}{Degree\ (V_i)} > MinWeight\ then$
Create a New Message New Msg
NewMsg.OID← *Msg.OID*, *NewMsg.SourceI D* ← V_i
NewMsg.MWeight ← $\frac{Msg.MWeight}{Degree(V_i)}$
NewMsg.TTL ← (*Msg.TTL* −1), *NewMsg.MID* ← $Msg.MID$
for Each node $V_j \in Nbr(V_i)$ do
Send $Msg\ to\ V_j$
end for
end if
Wait for *WaitTime* in anticipation of other messages
if *MaxWeight*>*WeightThreshold***then**
Join the cluster led by *MaxWeightID*
else
Remain an outlier
end if

4.4. Relay Node Selection

With the selection of CHs, to prevent higher energy depletion CHs are lies far away from the BS, the developed protocol elects the relay nodes for every node in such as wat the relay is utilized by the CH. In case if multiple CH uses the relay, then the assigned relay has different timeslots to handle communication between nodes with the decreased network throughput. Therefore, in the proposed model relay node uses the only one CH. This leads to lack of relay in CH and directly transmits the data to the BS. The relay node selection is based on the node distance from the BS with assignment of appropriate relay node and it proceeds the same procedure for every CHs. To select the appropriate node relay for CH two characteristics are considered i) reduction of the toral energy consumption and ii) energy consumption balance between CH and the relay. In figure 4 presented the hypothetical relay between CH and BS. The distance between BS and CH are partitioned as equal distance r_0 with estimation of relay and BS distance.

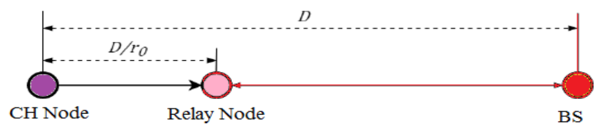

Figure 4. Location of CH, Relay node and the Base Station

The proposed model comprises of the dual hop routing and the relation between one-to-one hop lies between CHs to the relays. The fixed values of the $r_0$with balance and reduction of energy consumption. In other words, the line segments between point lies are perfect for relay for CH and BS. To ensure reduced energy consumption data packets need to be delivered between BS and the CH in which each relay shares equal amount of energy. The proposed model calculates the r_0=1.8169 to select the relay and CH. The relay node between perfect point is lies between CH and the BS are calculated with the fixed distance ratio r_0=1.8169. The point of the CH is the closest those are not already selected relay. If relay does not have any relay closer to the threshold value T_r for the perfect time, the CH those does not have relay transmits the BS directly.

The developed procedure exhibits different advantages those are presented below:

1) It completely eliminates the hot-spot problem for relay consumes at equal energy amount of CH where it serves and select the different relays in the rounds.
2) It reduces the amount of energy consumed for packet delivered to BS.
3) It involved in assignment of relays to the different CHs relay as much as possible.

4.5. Multi Objective Genetic Algorithm for Compressive Sensing:

The proposed multi-objective optimization model uses the genetic algorithm to reduce energy consumption with the error reconstruction. This section presented about the computation of the reconstruction error and energy efficiency.

4.5.1. Energy Efficiency:

In a WSN network, the transmission distance, represented as d, is used to compute the route loss exponent α, which is directly proportional to the dα. Statistically, the node transmission range is defined as R, the communication mean square distance are computed as $E[r^2] = R^2/2$ [24]. In the every path in M the average path length is defined as n_c, the energy consumption of the node path is defined as in equation (14)

$$E_c h = M * n_c * (R^2/2)^{\alpha} \quad (14)$$

The average distance between path leaders M and BS is represented as d_{av} for the cluster head total energy consumption for the transmit unit of compressed data denoted in equation (15)

$$E_{LBS} = \sum_{i=1}^{M} d_{av}^{\alpha} \quad (15)$$

The densing field edge square for the D and BS of the centre involved in computation of the average distance lies between CH and BS as in equation (16)

$$d_{av} = \int_0^D \int_0^D \left[\left(x - \frac{D}{2}\right)^2 + \left(y - \frac{D}{2}\right)^2\right] f(x, y) dx dy \quad (16)$$

where f(x, y) denoted the pdf function joint probability function (pdf), those value is equal to 1/D2 . The total consumed energy between path in the node and CH is presented in equation (17)

$$E = M\left(n_c \left(\frac{R^2}{2}\right)^{\alpha/2} + \left(\frac{D^2}{6}\right)^{\alpha/2}\right) \quad (17)$$

Through the equation (14) it is observed that the increase sin M increases the total energy consumed.

4.5.2. Reconstruction Error:

The paradigm for the CS reconstruction error is based on the error measured for the original densed data (e_θ), the error in sparse is represented as e_x and observed error is denoted as (e_y). The evaluation is based on the consideration of the equation (18) – (20)

$$e_\theta = \frac{1}{N} \| \theta - \hat{\theta} \|_2^2 \quad (18)$$

$$e_x = \frac{1}{N} \parallel x - \hat{x} \parallel_2^2, (19)$$
$$e_y = \frac{1}{M} \parallel y - \hat{y} \parallel_2^2, (20)$$

The sensed vector is represented as θ, x, and 4 and the reconstructed vector is represented as $\hat{\theta}, \hat{x},$ and $\hat{y}$. In this paper the (e_y) is reduced with the $\hat{y} = \Phi\hat{x}$, using $\hat{x} = \Psi\hat{\theta}$,if Ω = ΦΨ ,then (20) becomes:

$$e_y = \frac{1}{M} \parallel y - \Omega\hat{x} \parallel_2^2 (21)$$

Through equation (21) illustrated that increase in M minimizes the e_y. Table 1 shows the different variable indications used in the different equations.

Table 1. Different variables indications

Variable	**Indication**
L	Messages
d	Distance
E_{Tx}(L, d).	Transmitting energy consumption
E_{Rx}(L).	Receiving energy consumption
E_{elec}	Electrical energy
ϵ_{amp}	Amplifier for the energy consumption
N	Sensor
Ψ	Sparse basis
R	Transmission range
n_c	Average path length
e_x	Error in sparse
e_y	Observed error
e_θ	densed data

5. SIMULATION RESULTS

The performance ofthe proposed model is evaluated in NS-2 simulation software. End-to-end delay, packet loss, packet delivery ratio, throughput, energy consumption, and energy efficiency are the parameters taken in to consideration for the analysis. The performance of the proposed Energy Aware Talented Clustering with Compressive Sensing (TCCS) algorithm model is evaluated comparatively evaluated with the existing model such as Compressive sensing-based energy consumption model (CDAS)[22], Energy-Efficient Compressive Sensing-based clustering Routing (EEPC) protocol [23]. Table 2 shows the simulation settings

Table 2. Simulation settings

Parameters	Values
Simulator Version	NS-2.29
Simulation Time	100 ms
Simulation Coverage Area	1000m×1000m
MAC interface	MAC/802.11
No of Nodes	100 nodes
Channel	Channel/Wireless
Radio Propagation Model	Two Ray Propagation Model
Antenna Type	Omni-directional Antenna
Queue Type	DropTail
Initial power	1000 Joules
Transmission power	1.0 Joules
Receiving Power	1.0 Joules
Idle Power	1.0 Joules
Data Packet Size	512 bytes
Transition Power	0.2 Joules
Transition Time	0.005 ms

Energy Consumption

The performance of the proposed TCCS-Distributed comprises of the clustering-based optimization model for improving the overall performance of the WSN environment. In WSN due to higher node mobility energy consumption is higher to reduce energy consumption proposed TCCS-Distributed model uses the optimization model. In table 3 the performance of the proposed TCCS-Distributed model is compared with the CDAS, EEPC and TCCS-Centralized.

Table 3. Energy consumption calculation(J)

Nodes	CDAS	EEPC	TCCS-Centralized	TCCS-Distributed
0	0	0	0	0
20	5.127	3.21	2.01	1.08
40	9.178	7.65	4.20	2.16
60	15.46	10.78	5.19	4.11
80	21.45	14.85	8.16	6.25
100	26.97	17.93	11.85	8.04

The energy consumption for varying time for the WSN environment is presented in figure 4. Energy consumption defines the amount of energy consumed by the network for different time instances in the network. Figure 5 shows the energy consumption calculations of the proposed method. The network's energy consumption is simulated and analysed for nodes 0, 20, 40, 60, 80, and 100. The energy consumption of the convention CDAS, EEPC and TCCS-Centralized is significantly higher than the proposed TCCS-Distributed. Initially, for time energy consumption of all nodes are equal to zero.At different nodes 0,20,40,60,80 and 100energy consumption of the proposed TCCS-Distributed us measured as 2.47, 4.78, 6.78, 9.12 and 11.11 (J) respectively**.**

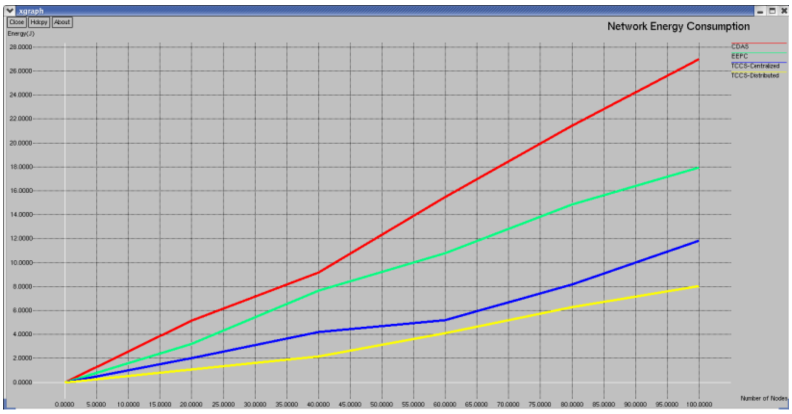

Figure 5. Energy Consumption Calculation

However, the energy consumption of conventional CDAS, EEPC and TCCS-Centralized exhibits higher energy consumption in the WSN network. The analysis of the simulation results expressed that proposed TCCS-Distributed exhibits ~ 6% reduced energy consumption compared with the conventional CDAS, EEPC and TCCS-Centralized.

Energy Efficiency

Energy efficiency defines the amount of energy remains in the network upon the transmission of data in the network. As WSN environment comprises of the higher node mobility and energy consumption level to improve energy efficiency of the WSN network proposed TCCS-Distributed model uses the optimization model. In table 4 the performance of the proposed TCCS-Distributed model is compared with the CDAS, EEPC and TCCS-Centralized.

Table 4. Energy efficiency calculation (J)

Nodes	CDAS	EEPC	TCCS-Centralized	TCCS-Distributed
0	0	0	0	0
20	9.24	13.54	15.11	17.22
40	23.46	33.48	39.64	42.19
60	41.89	49.13	53.89	56.11
80	59.17	64.88	71.45	75.23
100	74.86	82.98	88.67	91.04

Energy efficiency defines the amount of energy remains in the network upon the transmission of data in the network. As WSN environment comprises of the higher node mobility and energy consumption level to improve energy efficiency of the WSN network proposed TCCS-Distributed model uses the optimization model. In figure 5 the performance of the proposed TCCS-Distributed model is compared with the CDAS, EEPC and TCCS-Centralized. Figure 6 shows energy efficiency calculation.

Figure 6. Energy Efficiency Calculation

The simulation analysis of the energy efficiency of the network is evaluated for varying nodes 0,20,40,60,80 and 100. The energy efficiency of the convention CDAS, EEPC and TCCS-Centralized is significantly minimal than the proposed TCCS-Distributed. Initially, for time 0ms energy efficiency of all nodes are equal to zero. For the different nodes 0,20,40,60,80 and 100 energy efficiency of the proposed TCCS-Distributed us measured as 19.78, 32.14, 56.47, 78.14 and 89.12(J) respectively. However, the energy efficiency of conventional CDAS, EEPC and TCCS-Centralized exhibits minimal energy efficiency in the WSN network. The analysis of the simulation results expressed that proposed TCCS-Distributed exhibits ~ 2% improved energy efficiency compared with the conventional CDAS, EEPC and TCCS-Centralized.

Packet Delivery Ratio

The PDR defines the number of packets received to the total packets transmitted in the network. The analysis stated that the PDR values in the network are evaluated based on the evaluation of the proposed and conventional methods in the network as illustrated in the table 5.

Table 5. Packet delivery ratio calculation

Nodes	CDAS	EEPC	TCCS-Centralized	TCCS-Distributed
0	0	0	0	0
20	17.32	24.55	28.91	32.63
40	32.67	35.91	38.01	42.03
60	41.04	48.26	52.31	50.17
80	63.93	67.94	69.03	71.93
100	80.56	89.02	92.34	93.93

The PDR value of the proposed TCCS-Distributed evaluated for the existing CDAS, EEPC and TCCS-Centralized. The PDR analysis of the node parameters in the network are presented in figure 7.

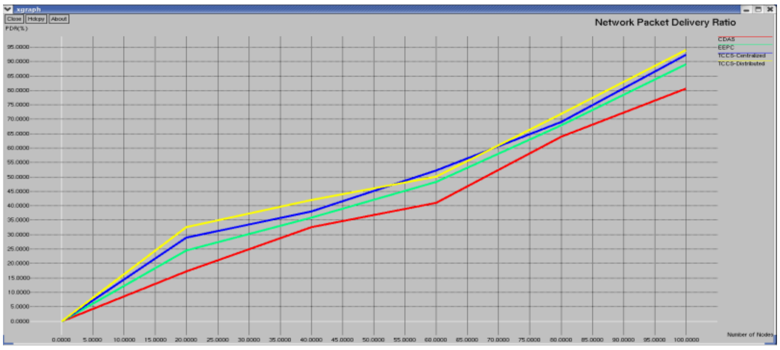

Figure 7. Packet Delivery Ratio Calculation

The simulation analysis of the packet delivery ratio network is evaluated for varying nodes 0,20,40,60,80 and 100. The packet delivery ratio of the convention CDAS, EEPC and TCCS-Centralized is minimal than the proposed TCCS-Distributed. Initially, for time 0ms packet delivery ratio of all nodes is equal to zero. At different nodes 0,20,40,60,80 and 100 packet delivery ratios of the proposed TCCS-Distributed is measured as 22.14, 37.43, 53.86, 76.47 and 94.26 respectively. However, the packet delivery ratio of conventional CDAS, EEPC and TCCS-Centralized exhibits minimal value in the WSN network. The analysis of the simulation results expressed that proposed TCCS-Distributed exhibits ~ 3% higher packet delivery ratio compared with the conventional CDAS, EEPC and TCCS-Centralized.

Packet Loss

The number of packets dropped or missed in the WSN network is presented as shown in table 6. The comparative analysis of the packet drops for the proposed TCCS-Distributed and the existing CDAS, EEPC and TCCS-Centralized are presented.

Table 6. Packet loss calculation

Nodes	CDAS	EEPC	TCCS-Centralized	TCCS-Distributed
0	0	0	0	0
20	89	76	59	31
40	143	137	147	98
60	221	226	204	149
80	349	318	269	223
100	450	396	320	282

The comparative analysis of the proposed TCCS-Distributed with the conventional technique for varying time instances are presented in figure 8. The analysis of the packet drop exhibits the proposed TCCS-Distributed is minimal.

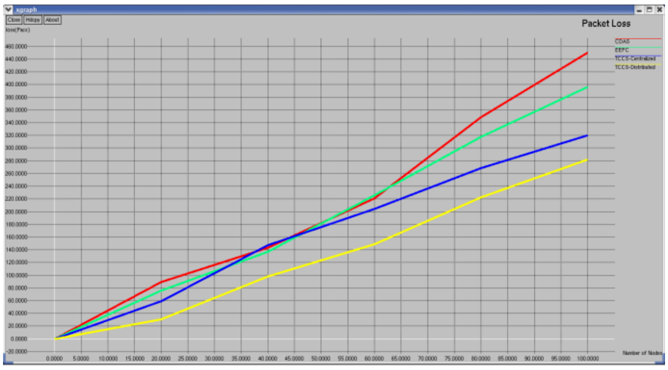

Figure 8. Packet Loss Calculation

The simulation analysis of the packet drop network is evaluated for varying nodes0,20,40,60,80 and 100. The packet drop of the convention CDAS, EEPC and TCCS-Centralized is higher than the proposed TCCS-Distributed. Initially, for time 0ms packet drop of all nodes are equal to zero. At varying nodes 0,20,40,60,80 and 100 packet drop of the proposed TCCS-Distributed is measured as 9, 17, 22, 36 and 46 respectively. However, the packet drop of conventional CDAS, EEPC and TCCS-Centralized exhibits higher packet drop value in the WSN network. The analysis of the simulation results expressed that proposed TCCS-Distributed exhibits ~ 5% minimal packet drop ratio compared with the conventional CDAS, EEPC and TCCS-Centralized.

End to End Delay

The time by the network for transmission of data from source node destination node is defined as the end-to-end delay. The efficient communication network should have minimal end-to-end delay in the WSN. In table 7 the measured End-to-End delay for the proposed TCCS-Distributed is presented comparatively with conventional CDAS, EEPC and TCCS-Centralized.

Table 7. End to end delay calculation (ms)

Nodes	CDAS	EEPC	TCCS-Centralized	TCCS-Distributed
0	0	0	0	0
20	42.18	31.82	15.48	9.22
40	85.19	61.22	43.71	29.34
60	133.97	96.41	79.12	63.85
80	185.17	146.23	134.96	113.47
100	245.94	193.45	176.68	146.72

The end-to-end delay for varying time in WSN environment is presented in figure 9. As the end-to-end delay involved in computation of the data transmission time between source to destination node in the WSN environment.

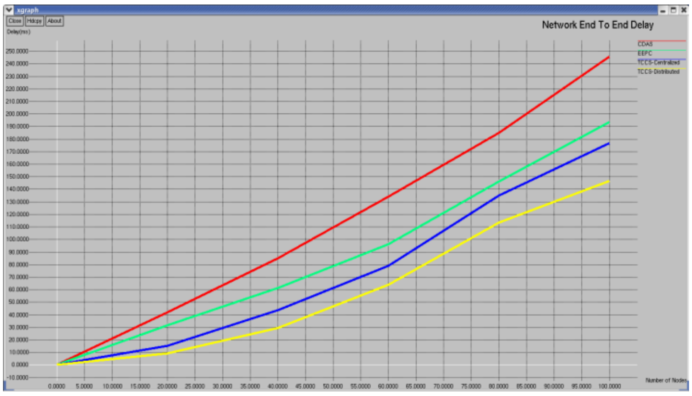

Figure 9. End to End Delay Calculation

The simulation analysis of the end-to-end delay network is evaluated for time varying nodes 0,20,40,60,80 and 100. The energy efficiency of the convention CDAS, EEPC and TCCS-Centralized is higher than the proposed TCCS-Distributed. Initially, for time 0ms end-to-end delay of all nodes are equal to zero. The different node 0,20,40,60,80 and 100 end-to-end delay of the proposed TCCS-Distributed us measured as 33.26, 61.24, 92.48, 135.48 and 168.25(ms) respectively. However, the end-to-end delay of conventional AOMDV and EHO-AOMDV exhibits higher value in the WSN network. The analysis of the simulation results expressed that proposed TCCS-Distributed exhibits ~ 3% minimal end-to-end delay compared with the conventional CDAS, EEPC and TCCS-Centralized.

Throughput

The computation of the network defines the ratio between number of successful data received to the total number of packets in the network. The throughput measurement of the network is shown in table 8.

Table 8. Throughput calculation (kbps)

Nodes	CDAS	EEPC	TCCS-Centralized	TCCS-Distributed
0	0	0	0	0
20	65.22	87.34	98.53	127.39
40	127.49	154.22	187.25	206.33
60	178.39	221.93	267.22	281.24
80	229.57	265.86	298.45	379.23
100	276.89	321.98	357.13	465.51

The computation of throughput is comparatively analyzed with the CDAS, EEPC and TCCS-Centralized. The performance of the proposed TCCS-Distributed for the estimation of the throughput for successful transmission and reception of data packets in the network is presented in figure 10.

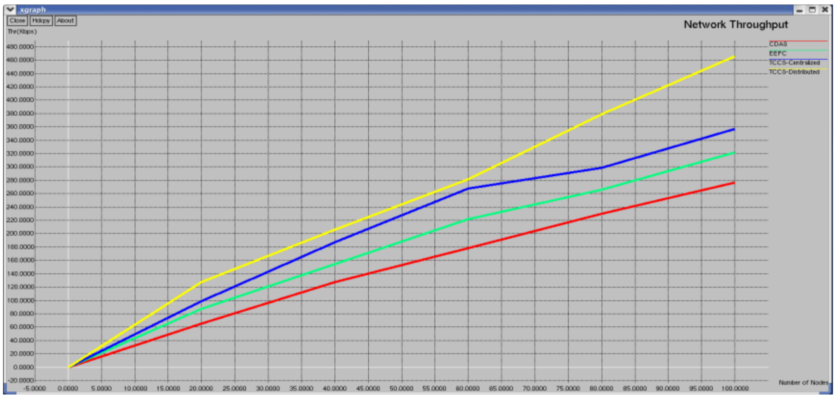

Figure 10. Proposed method throughput Calculation

The network's throughput is simulated and analyzed for nodes 0, 20, 40, 60, 80, and 100. The throughput of the convention CDAS, EEPC and TCCS-Centralized is minimal than the proposed TCCS-Distributed. Initially, for time 0ms packet drop of all nodes are equal to zero. At different nodes 0,20,40,60,80 and 100packet drop of the proposed TCCS-Distributed is measured as 54.23, 89.47, 134.16, 169.14 and 205.59kbps respectively. However, the throughput of conventional CDAS, EEPC and TCCS-Centralized exhibits minimal throughput value in the WSN network. The analysis of the simulation results expressed that proposed TCCS-Distributed exhibits ~ 5% improved throughput compared with the conventional CDAS, EEPC and TCCS-Centralized.

6. CONCLUSION

In this work, the impact of CS theory and decentralized clustering results in the betterment of network lifetime and QoS. To achieve this at the initial stage the network construction in done with formulated manner. Proposed the Energy Aware Talented Clustering with Compressive Sensing (TCCS). This approach combines principles such as Compressive Sensing (CS), Connection-based Decentralized Clustering (CDC), Relay node selection, and Multi Objective Genetic Algorithm (MOGA) (MOGA). CH selection here is done by computing the Euclidean distance, which considerably reduces the network's energy usage. The Connection-based Decentralized Clustering model focuses on the number of hops and the message weight employed in data transport. Selecting the right relay node might help to save energy usage. Finally, Multi Objective Genetic Algorithm (MOGA) is used for Energy efficiency and reconstruction error. When compared to the previous methods, the simulation results show that the proposed work performs better in terms of the calculation of maximum packet delivery ratio of 93.93 percent, minimum energy consumption of 8.04J, maximum energy efficiency of 91.04 percent, maximum network throughput of 465.51kbps, minimum packet loss of 282 packets, and minimum delay of 63.82 msec. In future, we will expand this work by creating multi-level trust model for TCCS method.

CONFLICTS OF INTEREST

The authors declare no conflict of interest

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