AI Based Energy Efficient Routing Protocol for Intelligent Transportation System

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***Abstract*—The future advancement of technology in Internet of Things (IoT) paradigm, Wireless Sensor Networks (WSNs) provide sensing services to connect all the devices. In the upper layer of OSI model designing an energy efficient routing protocol in WSN is a challenge, which can ease the work of Multi-access edge computing (MEC) in IoT applications. The advent of 6G is also playing key role for reliable communication between the sensing elements for IoT applications. These two phenomena are significantly influencing for the progress of next generation Intelligent Transportation System (ITS). Therefore, the proposed work presents a novel method of implementing Distributed Artificial Intelligence (DAI) with neural networks for energy efficient routing as well as a fast response for intra-cluster communication of the nodes to overcome the challenges for ITS. Although there exist several works on the inter-cluster energy-efficient network, our work proposes a new way of implementing the hybrid approach of DAI and Self Organizing Map (SOM). The proposed approach proves to be a better solution in terms of overall energy consumption by the network, along with the computational challenges. Further, the work presents mathematical analysis, simulation results and comparison with the conventional techniques for justification.**

***Index Terms*—DAI, wireless sensor network (WSN), self-organizing map (SOM), multi-access edge computing (MEC), 6G, ITS, energy efficient network.**

I. Introduction

THE MEC has emerged as one of the significant role player in terms of providing low latency, high-bandwidth real-time radio network resources in continuous evolvement of internet [1]. MEC does the job by enabling the cloud computing capability in edge of the network. In IoT paradigm, MEC serves as important tool to provide high quality of service (QoS) of the network. In the field of wireless communication, Wireless Sensor Networks (WSNs) also have emerged as an important technology which has a direct impact on everyday life [2]–[5]. The continuous advancement in the field of semiconductor technology made it possible to manufacture miniature low-cost sensors. Thus, the whole WSN consists of hundreds or thousands of sensor nodes. These nodes are deployed densely to measure or detect particular phenomena. Several works can be done or sensed by these sensors such as sound, humidity, light, temperature etc. [6].

A. Background

Therefore, for the smart applications, the sensor nodes of WSNs can connect al the devices. The evolution of technology directed to the world, where each and everything is smart [7]–[9]. The concept of smart applications, including smart city, smart car, and smart devices arise the necessity of having proper resources to achieve a particular goal [10] [11]. The WSNs can provide these necessities by sensing information and setting up a model for requirements through different techniques. However, due to small size and less power handling capacities, sensor nodes suffer many limitations in a WSN. The finite battery power, small memory, communication bandwidth, less computation all are the main constrains for having an energy-efficient system. In terms of computational challenges in WSN and 6G enabled services, 6G requires more ubiquitous computing for efficient communication through ITS for huge amount of data aggregation. MEC analyses data before sending to the cloud, which helps to reduce the CPU cost and efficient bandwidth utilization. But, before this operation in application layer, the less energy consumption in lower layer is a challenge. Specifically for application like ITS, where the number of sensors, as well as the congestion of the channels are high as multiple tasks to be completed at same time.

It means that the power should be used by each sensor nodes as less as possible maintaining the system performance. Otherwise, it may get eliminated from the network without completing the task. The low computational power and small memory of each node are not suitable to process a large amount of data. So, there are some requirements to improve the computational capability and optimization of the sensors.

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On the other hand, the limited bandwidth in WSN is not able to cover a large area due to the small size. The reason behind this, is the finite number of sensors around each node can access for the routing. Therefore, it is necessary to implement a smart method for finding the path from source node sink node without consuming a large amount of power, which eventually will result as energy efficient MEC for routing operation.

B. Authors' Contribution

In this work, a prediction based routing algorithm is designed, which considers number of observations of power consumption of nodes at the time of execution of particular application. At first, DAI is implemented for energy efficient node communication and the mathematical formulation is done to calculate power consumption by the communicating nodes. The neural network approach using Self-Organizing Map (SOM) forms the cluster utilizing the consumed power values of nodes for different time instant as training data. This power based pattern of nodes results in efficient routing for the next operation for certain application.

The paper is organized as follows: Section II presents the overall survey of related work, Section III describes the proposed model and system assumptions. Section IV analyzes the implementation of DAI for the optimized data collection for training and SOM based clustering to get power consumption pattern of nodes from different source node positions, Section V is to demonstrate the simulation results and finally the paper is concluded with discussion of results, supporting our proposed method in Section VI, discussing the results to s our proposed method.

II. Related Work

There are several algorithms have been developed for clustering and routing in WSN. As well as, in some of the papers are there, implemented MEC for different purposes in WSN. Edge computing is used for multisensory data collection [12] in smart agriculture. The quality of data is analyzed by edge computing and then send to cloud server. In [13], a demand based approach was introduced through heterogeneous networking for multi-access edge computing and fiber-wireless access networks. The machine learning algorithms are among them which are severely used for the purpose of parameter optimization in WSN. In this paper, as our proposed method is based on DAI and SOM, we have reviewed mostly such works which are related to these two methods. The other routing and clustering techniques using neural network and machine learning algorithms are also discussed.

The authors of the paper [14] introduced a new method for routing in a wireless sensor network. They implemented the neural network approach of self-organization. The method uses nodes for deciding the packet containing or to dropping it throughout the routing. They implemented it in MOBABER wireless nodes for real conditions. At last, they claimed that the method is useful as the time complexity of it is linear. Neural networks have a great impact on future research when it is applied as a hybrid technology with WSN [15]. The authors analyzed embedded network applications and presented an overview of it. They also discussed the different techniques related to sensor and neural network processing. They justified their claim by evaluating the results in the testbed. The routing problem is solved by implementing the A-star search algorithm in terms of having energy-efficient and optimal path-finding from source to sink node [16]. The simulation results depicted that the presented method is more efficient compared to the Fuzzy approach. A multi-criteria optimization technique [17] has used for clustering in WSN. In that technique, the decision of each node depended on local information only. It was found by the simulation results that the technique has a great performance to select the CH as well as optimizing the energy efficiency of the overall system. According to the author, the proposed method is better than the other well-known protocol like HEED, LEACH and EECS. They justified their claim by the simulation results. In the IoT based applications, for the better management and utilization of power [18] clustering algorithms can be used. The authors used the concept of Multi-Agent Systems [19] for the management of WSNs. They proposed a model for sensor power management named as Neighbors Power Comparison (NPC). In that method, the authors used 4 different power thresholds, whenever any of the sensor power reaches the amount of power of that threshold by using a power reduction algorithm reduce the energy. A residual energy based CH selection method [20] has proposed for the suitable Internet of Things (IoT) based smart applications. According to the authors, the method is energy efficient and able to increase the network lifetime compared to the LEACH protocol. An improved three-layer approach was proposed [21] for the low energy-based adaptive clustering for WSNs. The main approach was to control the topology in WSNs to balance the communication load of sensor devices to increase the network lifetime and scalability. The authors considered a hybrid of centralized gridding for the upper-level head selection and distributed clustering for lower-level head selection and presented a semi-distributed clustering approach. As a result, the number of communicating nodes to the base station was reduced, and the energy was conserved. In the paper [22], the authors claimed that the LEACH protocol is more convincing compared to other multi-hop approaches in terms of system lifetime for microsensor networks. They considered LEACH including a new clustering technique, which is capable of self-organization of a large number of nodes. The algorithms also include rotation of CHs positions and distribute energy load among all nodes based on that. The firework algorithm with adaptive transfer function [23] was introduced by the authors to increase the lifetime of rechargeable WSNs. They implemented the method by proposing swarm intelligence based hard clustering. They claimed that the method outperforms other existing methods with performance up to 80% regarding energy consumption. In this letter [24], the authors described a technique for CH selection, which is based on even distribution of energy consumption among the sensor nodes. Thus, it results in a longer lifespan of the network. They proposed a distributed CH selection algorithm based on the distances of sensors from the base station to get an optimal balance of energy consumption in the sensor nodes. A detailed analysis of clustering and routing is illustrated along with proposed a new protocol called joint clustering and routing protocol [25]. The algorithm was introduced based on gradient routing and back-off timer to get maximum transmission range. The author claimed that the simulation results with one-hop routing proved the protocol energy efficient. In the paper, [26], different meta-heuristic techniques are discussed. The possible solution of the different optimization problem is analyzed by using BAT algorithm. In that technique, the behavior of BAT was used to find and differentiate between obstacles and other necessary data. They have claimed that the modified BAT algorithm can provide optimal route and to route packet in WSN. The authors in [27] investigated and discussed different approaches of clustering using SOM. Particularly they used agglomerative and partitive clustering. They accomplished the process in two stages. First, they made prototypes based on SOM and then clustered to find a comparison between the normal clustering to reduce the computation time. The two routing paradigms Energy-Aware Routing and directed diffusion were analyzed [28] by the authors. They introduced their algorithm named as SIR, which is based on the implementation of neural networks in sensor nodes. They did their simulations in OLIMPO simulator to study the efficiency of neural networks and the importance of artificial intelligence in WSN. There is another paper [29] for the routing protocol based on SOM based clustering. The network clusters are optimized to reduce the transmission power for nodes. The simulation results showed that the system lifetime was increased by 57% by using that method compared to LEACH. A comparison of SOM and DSOM based algorithm was studied for image cataloging. [30] The performance of the DSOM algorithm found better for 2D map is better to compare to SOM. The authors in [31] used SOM for data aggregation. They used data aggregation and clustering technique for the huge amount of data and found the result is good to compare to another method of clustering. SOM can achieve classification and clustering as a good tool [32]. There are some limitations to achieve this. These limitations are mainly computation time and input space normalization. The authors investigated and overcame the problem by increasing the system performance. DAI is used with hybrid neural network approach [33] to solve the energy consumption problem in massive IoT. In [34], the authors defined attributes to the sensors which depend on location and neighborhood. These attributes were used for input and output for the neural network approach. They did power management and path discovery using this method. The simulation results based on designed simulator were shown, which claimed that the method is good enough for less consumption of power. In [35], a detailed review and literature survey is shown to demonstrate the importance and significance of intelligence-based tools, mainly neural networks in WSNs. In [36] an agglomerative approach of Hierarchical Maximum Likelihood based clustering was proposed for Cognitive Radio fusion center. They achieved power distribution of nodes as per the requirement based on the dynamic position of fusion center.

In [37] also the authors used HML and merged with the properties of Firefly algorithm for further efficient clustering for WSN.

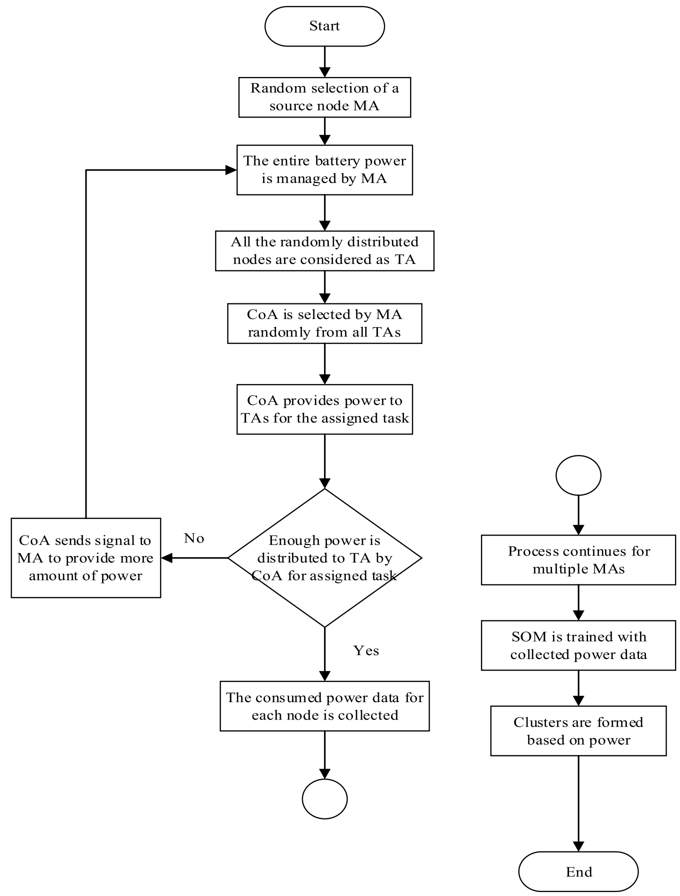

Fig. 1. Flowchart of the proposed model for power management and cluster formation.

In the above discussed literatures, some of the works used neural networks and other routing protocols for clustering and routing. However the SOM is only used for clustering and data aggregation in the literature [31] and the multi agent system is used with neural network for prediction of power level in the nodes in [19]. But compare to our work the method is different and best of our knowledge there is no such work to select cluster head and power managements with the formation of cluster in WSN using AI and neural network approach together.

III. Proposed System Model and Assumptions

The real-time environment conditions for WSNs are generally dynamic, location dependent and other hardware conditions. It changes over time, and it is a difficult task to accomplish a communication only by sensing all the data by the sensors. In this scenario, involvement of Artificial Intelligence (AI) and machine learning is essential to take the whole process in a smart and efficient way.

Therefore to have an improved and energy-efficient WSN we have designed a system implementing DAI and SOM for smart communication. The flowchart in Fig. 1 depicts step by step implementation of both processes in a clear way.

Initially, among all the nodes (or agents), a Manager Agent (MA) is selected randomly and the DAI approach is then implemented. The DAI includes the selection of Tasks Agents (TAs), initially all nodes in the network. In the next step, among the TAs, the Coordinator Agent (CoA) is selected by MA randomly. The power is provided after each communication of CoA with TAs based on the application task requirement. The power negotiation operation is done between CoA and MA for efficient utilization of battery power. Thereafter, the total amount of consumed power is calculated. This process continues for further from different source nodes and after collecting the power data SOM is applied. Then clusters of nodes are obtained, which can be differentiated by a unique patterns. This aggregated power data will help DAI in future communication to decide the path and selecting the cluster head (CH) with minimum energy consumption and data aggregation.

The system considers the following assumptions for our work:

1. The nodes are static and homogeneous placed in an area of 100 * 100 m^2 with random distribution in a 2-dimensional space.
2. The nodes in the network can transmit or receive the power of different levels based on the power requirements for any application.
3. The communication between nodes is considered in fading free channel.
4. The nodes can switch between active and sleep mode for any particular time instant to form dynamic clustering.

IV. Mathematical Analysis

V. DAI Implementation on Sensor Nodes

The main objective of Artificial Intelligence (AI) is to introduce a phenomenon, which can interact with physical object intellectually like human being. The DAI works on similar manner. It interacts and manage system properties with different multi-agents. In our proposed work, the interaction between the agents is done to have an energy-efficient and fast communication. We have defined some of the agents based on their scheduled work. Initially, all the source nodes are assumed to work as MAs [38]–[40]. In the first phase, the number of source nodes depends on the desired communication of user or application from a particular point. Here, we have considered four source nodes for different path of routing. The work of the MA is to manage the whole process in terms of power distribution to nodes for the DAI implementation and assign the work to other agents. At the time of consideration of MA, the other sensor nodes of the network are assumed as TAs. Among the TAs a CoA is selected randomly by MA. This CoA negotiates with MA for available resources to complete the task by each TA. We have set a threshold power value as θ, which is considered as required power to complete task by each TA. After each CoA-TA communication for time instant 't', the consumed power will be determined and CoA informs the MA for more power requirement. This process continues until the required power for all TAs are calculated. Then for every time interval of 't' the power for CoA-MA and CoA-TA communication is calculated based on the distance between nodes. The consumption of power by each TA for every step can be calculated by following equations:

$$P_{(t,TA)} = P_{(t-1)} P_{r_{(CoA)(TA)}} \tag{1}$$

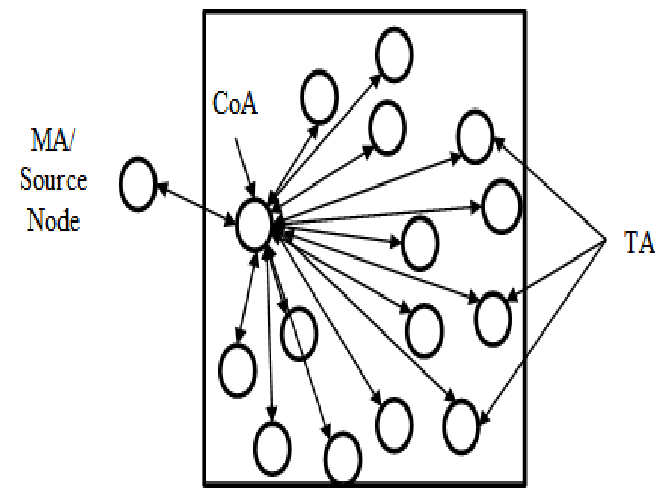

Fig. 2. Proposed DAI architecture.

Here, eq^n (1) shows the power consumption for each TA after the first time communication between CoA and TA. The assumed initial power is denoted as $P_{(t-1)}$ and $P_{r_{(CoA)(TA)}}$ is the power consumption during CoA-TA communication. If $P_{(t,TA)}$ doesn't consume equal power as θ, then the remaining power to be achieved by system is:

$$P_t = \theta - P_{(t,TA)} \tag{2}$$

The equation (2) can be represented in terms likelihood function and CoA-MA communication for power $P_{r_{(\mathrm{CoA})(\mathrm{MA})}}$ as:

$$P_t = (P_{(t-1)} P_{r_{(\mathrm{CoA})(\mathrm{MA})}} + P_{(\mathrm{t},TA)}) L_t \tag{3}$$

The above equation is showing the possibility of enough power consumption in the first process of negotiation and likelihood function representing this. But, the required number of times of CoA-MA communication is not fixed and can be varied. As well as the likelihood function of providing enough power to TA to complete task changes after each negotiation. Therefore, again the above equation can be written in terms of total amount of remaining power as:

$$P_{total} = \sum_{k=1}^{n} k(P_{(t-1)} P_{r_{(\mathrm{CoA})(\mathrm{MA})}} + P_{(\mathrm{t},TA)}) \times (L_i + L_j + \ldots. + L_{k-1}) \tag{4}$$

$L_{t_{(t-1)}}$ is the likelihood function of providing enough power to TA for completion of task at '$t-1$'. $(L_i + L_j + \ldots. + L_{k-1})$ is the summation of all the likelihood to ask for desired power by TA to CoA. In that case k is the number of times from 1 to n for negotiation of power by CoA with MA. In our work, we have achieved the power with the minimum value of n is 3 and maximum value is 10.

In the below Fig. 2, the proposed architecture of DAI implementation is shown.

A. SOM Based Cluster Formation

In machine learning based application, nowadays the implementation of neural network has very much importance. There are several applications that can be achieved through the

Algorithm 1

Inputs : MA, TAs, CoA, θ

Outputs : $P_{r_{(CoA)(TA)}}$, $P_{r_{(CoA)(MA)}}$, $P_{(t,TA)}$, P_{total}

1. Initialize the location of MA, TAs in matrix form and select CoA randomly
2. Assume initial power $P_{(t-1)}$ based on task
3. Set a threshold power value for the completion of task as θ
4. Find $P_{r_{(CoA)(TA)}}$ and $P_{r_{(CoA)(MA)}}$ for distance between nodes
5. Compute $P_{(t,TA)}$ for time instance 't'
6. ***if*** $P_{(t,TA)} \geq \theta$, **then** enough power is provided to TA
   end and power for TA operation is achieved
7. ***if*** $P_{(t,TA)} < \theta$, **then**
   for *k*=1 to *n* ***do***
   7.1. Update $P_{(t-1)}$, $P_{r_{(CoA)(MA)}}$ and $P_{(t,TA)}$
   7.2. Calculate likelihood of power consumption after each negotiation
   7.3. Continue the operation. until $P_{total} \geq \theta$
   end
8. The consumed power by TA is collected

Fig. 3. Proposed power management algorithm.

implementation of neural networks; especially where plenty of data is used for the process. There are various types of neural networks; among these the SOM Neural Networks is one of the kind which uses unsupervised learning. The meaning of unsupervised learning is that the system doesn't require any training about the type of data with which the system is going to process. It automatically learns and organizes by itself. In SOM, nodes form cluster and each cluster can be distinguished by the defined quality. This is how the non-parametric partitive clustering is done by self-organizing.

The clustering of self-organizing map can be done following few steps.

Initially weights will be set as W_{ij} values to neighbor nodes based on the clustering parameters, which the system needs to learn.

Step I. The While loop started and continues until the stopping condition == false comes.

Step II. Each set of input values is given to X_1 to X_n and loop continues

Step III. After each loop, for each j node, the $D(j)$ is calculated, from the equation: -

$$D(j) = \sqrt{\sum (w_{ij} - X_i)^2} \tag{5}$$

Step IV. The index value of J is calculated such that D(J) is minimum.

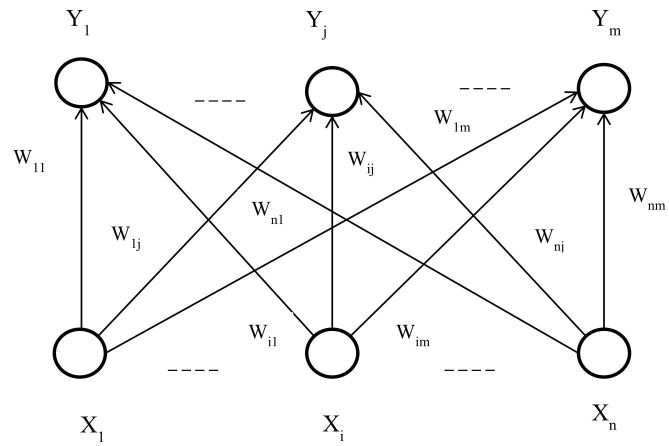

Fig. 4. Architecture of SOM.

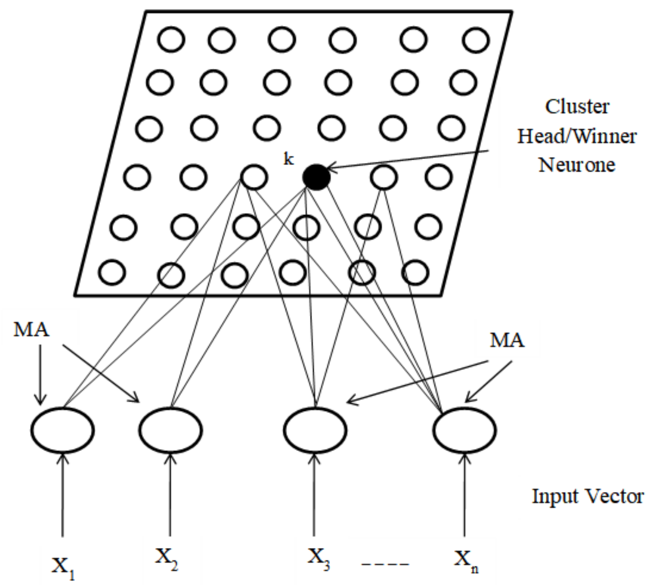

Fig. 5. SOM operation of the proposed method.

Step V. For all neurons j, within a specified neighborhood of J, and for all

$$i : W_{ij}(new) = W_{ij}(old) + \eta[X_i - W_{ij}(old)] \tag{6}$$

Here, J denotes the winner neuron and j specify all the neurons

Step VI. The learning rate parameter is updated.

Step VII. The radius is minimized of neighborhood nodes after specific interval of time.

Step VIII. Test is continued until the cluster is formed with minimum separation between nodes. (stopping condition).

In our work, the input vectors are directed from MA as discussed in the previous section. According to the Fig. 5, k is the winner neuron or Best Matching Unit (BMU), which is considered as CH.

X_1 to X_n are input vectors of training data provided to MAs, which are considered as source nodes or starting end for communication power supply. In this process, the weight is assigned to the nodes with random value in between 0 to 1. Then the Euclidean distance based nearest neighbor

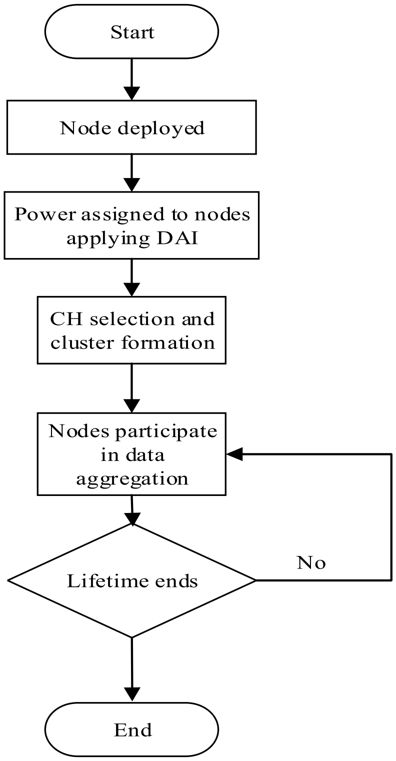

Fig. 6. Proposed D-SOM routing operation.

is determined. After that, each node is selected from the winner neuron according to the distance, and the cluster is then formed.

In this process, an efficient optimized power based clustering pattern is recognized. This also eventually results less battery power consumption at the time of clustering.

B. Routing

The routing of the data in the network is considered for one path, for which the total battery power consumption of the nodes is least. After the formation of clusters based on assumed power consumption the routing operation starts. The transmission of data through cluster heads to base station continues until the lifetime of assigned node ends. The optimal selection of CH and nodes makes the system more efficient, in terms of lifetime and energy consumption. As we have considered the communication is through fading free channel, then we can also consider free space model for intra cluster and inter cluster communication between nodes. If the distance between CH to nodes in a cluster is denoted by 'a' then for symmetric propagation of 'g' bits of data in channel the energy consumed by transmitting sensors can be calculated as:

$$E_{Tx}(g, a) = E_b g + E_{fs} a^2, \quad \text{for } a \leq a_0 \tag{7}$$

Similarly for the large distance communication from CHs to BS the consumed energy can be written as:

$$E_{Tx}(g, a) = E_b g + E_{fs} a^4, \quad \text{for } a \geq a_0 \tag{8}$$

here, according to free space model a_0 defines the reference distance point to calculate the energy loss in receiver for large distance communication. E_b, E_{fs}, $E_{Tx}(k, a)$ denote per bit energy, transmission parameter for free space model and energy consumed in transmitting sensor respectively.

The consumed energy by the sensor is provided based on the assigned power to nodes according to equation (3). The proposed routing operation is shown as flowchart in below Fig. 6.

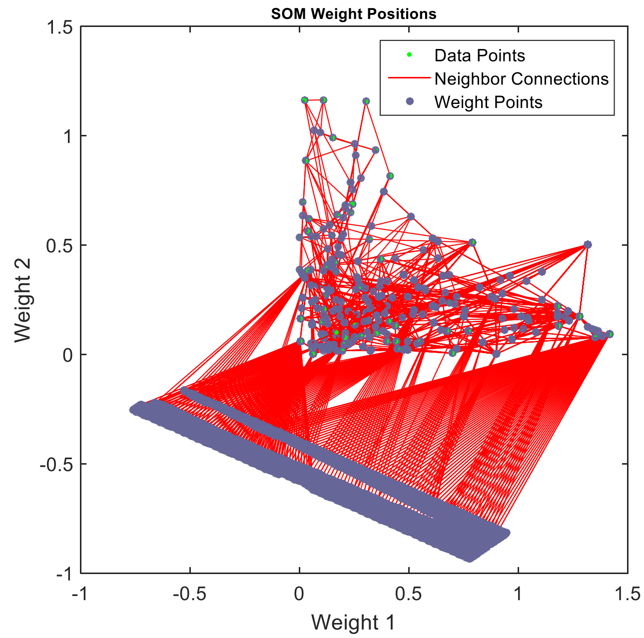

Fig. 7. SOM weight positions at the time of clustering.

TABLE I
SIMULATION PARAMETERS

Parameters	Value
Network diameter	10000m^2
Total number of nodes	10000
Total network energy (E_t)	1 J
Number of simulations	10000

VI. SIMULATION RESULTS AND DISCUSSIONS

The simulation environment for the network is considered with some assumed network parameters shown in Table I. The base station (BS) is considered in the center of the network.

A. Analysis of Network

In the below Fig.7, the MATLAB simulated SOM clustering result is shown for four input vectors from different source nodes in 2-D plot for our proposed 100 * 100m^2 area.

The system time response is important for any system. Therefore, a comparison of theoretical and simulated result is shown for overall communication In the Fig. 8, we have shown that the response time increases with the increasing number of communicating nodes.

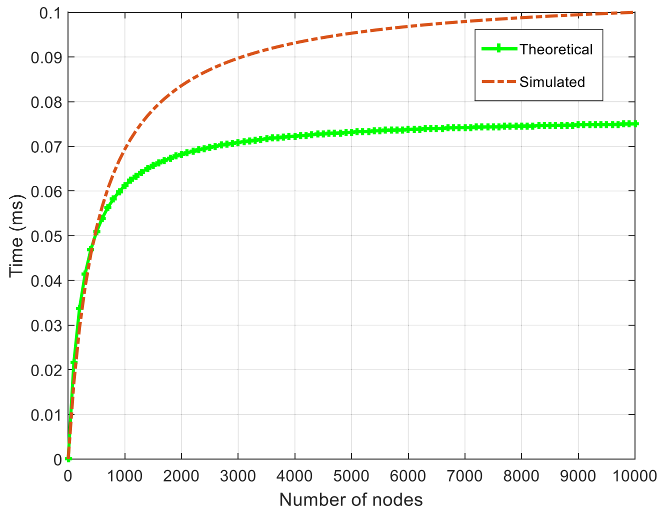

Fig. 8. System response time for overall communication.

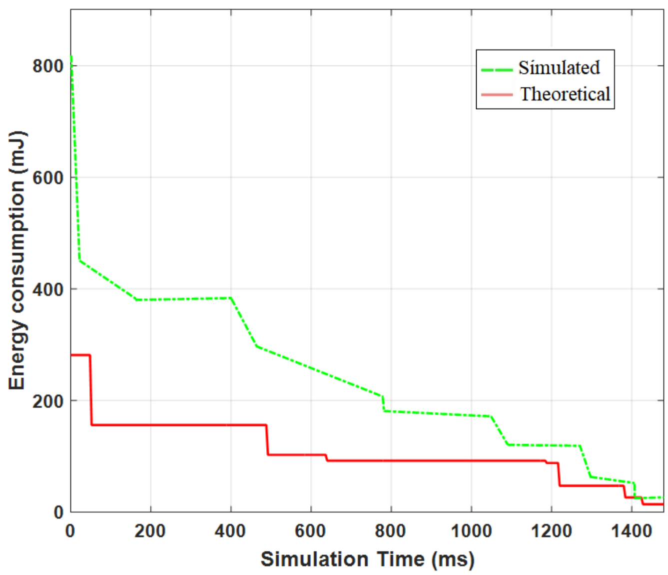

Fig. 9. Performance comparison of network.

In this case, it can be observed that initially, all the lines are in the same position and with the increase of the number of nodes, simulated result response time varies more comparatively theoretically calculated value.

In the next simulation Fig. 9, we have compared the energy consumption of the network with our theoretically calculated value and simulated result. It can be observed the changes in energy consumption concerning simulation time.

The energy occupancy of the network defines the amount of energy consumed by the nodes at the time of communication. As illustrated in Fig. 9, that the energy consumption during routing is taken higher value for our experimental simulation, compare to theoretically implemented result.

In the Fig. 11, we have calculated the energy consumption of the network considering 10000 numbers of simulations. Here, also we have compared our proposed method in terms of theoretical and simulated values, where it can be seen that with the gradual increase of the number of simulations, the consumption of energy becomes constant approximately.

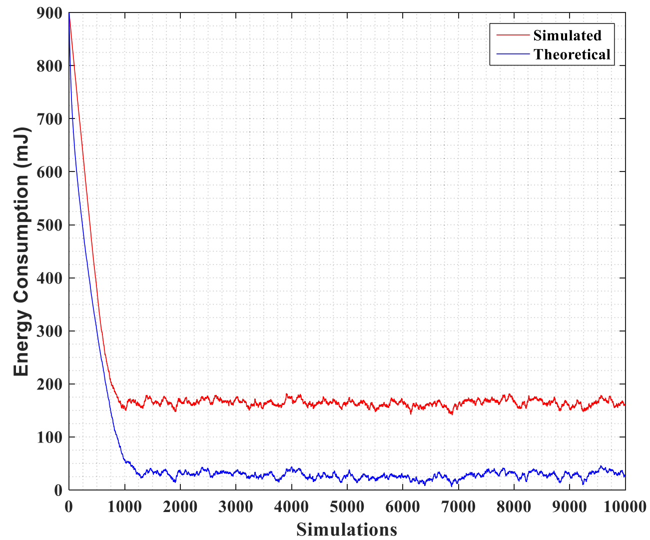

Fig. 10. Network performance with respect to simulations.

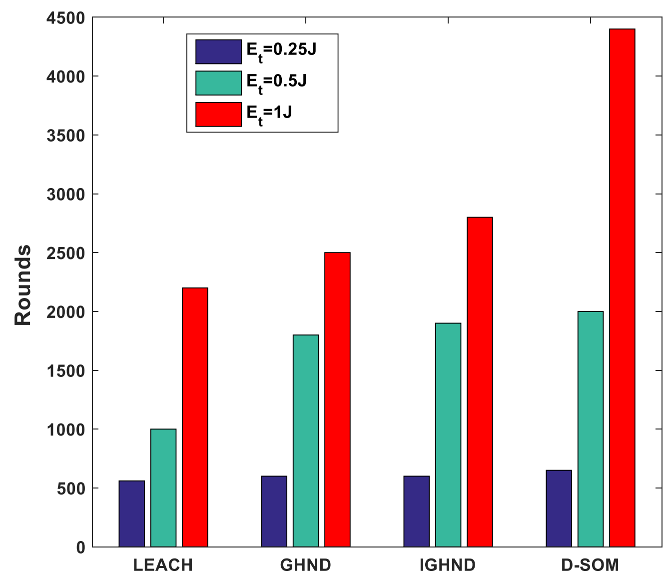

Fig. 11. Stability comparison of network.

It shows theoretically consumed energy is less compare to simulated.

B. Comparison of Network Performance for Different Assumption of Net

The performance of any network depends on several parameters. As we have designed and considered our system for IoT based applications such as; ITS, the system robustness should be analyzed for effective network performance. Therefore, two important parameters, network life and network stability need to be considered for IoT scenario. The network stability defines the death of the first node (FND) from the beginning of the network operation. For the network lifetime consideration, it is determined by the time between the deaths of the first node to last node (LND) during the communication process. The proposed method is named as D-SOM protocol and the behavior is studied for FND to analyze network

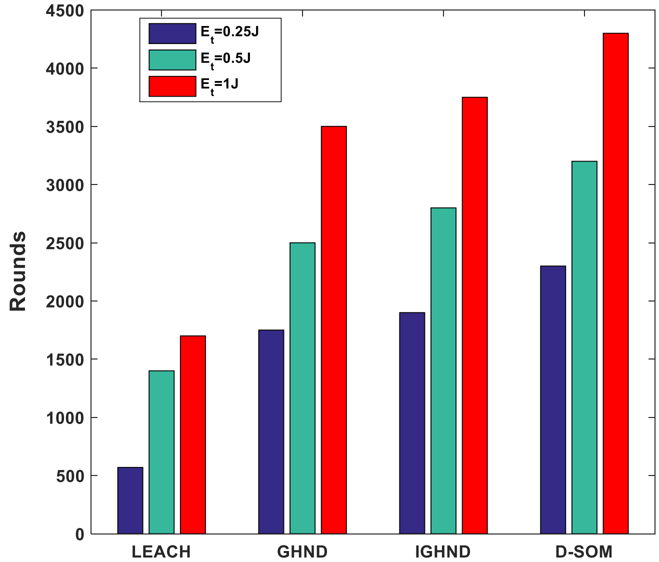

Fig. 12. Network performance in terms of half node dead.

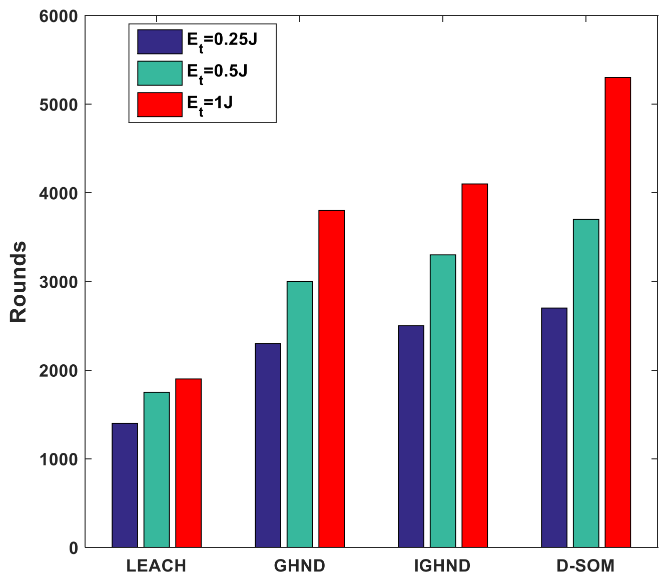

Fig. 13. Lifetime comparison of network.

stability, network lifetime is analyzed in terms of LND and half node die (HND). The performance comparison is done with LEACH protocol along with some recently proposed methods of IoT GHND [41], IGHND [42]. The system considers packet size 2000 and energy E_t as 0.25, 0.5 and 1 J.

According to Fig. 11, the proposed method D-SOM shows better network stability compare to other routing protocols. As in D-SOM, DAI based power management is considered, therefore system results in maximum number of rounds for the death of the first node. Whereas, the first node in LEACH dies at first for all the values due to not considering any power efficient method or parameters. In the other two methods, GHND and IGHND the nodes stability remains for the more number of rounds. The reason behind this is that for the clustering purpose the grid based method GHND considers some parameters and in IGHND also average distance and residual energy is considered for the utilization of power.

TABLE II
PERFORMANCE COMPARISON OF PROTOCOLS

Protocol Name	Network Lifetime and stability	Energy Utilization
LEACH	least	least
GHND	moderate	moderate
IGHND	moderate	moderate
D-SOM	optimum	optimum

But, none of this method uses any artificial intelligence based system monitoring for energy efficient clustering based routing. Thus, our proposed method outperforms all the compared existing methods.

Similarly in Fig. 12, for the calculation of half node dead the three methods are compared with D-SOM. In that case also, equally nodes in LEACH protocol dies early and D-SOM results in maximum timespan for dead of half node.

In Fig.13, the network lifetime compared with other techniques as mentioned earlier in paper. In that case also the lifespan of the network from the death of first node to last node is depicted. Therefore the proposed model for IoT based environment, can be considered as energy efficient for WSN. The smart method for utilizing power outperforms the other routing protocols. It makes the nodes based on intelligence to consume power and form the cluster based on power requirement of nodes. This maximize the system lifespan. In the case of other methods, absence of such power management system lags the optimal utilization of battery power. In Table II, an overall comparison chart is shown of these methods with D-SOM for clear view.

VII. CONCLUSION

In our work, we have introduced a smart method for efficient utilization of the power through the overall routing based WSN scenario for 6G enabled MEC based ITS. The approach of DAI with SOM justifies that the response time of the routing is decreased when compared with the traditional other protocols. In this prediction based routing method, the SOM based clustering gives a power pattern of nodes for communication, which makes easier to select path for next operation for routing as well as power is optimally distributed according to requirement. The simulation results with respect to different existing protocols show that the proposed technique outperforms in terms of network performances. The routing process also results in less computation time along for the overall cluster to cluster cooperative communication. This eventually leads the MEC technology to be implemented in smart transportation system efficiently. The work can further be extended by considering real-time heterogeneous WSNs and considering more number of network parameters.

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