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# DEEP TRUST MANAGEMENT AND EMPOWERED MAP REDUCE (DTP-EMP) FOR MITIGATION OF VOID AND ENERGY HOLE IN WSN-IOT

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**Abstract**
In this modern era, the usage of Internet of Things enabled Wireless Sensor Networks are booming and promising to reshape the communication means more reliably. But there are two major factors which affects the network performance due to the presence of energy and void hole. This research work focused on developing three different methodologies with an ultimate objective of reducing the energy depletion problem in IoT enabled WSN. This is accomplished by alleviating the energy and void hole issues which commonly occurs in WSN. Though there are many efforts done to reduce energy depletion, the problem of uncertainty in selecting forwarding nodes and distribution of sensor nodes are the major challenges. This paper incorporates both energy consumption and security mechanism which are primary challenge of WSN during data transmission. To evenly distribute the sensor nodes, wedge method is adopted and best route for data transmission is selected in a parallel manner by applying Fuzzy C Means clustering with Map Reduce for alleviating void and energy hole depletion respectively. A novel deep neural network trust management is anticipated to monitor the forwarding nodes in a regular interval to determine malicious forwarding nodes and eliminating them from the transmission process. From the results obtained it is evident that the anticipated Empowered Map Reduce and Deep Trust management (EMR-DTM) effectively accomplishes the objective of highest rate of energy consumption along with trust managed data transmission in WSN-IoT.
Index Terms – Wireless Sensor Network, Internet of Things, Map Reduce, Data Transmission, Energy consumption, Sensor Node, Fuzzy C Means Clustering

## INTRODUCTION

Wireless Sensor Network (WSN) is a collection of tiny, low-cost sensor nodes which works in a distributed environment. Ad hoc networks, in contrast to sensor networks, will have a smaller number of nodes with no infrastructure(Bello&Zeadally,2014). A sensor node is a self-contained unit that includes a transceiver, batteries, sensors, and a microprocessor. Due to low battery power, limited communication bandwidth, and constrained storage capacities, these sensor nodes are small and have limited energy. The sensor nodes are used in open fields where they may monitor physical and environmental factors in a co-operative manner(Huang et al., 2017). WSN uses sensor nodes in conjunction with an integrated CPU to control and monitor the surroundings in a specific region. These sensor nodes assemble all data packets, which are then sent to the base station, also known as the sink node (Sahoo & Liao, 2014). The base station connects the WSN to the rest of the internet. The edifice of a Wireless Sensor Network Station is shown in Figure 1.1.

The basic elements of WSN are sensing component, a processing component, a communication component,and a power unit are all included in wireless sensor nodes. Every node has the ability to collect data, sense it, process it, and communicate with other nodes. The sensing unit perceives the environment, the processing unit computes restricted permutations of the sensed data, and the communication unit exchanges processed data between the surrounding sensor nodes(Khan et al., 2016). Figure 1.2 shows the basic elements of WSN.

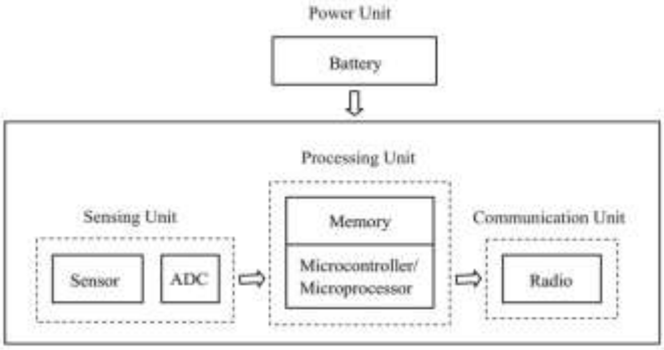


**Figure 1.1: Basic elements of WSN**

Wireless Sensor Networks (WSNs) are made up of a huge number of sensor nodes which are resource constrained used for many applications, mainly for IoT applications (Haseeb et al., 2019). The fundamental purpose of the sensor nodes is to gather useful data from the atmosphere and interconnect it to the Base Station (BS) via multi-hop communication (Priyadarshi et al., 2018). In multi-hop WSN, nodes closer to the BS must transmit more traffic than nodes further away. Because of this topological disadvantage, the closest nodes to BS deplete their energy at a much faster pace, potentially causing energy holes in WSN (Liu & Wu, 2019). This energy hole problem can cause the total network to collapse in a multi-hop network situation. As a result, regulating the energy usage among deployed nodes is critical, proactive and more effectively grouping the nodes is an emerging strategy for accomplishing this goal (Anzola et al., 2018). In the recent decade, many medium access protocols have been developed to improve the energy efficiency of sensor networks, but very few of them address the adverse effects of energy holes.

This phase focuses on three important factors to mitigate void and energy hole along with trust based potential route selection in WSN-IoT. The network is partitioned using wedge method so that sensor nodes are evenly distributed to overcome the issue of void hole. The clustering of the sensor nodes is done using fuzzy C Means clustering and the best cluster head is selected by applying map reduce model to accomplish parallel clustering to overcome the energy depletion and void energy hole. The forwarding nodes has to be monitored regularly to improve the packet delivery ratio by adapting deep neural network trust management. The simulation results proved the efficacy of proposed empowered map reduce and deep trust management algorithm in WSN-IOT. Empowered Map Reduce and Deep Trust Management algorithm for void and energy hole alleviation is discussed. The deep trust management based routing system with simulation result are well explained in this work.

## RELATED WORK

The WSN protocol uses the K-means clustering method, which culminates in the cluster's member nodes being as homogeneous as feasible, although it takes more time to cluster than standard hierarchical techniques (Lee, J. & Lee, D., 2021). In addition, cluster head voting has the issue of prolonged group head candidate on the identical node, only with contemplating the residual power of the node or node which is mostly nearer to the cluster's middle spot. As a result, the network's lifespan is reduced. When choosing a cluster head without factoring the distance between the node and the base station, the network's overall energy efficiency might suffer.Khan et al.,2016eliminates energy hole by implementing super nodes to the region which are closer to sink. Once the super nodes on the boundary region of the sink gathers all the data, then the nodes near the sink turn on their scheduling power and thus it enhances energy consumption.

An information entropy-based trust evaluation Lingdaet al., 2021 addresses the problem of trust in the power circulation among the Internet of Things. The direct trust value was first estimated using the reputation of an exponential distribution, and then the forgetting factor and sliding window were used to update the direct trust value. Uncertainties in the direct trust value were evaluated, and the indirect trust value was increased to compensate for direct trust judgement mistakes. Additionally, the indirect and direct trust values were thoroughly evaluated in order to improve decision accuracy.

Pavan Kumar et al., 2021suggested shortest path routing methods that follow a multi-hop node route to the matching sink. The nodes closest to the routing node and sink node are chosen via the shortest path based on the geographical routing strategy. a novel routing system was proposed that combined the shortest path with trust-based routes. The energy of a node is used to determine whether it is a dependable node on the routing path, ensuring packet delivery and avoiding node failure due to low energy. Three types of trust values are checked for each node, ensuring that the paths formed are additional consistent.

Belalet al., 2020presented an effective model for a heterogeneous WSN based on the probabilistic sensing model and harmony search approach. The HSA is utilized for node deployment optimization that strikes a compromise between coverage and cost. The probabilistic model is used to solve the problem of sensor overlaps. The suggested model's performance is evaluated in terms of coverage ratio and cost estimates.

This KMC protocol improves the network's energy efficiency even while addressing these issues. To mitigate the problem of spending lots of time to establish a cluster, the suggested protocol confined the cluster configuration point to the first round, during which the system was initialized, and the following round, during which all remaining energy was used by new sensor nodes. Because cluster setups do not occur in every cycle, this can help with the time-consuming problem. The problem of not considering the transmission distance to a base station that uses a lot of energy is solved by considering the distance from the cluster center point and the transmission power of the node while electing the cluster head(Bidaki, 2016).

To address these issues, the cluster head was chosen in KMC based on the node's remaining energy and the distance to the cluster's centre point or base station. If just the remaining energy of the nodes in the cluster is factored, the cluster head candidate has been chosen by the node with the largest residual energy. However, keeping in view the distance to the base station and the available energy, merely selecting the cluster head based on the ranking choice might result in an inefficient use of energy.

The Fuzzy-Logic Dijkstra algorithm splits the entire network into multiple clusters and chooses a CH for every cluster. Clustering systems aggregate nodes into clusters, each of which is led by a master node. After the cluster heads have been chosen, they create a backbone network that collects, aggregates, and forwards data to the base station on a regular basis utilizing low-energy. This strategy considerably increases the network's life. As a result, this research presents a novel cluster head selection technique that uses the weighted sum method to calculate the weight of each node in the cluster and compare it to the cluster's standard weight. The cluster head is the node with the closest weight to the average cluster weight. This approach distributes the load evenly and selects the network nodes with the most leftover energy (Razzaq & Shin, 2019) A data routing method for selecting the most energy-efficient path from the source to the destination node is also given. This technique assigns a weight function to each link based on a fuzzy membership function and intra-cluster communication cost inside a cluster. But while using fuzzy logic it considers only the membership degree of weight function and the distance measure, but its hesitation grade which occurs due to inconsistency is not focused in this Fuzzy-Logic Dijkstra algorithm and lacks in optimizing the energy consumption in adversarial environment.

Shukry, 2021 designed an efficient node stable routing protocol which guarantees the transmission stability in WSN. It chooses more stable packets by considering the quality of link, residual energy, and number of hops.Sama et al., 2020) anticipated a dynamic protocol to improve the lifetime of WSN with least edge computation. The size of the virtual grid is identified using this model to produce better result with improved energy consumption and reducing the distance of data transmission by multi hop nodes.

There are many existing literatures which have reported the problem of energy efficiency through different approaches like conventional clustering, grid, chain, heuristic methods for clustering and multi criteria clustering. The aim of these approaches is to enhance the usage of resources to extend the lifetime of a network by alleviating void and energy hole occurrence in WSN which is primary challenge which drains the nodes energy rapidly. The works related to energy consumption in WSN, avoidance of hole occurrence in IoT enabled WSN is discussed in this chapter.

## PROBLEM STATEMENT

The most prevalent challenges in Wireless Sensor Networks are occurrence of void holes and energy holes, which shorten the lifetime of sensor nodes and cause rapid energy depletion. Most of the existing literatures are not suited for energy depletion due to indeterminacy in selection of cluster heads and uneven distribution of sensor nodes in WSN. The optimized clustering in presence of noisy and border lying sensor nodes are the main disadvantage while using the standard energy hole alleviation algorithms. The characteristics of the Internet of Things, such as the heterogeneity of shared information, versatility, and gadget variability, create a completely new problem for IoT services and devices (Kallam et al., 2018). The majority of these problems are tackled by looking at security issues in general rather than evaluating the subjective dangers that IoT devices and applications confront.As a result, trust management is more difficult than security, particularly in the rapidly evolving sector of information technology, such as the Internet of Things.Thus, to overcome the problem of void alleviation, mitigation of energy hole and to perform secure data transfer, this proposed work introduced a tristate model whose objectives are

- Partitioning the network area into equal divisions and deploy the sensor nodes using wedge pattern
- Performing clustering of sensor nodes using fuzzy C means clustering and selection of optimal cluster head by adapting map reduce technique to handle the vast size of network
- Determining the secure route for transmitting data packets to the based station by devising a novel deep neural network-based trust management to detect and isolate untrusted forwarding nodes in the network.

This phase improves the process of alleviating void hole occurrence in WSN by devising a wedge-based partitioning to distribute the sensor nodes evenly. The standard Fuzzy C Means algorithm's efficiency is low when dealing a huge volume of traffic with limited memory. Another difficulty is how to optimize Fuzzy C Means is a major challenge and it is achieved by integrating MapReduce framework to improve clustering reliably. The map reduce based fuzzy C-means clustering is developed in this research work to determine the optimized cluster head in presence of indeterminacy due to the dynamic nature of the environment and mobility of sensor nodes. Hence, it can be able to perform parallel clustering of sensor nodes to improve the speed of the algorithm. Additionally, security is also considered as an important factor to accomplish better energy consumption in WSN. This proposed work introduced a deep neural network-based trust management scheme to overcome the issue of data packet loss and time delay. extracting the trust features and feeding them into the DNN model to identify the trusted sensor nodes to overcome the trust issues (Kong& Yu, 2018).The simulation results proved that the proposed Empowered Map Reduce and Deep Trust management (EMR-DTM) with its ability of tristate mechanism greatly overcomes the problem of energy depletion and secure data transfer more precisely compared to other standard state of art clustering algorithms in WSN-IoT.

## METHODOLOGY OF EMR-DTM

The newly devised method is a tristate model which focuses on alleviation of void hole due to uneven distribution of sensor nodes, mitigation of energy depletion due to inappropriate selection of potential cluster head and insecure data transfer by considering only the shortest path for data

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transmission. The figure 4.1 depicts the three different methods designed in this proposed work to overcome the aforementioned issues, achieve the empowered energy consumption and secure data transfer in WSN-IoT. First, wedge partition is adapted for even distribution of sensor nodes to avoid void hole. Second, the potential cluster head is elected by integrating Fuzzy C Means with map reduce algorithm to achieve both parallel processing and effective usage of sensor nodes with even load distribution. The third state is trust management while transferring data packets through the most promising forwarding nodes accomplished by adapting the intelligence of deep neural network.

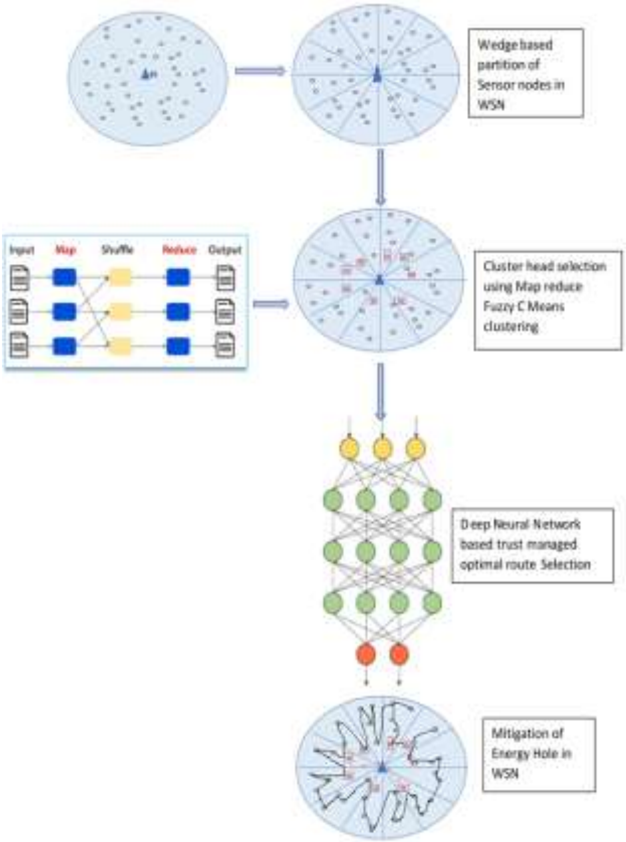


**Figure 4.2: Overall architecture of Empowered Map Reduce and Deep Trust Management for mitigation of void and energy hole in WSN-IoT**

**4.1 Mitigation of Void Hole using Wedge Partition of Sensor Nodes in WSN**

Initially sensor nodes are deployed in a random environment and the WSN is configured to be clustered architecture. To partition the WSN into equiangular wedges (Wang et al., 2012), the Base Station (BS) turns its antenna to a particular region of the network and broadcasts a packet for wedge creation along with sink ID and a wedge number. The packet for wedge creation is sent with maximum power of transmission to ensure to ensure that every node in that path is covered. When a sensor node that receives packet with the information of wedge creation, it assigns the wedge number except it has previously joined a wedge with equal or lower number. Wedge creation process continues by altering the angle of directionality and wedge number by 1 until all sensor nodes obtain their wedge number from the BS. A WSN with wedges is depicted in Figure 4.2. The entire network is separated into wedges.

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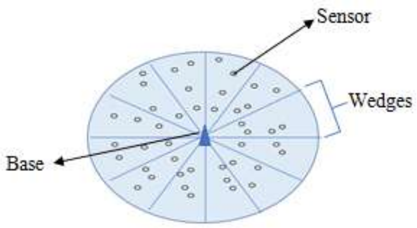


**Figure 4.3: WSN partitioned with wedges**

After the entire wireless sensor network has been divided into wedges, each sensor node is assigned a wedge number. The wedge construction technique ensures that each node in the coordinate system corresponds to just one wedge partition. At the position where 0 angle is determined by a ray that commences at the base station, a coordinate system is generated. There are a lot of equiangular wedges in the WSN. Each wedge's length is equal to the total of the lengths that fall within it. Since the Z data has been lost in projection, the tracing is foreshortened, but length computations nevertheless carry the Z aspects into consideration. All wedges have the same total length as the overall length among all dendritic pathways used in the evaluation.

**Fuzzy Clustering with Map Reduce based cluster head selection**

This stage focuses on determining the potential cluster head by applying Map Reduce based Fuzzy C means clustering to work in a parallel manner in-order to speed up the process. To overcome the existing issues of the standard Fuzzy C Means technique (Ludwig, 2015) in processing huge data passed to the sensor network, an improvised parallel clustering algorithm is presented in this proposed work.

Fuzzy C Means with MapReduce (FCM-MR) model of computation is designed to improve clustering flexibility and reliability (Bhatti, 2016). The following three aspects make up most FCM-MR tasks:

- Calculate the non-CH nodes distance from the Cluster Head (CH).
- Allocate each node to the cluster head CH. Assign each object to the centroid that is closest to it.
- For each cluster, recalculate new cluster heads

MapReduce is used in this proposed to complete the aforementioned tasks on a WSN. From the input data collected about sensor nodes, first select C number of sensor nodes are considered as initial centroids of clusters. After iterating, the centroid in each cluster gets updated. To accomplish parallel clustering, map, combiner and reduce phase are used.

**Fuzzy C Means Algorithm**

The clustering model which works based on the membership degree and it allows each instance to belong to more than one clusters. It works based on the minimization of the objective function (Hoang et al., 2010). The degree to which instances belong to each cluster is specified by membership ratings. As a result, instances in the cluster's periphery, which have less degree of membership might be in cluster to a lower degree than cluster center.The basic procedure involved while using Fuzzy C-means clustering are explained as follows:

**Step1**: Randomly assign C no. of. Sensor nodes as initial cluster heads.

**Step2**: Do until the stop criteria is met:

Calculate the membership matrix U rendering to the equation (1):

$$U_{wi} = \frac{1}{\sum_{l-1}^{k} \left( \frac{d(NC_i, CH_w)}{d(NC_i, cH_l)} \right)^{2/(m-1)}} \qquad (1)$$

Where $U_{wi}$refers to degree of membership of $i^{th}$ NC node on $w^{th}$ cluster.

Reassign fuzzy cluster centers rendering to the equation (2):

$$CH_r = \frac{\sum_{i-1}^{k} u_{wi}^{m} NC_i}{\sum_{j-1}^{k} u_{wj}^{m}} \quad (2)$$

**Map Phase:**

During this phase, the Map task gets information about each sensor node as a unique key-value pair, which serves as the Map function's input (Razzaq&Shin, 2019). The Map function distance is calculated among each non-CH (NC) node and each Cluster (CH) first, after that it allocates each NC to its nearest CH based on the shortest distance, before passing the midway data about nodes to the Combiner function.

**Combine Phase:**

The Combiner phase retrieves all NC nodes information from Value1, which is the output of the map function and merges NC nodes that belong to the same cluster CH. Then, in order to compute the mean value of NC nodes, it adds up the values of NC assigned to the same cluster and records the number of NC in that cluster. Lastly, reduce function is applied with the local information about the cluster head and NC from each cluster.

**Reduce Phase:**

The Reduce function collects all information from Value 2 which is the output from the combiner function and masses the local outcomes of all clusters in this phase. The new cluster head for each cluster is then computed. It then determines whether or not the criterion function converges. At last, if its dispute is true, it outputs the final results; otherwise, it executes the next iteration.

Table 4.1 summarizes the algorithm for map reduce based cluster head selection.

**Table 5.1: Algorithm for Map Reduce based cluster head selection**

***Input:*** *Sensor data*
***Output:*** *List of optimized cluster heads in each wedge.*
**Begin**
**Map Function**
Calculate the distance among each sensor node and each cluster head
Choose the cluster head which has shortest distance with non-cluster head node
Generate the intermediate information about the CH and NC
**Combiner Function**
Merge sensor nodes belonging to the same cluster head
Compute the sum of values of NC nodes allocated to the same cluster
Generate the local output of each cluster head and its non -cluster nodes
**Reduce function**
With the gathered local information aggregate all the clusters
Calculate the new cluster head for each cluster
If the criteria of optimal cluster head are not met then
Update the centroids
Go to step 1 for re-clustering
. Else Output the list of optimized cluster heads
**End**

**Deep Trust Management based Secure Route Selection in WSN-IoT**

The term trust in WSN enabled IoT defines as the study of how nodes connected to the same network behave. The level of trust between two nodes has an impact on how they interact in the future. When nodes are trusted, they are more willing to share services and resources. Trust management allows for the computation and analysis of node trust in order to make informed decisions about how to establish secure and economical communication between sensor nodes. This proposed model develops a trust management technique in IoT devices and services by leveraging the intelligence of Deep Neural Network (DNN) to discover the suspicious activities of sensor nodes involved in data transmission and

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take relevant actions like redirecting the data transmission to trustworthy routes and isolating untrusted sensor nodes in WSN (Zheng et al., 2021).

A kind of machine learning method which is developed similar to artificial neural network which is knowns as Deep Learning model (Luo aet al., 2011). It is represented as a nested deep hierarchy and these perceptions with more intellectual representation. DNN consist of multiple layers in between the input and output layer The DNN works as a feed forward network, which transmits the input data to the output layer.

The Virtual neurons are mapped by DNN and random numeric values which is knows as weights assigned to the links (Schmidhuber, 2015). The input data is multiplied with the weights and all the output of the intermediate node is summed as processed by the activation function. The output value produces the single value which is compared with the target value of the dataset and its difference is treated as error rate as shown in the figure 4.3.

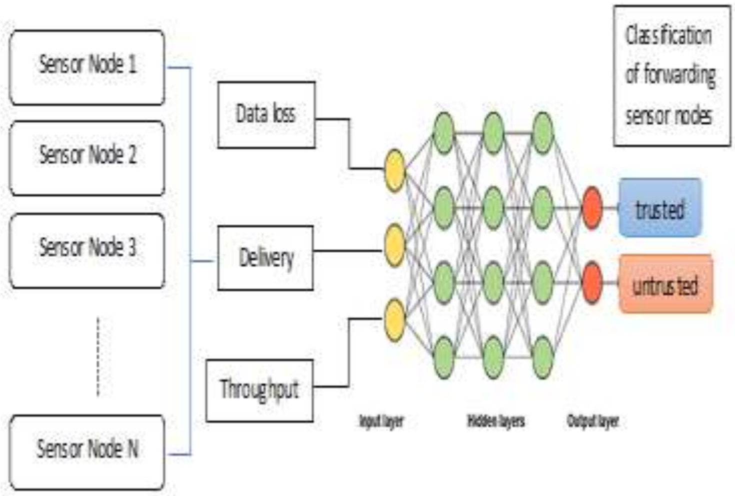


**Figure 4.4: Deep Trust management for secured route selection to mitigate energy hole in WSN-IoT**

Table 4.2 summarizes the algorithm for secure route selection using deep trust based management.

**Table** Error! No text of specified style in document.**.2: Algorithm for deep trust management for secured route selection**

**Input:**
IC: Candidate forwarding sensor nodes < data loss, delay, throughput>
Y: Label of forwarding nodes
Wt: Weight of each hidden layers
L= Number of deep neural network layers
**Output:** Label forwarding sensor node as trusted or untrusted
**Begin**
For i = 1 to m // forwarding nodes
$S^{L} =$ feedforward($IC^{(i)}$, wt)
$d^{L}$= S(L)-y(i)
$t^{L}_{(i,j)} = t^{L}_{(i,j)} + S^{L} * t^{L+1}_{(i,j)}$
if $j \neq 0$ then $D^{L}_{ij} = \frac{1}{m} t^{L}_{(i,j)} + \lambda wt^{L}_{(i,j)}$
else $D^{L}_{ij} = \frac{1}{m} t^{L}_{(i,j)}$
**End**

By applying the DNN the forwarding nodes can be classified as trusted and untrusted. The untrusted nodes are isolated from the route and only the trustworthy nodes are involved in data transmission in WSN enabled IoT. Thus, this proposed method achieves void hole alleviation and mitigation of energy hole in WSN more effectively.

## RESULTS AND DISCUSSION

The proposed Empowered Map Reduce and Deep Trust management (EMR-DTM) technique is compared with two standard algorithms namely K-means clustering (KMC) Scheme, and Fuzzy-Logic Dijkstra-Based cluster (FLD) algorithm are discussed in this section. The performance comparison is done based on energy consumption, end-to-end delay and packet delivery ratio. The number of nodes deployed is 250. The initial energy of sensor nodes is 0.5J, size of data packet is 500 bytes, Base station allocation is 50, 50.The simulation was developed utilizing MATLAB 2018b and Python software. Table 5.3 shows the environmental variables of MATLAB simulation that was used to test the performance of EMR-DTM,

**Table** Error! No text of specified style in document.**.1: Simulation setup**

| Parameter | Value | Description |
|---|---|---|
| Nsize | 500x500 | Network size |
| N | 250 | Number of nodes in WSN |
| $E_0$ | 0.5J | Node's initial energy |
| $BS_{LOC}$ | 50,50 | BS location |
| $\varepsilon_{fs}$ | 10 pJ/bit/m2 | Energy spent by the amplifier to be transmitted at a short distance |
| $\varepsilon_{mp}$ | 0.0013 pJ/bit/m4 | Energy spent by the amplifier to be transmitted at a longer distance |
| $E_{elec}$ | 50 nJ/bit | Energy consumed in the electronics circuit to be transmitted or receive the signal |
| $E_{DA}$ | 5 nJ/bit/signal | Data Aggregation Energy |
| size(pkt) | 500 bytes | Data packet size |
| nh | 4 | Number of holes |

### *Packet Delivery Ratio*

The figure 5.1 illustrates the performance of the three-clustering based energy hole mitigation algorithms deployed in WSN based on packet delivery ratio. The results show that the proposed EMR-DTM accomplishes highest delivery ratio compared to other standard KMeans Clustering algorithm and Fuzzy Logic Dijkstra-Based cluster algorithm. The EMR-DTM works as a tristate model, where the area of the network is equally partitioned using wedge pattern and the indeterminacy of sensor node clustering is done by applying Fuzzy CMeans Map Reduce (FCM-MR) clustering. In addition, the optimized route selection is achieved by deep neural network-based trust model.

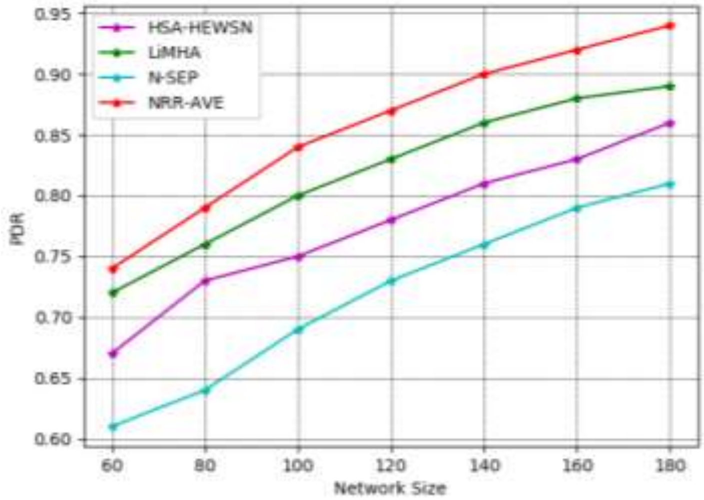


**Figure 5.1: Comparative analysis based on packet delivery ratio**

***Total Energy Consumption***

The total energy consumed by three different clustering algorithms to mitigate void and energy hole in WSN-IoT is shown in figure 5.2. The proposed EMR-DTM wedge partitioning performs well in dividing the area of network by equiangular wedges. The optimized cluster head is selected using fuzzy C means clustering which defines each node in terms of membership degree and their objective function are used for electing the cluster head in each cluster. The map reduce algorithm is used for empowering the assignment of non-cluster head nodes to appropriate cluster head. The standard KMC and FLD clustering models suffers from local optima while selecting the cluster heads and results in earlier convergence. Hence, EMR-DTM achieves best energy consumption compared to other two standard clustering algorithms.

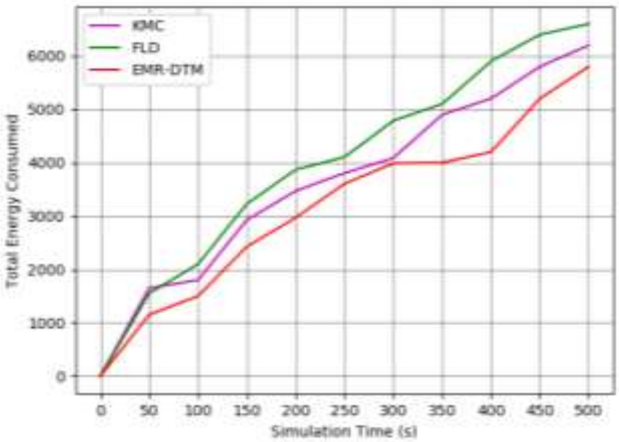


**Figure 5.2 Comparative analysis based on total energy consumption**

**End-to-End Delay**

The end-to-end delay based comparative assessment of KMC, FLD and proposed EMR-DTM for alleviating the void hole and mitigation of energy hole in WSN-IoT is depicted in the figure 5.3. The secure route for forwarding the data packets in WSN is promisingly achieved by the EMR-DTM by adapting the intelligence of deep learning algorithm for determining the trust worthiness of forwarding nodes. Thus, the end-to-end delay because of suspicious activities done by any of the forwarding nodes is detected and isolated using EMR-DTM. The deep pattern observation of sensor nodes assists to classify as trust or untrusty ones. Whereas KMC and FLD only focuses on selecting the nearest nodes to transmit the data packets to the base station without any security measures.

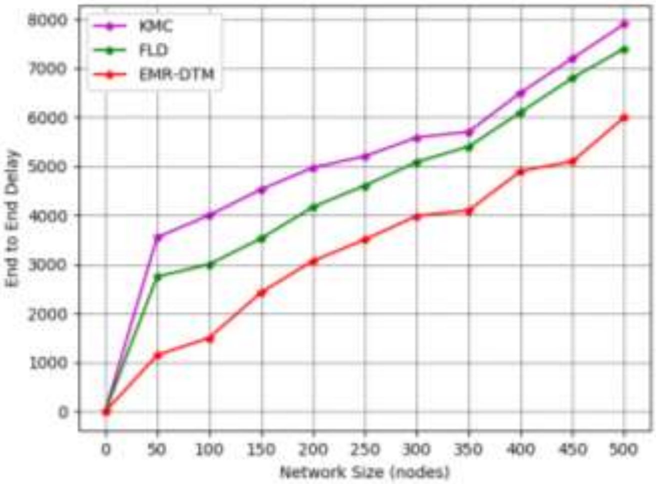


**Figure 5.3: Comparative analysis based on end-to-end delay**

## CONCLUSION

This chapter involves in establishing empowered mitigation of void and energy hole alleviation in WSN-IoT by introducing a tristate model that handles the indeterminacy. The dynamic and adversarial deployment of sensor nodes in WSN is balanced by devising wedge partitioning technique. With the even distribution of sensor nodes, the cluster head is selected with potential model by integrating the concept of FCM-MRclustering to handling the indeterminacy in border lying sensor nodes. The secure shortest path discovery is also focused in this work by devising a deep neural network-based trust management to detect the suspicious and malicious sensor nodes and isolate them in route of forwarding data packets. The simulation results proved that proposed Empowered Map Reduce and Deep Trust management (EMR-DTM) effectively accomplishes the objective of void and energy hole along with secure transfer of data packets in WSN-IoT. The objective is to improve the energy consumption by considering trustworthiness of forwarding nodes by introducing EMR-DTM. It starts by partitioning the area of sensor network by equiangular wedges. While dealing with a large volume of traffic and limited memory in a WSN, the traditional Fuzzy C Means method is inefficient. Another difficulty is optimizing Fuzzy C Means to overcome local optima is in the selection of cluster head. It is accomplished by integrating MapReduce framework to improve clustering reliably. To maintain trustworthiness of forwarding nodes, deep neural network is used for determining and eliminating malicious forwarding nodes during data transmission. The software used for designing the proposed EMR-DTMareMATLAB and Python. The simulation results proved that the end-to-end delay is reduced to 60% when compared to K-Means Clustering and Fuzzy-Logic Dijkstra-based cluster. This is because the existing algorithms consider only the nearest nodes to transmit the data packets to the base station without any security measures.

## FUTURE ENHANCEMENT

This research work can extend its scope of energy consumption in WSN-IoT as suggested below:

- Various partitioning methods can be incorporated to overcome the void hole alleviation. Additionally, black hole attack detection can also be considered for improving the transmission rate.
- Different evolutionary algorithms can be used for sensing the best forwarding nodes. Security mechanism like Intrusion detection in dynamic environment of mobile sensor nodes can be considered.
- Key Management System (KMS) and blockchain methods to address IoT security,privacyand trust threats. Fog/Edge computing techniques to reduce latency in real-time IoT sensor applications.

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