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Double Deep Q Newtork Based Data Aggregation and Trust Energy Aware Multipath Routing (TEAMR) in Wireless Sensor Network (WSN)

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Abstract

In a variety of applications, a Wireless Sensor Network (WSN) is composed of multiple Sensor Nodes (SN) in a random distribution within a challenging environment that is open. Security and energy efficiency are considered two major criteria in designing protocols of WSN routing due to the limited resources in SNs and adverse deployment networks of SNs. Data Aggregation (DA) enhances Energy Efficiency (EE) and security by reducing the total amount of information relayed in a WSN, and removing Data Redundancy (DR) at every node of the network. Close analysis of Quality of Service (QoS) parameters and trust parameters are considered; the DDQNDA with Trust Energy Aware Multipath Routing (TEAMR) protocol in MR optimization is proposed in the given paper. To select routing paths which have the highest optimization in terms of network efficiency and security, the proposed optimization process can integrate trust factors to QoS parameters, the delays, Energy Consumptions (EC), Network Lifetime (NL), and distances. In the case of MR, DA is presented through the usage of DDQN. Because of the rules of the major network, DDQN selects the action that has high Q value during DA. A SN will then make use of DDQN classifier when receiving the combination of information of other nodes. Then it sums all the observed and received data using the proposed aggregation method and to send the DA to the next node it uses the shortest MR. MR implements the average and subtraction-based optimizer (ASBO) system. The effectiveness and robustness of the technique to augment MR mechanisms are demonstrated using wide-spread simulations and tests. The results reveal the flexibility of the algorithm to cope with changing conditions on the network and the ability to adjust reliability and QoS parameters to the utmost.

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Introduction

The use of WSN has become widespread in many applications such as target tracking, biomedical health monitoring, environmental monitoring applications among many others. Cluster-Based Routing (CBR) is an Energy-Efficient (EE) strategy of prolonging the NL of WSN.[1,2]. The clustered WSNs consist of a sink node and some pre computed number of clusters. Every cluster normally has a Cluster Head (CH) node and a number of Cluster Member (CM) nodes. Because the Cluster-based (CB) WSN play the role of receiving and processing the information in the same cluster with this CH. In Cluster based WSN, CH frequently have a considerable toll to pay. Data collected by CH can be directly sent to sink or other CH use Multi-Hop Routing (MHR) after data processing.[3]

Dynamic clustering is reactive formation of a cluster that is in close proximity of the event sensing nodes, and on the other hand, static clustering is the creation of cluster division of the network in a proactive manner. Such CBR algorithms have proposed many CH selection (CHS) and EE routing strategies. Alternatively, not much attention is given to the energy needed in CHS. The development of EE CHS technique is significant to CBR to remodel the life span of WSN because SN in the conventional WSN are commonly supplied with batteries and exhaustion of batteries is inevitable.[4]

The consequences of random CHS in a cluster type of structure are low NL, unexpected node failures as well as inadequate connections. On the contrary, choosing the best CH improves the WSN maintenance and performance. Larger-scale WSN demands an effective CHS procedure as well as an Optimized Routing Algorithm (ORA).

In order to allow the wireless network to have a longer life, the CBR supports the fault tolerance (FT), trusted communication and load sharing. CHS with its focus on node location, node centrality, the number of neighbors, residual energy (RE) and node rank (which is computed based on the number of links and link cost) attempts to look beyond the limitation of Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol. Dynamic and on-demand CHS considering event occurrence reduce message and computational overhead and they ensure energy balance among CHs.[5, 7]

In an attempt to ensure that the network is reliable in communication data, there have been developed extensive techniques of clusting in order to optimize the CHS.[7] Nevertheless, each method had some disadvantages. Metaheuristic optimization (MHO) algorithms are created in order to observe exploration and exploitation through providing the optimal result. The ability of the MH algorithm to find any A globally optimal solution that escapes local optima can rely upon that search being performed in the solution space. Exploration and exploitation needs to be constant to have the best results.[8] Specifically, the search process that could allow finding the solution that is likely to be optimal is terminated; to be able to pick CHs, a famous MH method has been developed.[9,10]

On the other hand, EE routing algorithm design is important to communication. The key goals sought by most of the studies conducted on energy-aware routing up to date are; maintaining constant RE levels on a routing path, and minimizing the overall EC across the routing path. Adopting the least hop count (HC) path is widely used in WSN routing and it is commonly referred to as the shortest distance path since the total EC is likely to be affected by distance between nodes and the number of nodes in the path.

Path disconnection and network split avoidance is through RE level (per node) or power drain rate.

This is because of the reason that the WSN applications often generate vast amounts of redundant sensing data to be monitored and investigated.[8, 9] This is a good DA method applied in order to minimize EC by management of these data in the network.[11,12] Cluster methods help in aggregating the huge amounts of data gathered by the sensors to form what is termed as target tracking programs. The three major factors that determine the form DA is categorized into are network architecture, network flow and the quality of service. In a bid to reduce the amount of Data Transmission (DT) to the sink node, Redundancy removal is performed after collection of data from different SN is merged.[12]

Aggregation technique which transmits the DA to the sink node only through a few nodes.[11] To reduce DR, DA serves as MAX, MIN, MEAN, MEDIAN, etc. operations to send the acquired data to the sink node after it removes any unnecessary information out of it. The problem of the already present systems is that the systems are too dependent on the CH and sink node (SkN) on DA. This automatically maximises EC as network size and node density grows up to move NL downwards.

To achieve the best MR, this paper develops the protocol of DDQNDA with TEAMR. In the case of MR, DDQN-based DA is presented. SN utilises the DDQN classifier when it acquires combined data of other nodes. Then, there is the suggested aggregation method to gather all the received and locally monitored data, and it employs the shortest MR to send the aggregate data to the adjacent node. With MR, ASBO algorithm is used. As per testing findings, TEAMR procedure performs better than other prevailing methods with regard to abilities of competing with global optima.

Literature Review

The approach by Zhang et al. [13] is a remarkably innovative in network DA based on a ring. The partitioned network is done ring by ring, beginning outside and run inwards, DA. Instead of unicasting one copy of the aggregated packet, the source or intermediate aggregating node unicasts multiple copies of the aggregated packet to its next hop with the most RE where the packet will next travel in the inner ring in order to ensure reliability in transmission. The reliability goes up with increased unicasting copies of packet. Nevertheless, transmission of more copies of packets will imply an increased use of energy. Also, nodes close to the sink usually forward bigger Data Packets (DP) and consume energy more rapidly than nodes that are distant to the sink.

The number of copies of packets performed in unicasting is adapted using Fuzzy Logic (FL). The suggested approach flexibly unicasts adjustable number of packet copies of aggregates continuously in a window depending on the imbalance in energy cost of nodes and the reliability of request transmission. The proposed structure is viable, which is proved by the outcomes of the analysis and the simulation.

In order to ensure that the delay would be controlled within the QoS requirement limit restriction as well as minimizing EC, a Differentiated DA Routing (DDAR) approach was proposed by Li et al.[14] The DDAR main contributions are as follows: (A) DDAR system routes data with different QoS requirement to the sink using different channels. The QoS requirements identify the parameter of each path aggregator such as aggregation threshold and deadline. As a result, EC reduction is achievable at the expense of the DT performance. Instead, based on DDAR scheme, a modified scheme referred to as enhanced DDAR scheme is proposed to make optimal utilization of the RE in the nodes that are further away in terms of topology to the sink thereby enhancing performance further. According to simulation findings, DDAR can enhance NL by 55.45 percent, EE by 83.99% and service guarantee rate by 25.1 %.

In order to improve the efficiency of DA operations in multi hop (MH) WSN, Sert et al. have proposed the Two-Tier Distributed FL Based Protocol (TTDFP).[15] Clustering is employed where maximal aggregation is needed on the EC determination front. Clustering of a network ensures that CHs receive packets and transmit them to the Base Station (BS) through member (leaf) nodes. The TTDFP is used in order to maximize the lifetime of MH WSN through simultaneous optimality of the routing and the clustering phases. A powerful approach to provide and regulate sensor network systems is TTDFP, distribution-adaptive protocol. In addition to that, a framework of optimization is described, since fuzzy clustering tier within the parameters has to be optimized in order to maximize the efficiency of a wireless network when used along with a TTDFP. The test results under the Y value in EE and NL formulas indicate that TTDFP is bound to outdo all the other protocols when working with exactly the same network setting.

Bongale et al.[16] have proposed an intra-cluster DA method (ICA) of WSNs. ICA builds an EE ICA path between a source node to its CH node. Till the time the specified CH node receives the message, the DP is aggregated by the intermediate relay nodes along the aggregation path. Such parameters as the number of live nodes, EC, and the number of DP sent to the BS is considered in carrying out a comparative analysis. The findings indicate that ICA is better as compared to LEACH and LEACH-Centralized (LEACH-C) approaches.

Zhang et al.[17] came up with a technology that had various algorithms of sensor placement whose aim was to maximise a WSN lifetime. The Entropy-driven DA with Gradient Distribution (EDAGD) consists of Entropy-driven aggregation tree-based routing algorithm, multi hop tree-based DA algorithm, and gradient deployment algorithm. Numerical and experimental data indicate that EDAGD approach is better than the classic choice of algorithm with a random deployment strategy.

To apply fuzzy logic to construct a tree and select Parent Node (PN) in heterogeneous network, Bhushan et al.[18] introduced a Fuzzy attribute based Joint Integrated tree creation and Scheduling (FAJIT). FAJIT is mainly dealing with PN selection problem of heterogeneous networks to optimize EE by combining multiple types of DP. The analysis of the candidate nodes (CN) having the minimum dynamic neighbours is in a position to facilitate the selection of the the PN to be chosen. Once FL was applied to WSN, MinMaxNormalization (MMN) is then used to generate the normalized weights (membership values) of the given edges of the graph.

Some metrics would be employed in comparing FAJIT to the popularly applied Integrated tree Construction and DA (DICA) approach. Such metrics are the number of transmission slots which are transmitted altogether, EC at the control period, the average schedule length and EC data interval. The results show that the suggested strategy is effective according to EE.

Jan et al.[19] proposed a new high-level and EE functions based DA technique of a CB hierarchical WSN. The suggested technique serves both node level and CH level. In order to improve on the accuracy of DA, the outliers are identified by making use of a threshold method. The DA is implemented at the node level and is executed through the application of the Exponential Moving average (EMA). A very polished DA is subsequently passed to the BS at the CH level through a slightly altered Euclidean Distance (ED) based functionality. According to the experimental outcomes, the technique offers very sophisticated DA to the BS to reduce EC, transmission costs, and communication costs at the nodes and CH.

To optimize the NL to distributed WSN, Sanjay Gandhi et al.,[20] elaborated a grid clustering and fuzzy (RL) Reinforcement Learning based EE DA system, referred to as FRLEEDA. In the case of cluster formation as well as CHS, grid clustering is first employed. In addition, an RL technique based on fuzzy rule system is applied to choose the DA node using such variables as overlap neighborhood, distance, and algebraic connection. Finally, mobile sink is dynamically moved within a grid-based clustered network area by the use of Fruit Fly Optimisation (FFO) approach. The results of the simulation study showed that the prescribed DA method outstrips other methods in the light of EC and NL.

Yun and Yoo[21] considered potential neighbor node DA degrees and such a node had to identify its routing path. To achieve an optimal route, RL is offered in a new Q-learning based DA-aware EE Routing (QDAEER) algorithm. It will streamline the R at every SN taking into consideration the efficiency of sensor-type (ST)-based DA, node RE, and communication energy.

Next, in order to compare the efficiency of suggested routing technique to the traditional ones, the energy-aware routing algorithms, simulations are made. The recommended framework will be able to achieve the reduction of NL and decrease the quantity of data and its exposure is borne in the results.

Network Model

It is considered that the sensor field is presented by a heterogeneous set of sensor nodes (SNs) that have temperature, humidity and photo sensors as shown in Figure 1. The sensor is functional through sensor-specific interval of sensing depending on the need of the application.

Every SN has a number of sensor-type-specific buffers where the local sensor data as well as the incoming data at one hop neighbor is stored in. There is large spatial correlation across local nodes of the same sensor type, and thus data of the same category can be aggregated across each node prior to a transmission.

Propagation and Packet Forwarding Framework

Under the algorithm of the Average and Subtraction-Based Optimizer (ASBO) routing protocol, every SN sends its accumulated data into a designated one hop neighbor.

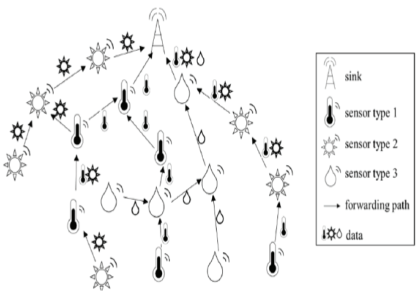

Fig. 1: WSN Framework using Multiple ST

By use of a publish/subscribe communication paradigm, the sink node broadcasts continuously the Hello messages that have an increasing sequence number.

When an SN receives a Hello packet it increments a hop count (HC) and broadcasts the Hello packet to its neighbors. With each retransmission the sequence number remains unchanged but its HC is advanced. Such gradual flooding finally forms the multi-hop routes to the sink node and allow data dissemination in a decentralized manner.

Antenna Design Integration in WSN Node Architecture

Directional microstrip patch antenna, designed to operate at 2.4 GHz ISM band, is attached to each sensor node in the suggested WSN. The design of this antenna enhances the quality of wireless links, energy consumption, and minimizes interferences by workings as directional antennas.

Antenna Specifications:

- Type: Rectangular Microstrip patch
- frequency of operation: 2.4 GHz
- Gain: It is about 6 dBi
- Beamwidth(3 dB): ~ 90 o
- Front to back Ratio: > 20 dB
- Polarization: Linear
- Substrate: FR4 (ear -4.4, thickness- 1.6mm)

The TEAMR proposed algorithm has these antenna parameters encoded in the logic of their routing decisions. The Double Deep Q Network (DDQN) module is dynamic in route choice by consideration to a directional antenna alignment with prospective next-hop nodes gain. The link quality is estimated considering the antenna radiation patterns but these affects are applied during learning iterations in updating Q-values.

This combination of physical-layer antenna features with network-layer intelligence helps to aid propagation-aware routing and makes the systems more robust, which makes the architecture in line with the current trends in the field of antenna-constrained wireless sensor network systems.

Antenna Simulation and Radiation Characteristics

A patch antenna is a rectangular microstrip patch antenna with a frequency of 2.4 GHZ in order to confirm the proposed antenna built within the WSN nodes, in this case, CST Microwave Studio was used. The antenna has been designed on substrate FR4 (substrate: 4.4 4.05-4.69(The number of total out-of-band suppression), 1.6 mm).

Key Results:

- The Impedance Bandwidth (-10 dB): 2.382.48 GHz
- Resonant Frequency- 2.4 GHz
- peak Gain 6.12 dBi
- VSWR:~ 1.4
- Radiation Efficiency: 82 %

Cluster-Based Hierarchical Network Model

The WSN is based on a two dimensional cluster topology in which every SN are almost identical concerning processing and communications. Nodes do not depend on location-aware hardware and, therefore, nodes communicate with each other on the basis of signal parameters.

There is a Cluster Head (CH) that controls each cluster and is chosen using parameters like residual energy (RE), distance, node density etc. SNs on the broadcast range of the CH may only become Cluster Members (CMs).

CH selection and cluster formation is done in a series of rounds with CHs and Base Station (BS) constant during each round. Intra-cluster communication Intra-cluster communication takes place when CMs transmit their data to the CH and this conducts data compression and aggregatory functions. CHs can use the CSMA/CA to access the medium when they communicate with the BS and vice versa in inter-cluster communications.

The BS is also mobile and changes position in response to changes in the network topology responding to move into areas of better data gathering.

Propagation Model and Its Impact on Routing

With the purpose of modeling wireless communication between sensor nodes in the WSN realistically, we put the physical-layer radio propagation characteristics into the routing strategy.

In the case of short-range intra-cluster, the adoption of Free-Space Path Loss (FSPL) model with path-loss exponent 2, where the facing is ideal line-of-sight (LoS) is considered. The signal power being received, P_r at distance d along that direction is modeled as:

$$P_r(d)=P_t\, G_t\, G_r\left(\frac{\lambda}{4\pi d}\right)^2 \tag{1}$$

in which the transmit power is denoted by P_t, G_t and G_r are transmit antenna and receive antenna gains and the wavelength is denoted by 2.4 GHz ISM band. To adjust the effect of environmental variation and signal fading when communicating inter-cluster and longer distance we use log-distance shadowing model. A Gaussian shadowing component of X_σ, is added in this model and the path loss in dB will be:

$$PL(d)= PL(d_0)+10\ \beta\log10\left(\frac{}{d_0}\right)+X_\sigma \tag{2}$$

where:

- $PL(d_0)$ is path loss at the reference distance d_0 ,
- β is a path-loss exponent, usually, 2.7 to 4 in obstacle WSNs,
- $X_\sigma \sim N(0,\sigma^2)$ models the random fading with standard deviation σ.

These propagation models can be incorporated in DDQN reward function where the quality of link between adjacent nodes is determined using optimal anticipated signal power, space variation and antenna properties. The output and consequently the updates to the Q-value determine how learning and selection of routes take place over time.

Through propagation-aware metrics, TEAMR protocol provides routing that is more reliable and energy efficient especially in dynamic environments and when nodes are either moving or changing connection points.

Proposed Methdology

In this paper, a new MR protocol that is labelled as DDQNDA and TEAMR is introduced. In the case of MR, there is the introduction of DA with DDQN. SN uses DDQN classifier when obtaining the composite information available in other nodes. It then aggregates all the received data and locally observed data using the proposed aggregation method and it puts the DA to be sent to the next node using the shortest MR to transmit the DA to the next node. ASBO algorithm is used by MR. Experimental outcome yields that the recommended procedure is superior to the other options in the competitive ability to global pools than that of the other alternatives. Can be seen in figure 2, the overall process of the suggested methodology.

Cluster Formation Using MGEO

To establish a cluster in WSN, the Golden Eagle Optimization (GEO) approach that has the ability to enhance the exploration power of Spiral movements (SM) can be used, especially where the nodes are placed in a 2-D environment.[23-24] These are the steps as follows:

1. **Initialization:** At the initial stage of the study, the population of the eagles ought to be scattered randomly within the WSN domain. With this random placement we can consider the whole area.

2. **Spiral Movement Strategy:** Application of a SM in search of potential CHs or best cluster structure is termed as the SM strategy.

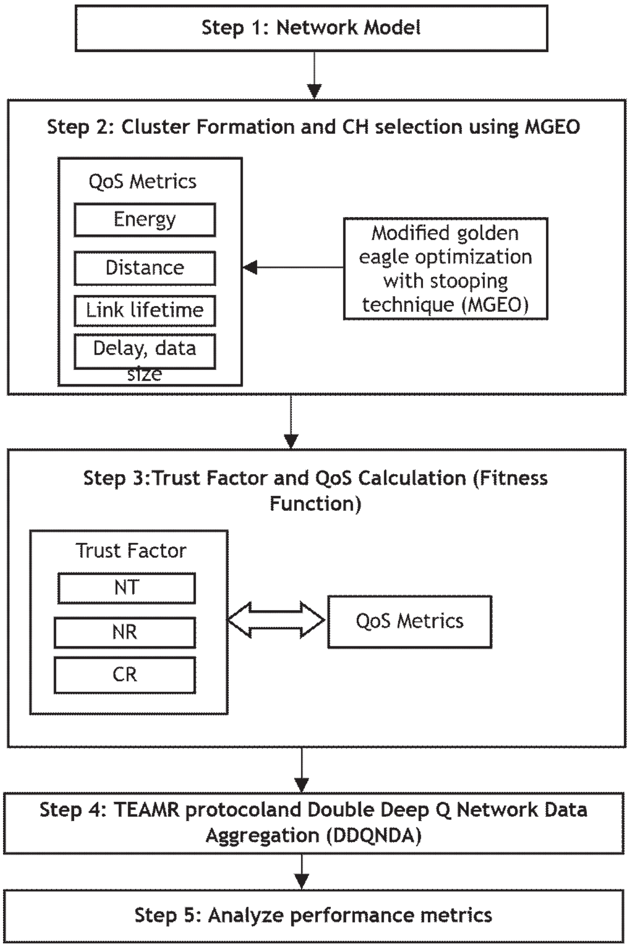

Fig. 2. Overall Flow of Suggested Method

3. **Spiral Direction and Parameters:** Explain the orientation of spiral and also its characteristics, such as the pitch, number of spirals in it, radius of spiral. These parameters are dependent on the features of the cluster, and a WSN, therefore, may be altered.
4. **Local Search and Cluster Formation:** During the spiral movement, eagles are able to carry out local searches to locate the potential candidates of CH candidates in their locality.
5. **Qos-Aware Spiral Exploration:** Maximizing EC in WSNs can be achieved by incorporating QoS aware in the SM approach by using equation (1). When not avoiding depleted sources of energy, eagles could also focus on accessibility of nodes or high levels of energy.
6. **Dynamic Spiral Adaptation:** Let SM adapt itself dynamically to a change in the environment around it or the improvement of optimization. Eagles are able to adjust by varying the spiral parameters or direction in the event of the change of network situation or convergence rate.
7. **Evaluation and Validation:** Through its comparisons and checks in the various clustering forms, the efforts are made to assess the effectiveness of the enhanced treatment of the GEO procedure with regard to the spiralling movements.[25-26]

Regardless of large-scale or disparate deployment situations, in the GEO algorithm, the spiral motions can be incorporated so as to enhance more powerful search capability and effective cluster creation could be achieved in the occurrence of WSN. In order to get optimal path selection in WSN and consecutive cluster formation, of(x) could be used as objective function. It is characterized as follows.

$$OF(X) = SF \times F_1 + (1 - SF) \times F_2 + (2 - SF) \times F_3 + (3 - SF) \times F_4 + (4 - SF) \times F_5 \quad (3)$$

The scaling factor (SF) can vary up to 0 to 1. In WSNs, the formation of the clusters is affected by a number of factors such as delays, EC, lifetime of links and distances.

Delay (: are the causes which may influence WSN delay. The formula of delay is below:

$$Delay = Transmissiontime + Propagationdelay + Processingdelay + Queuingdelay \quad (4)$$

Energy Consumption: The WSN battery capacity of SN is limited hence EC is essential. EC will be computed using the following factors, they include: *TransmissionEnergy* + *ReceptionEnergy* + *ProcessingEnergy* + *IdleListeningEnergy*. The following formula can be employed to calculate EC :

$$EnergyConsumption = TransmissionEnergy + + IdleListeningEnergy \quad (5)$$

$$ReceptionEnergy + ProcessingEnergy$$

Link Lifetime: The period that a communication connection between two SN is in use is termed link lifetime. Some of the parameters that influence it include data rate, transmission distance and EC. The formula that describes link lifetime is given in equation (5).

$$Link\ Lifetime = \frac{Remaining\ Energy}{Energy\ Consumption\ Rate} \quad (6)$$

Distance: The distances between SN have influence on communication ranges and EC. In a WSN the distance formula can be influenced by such variables as path loss, interference and signal strength. The path loss model of the network could be deployed to come up with a simple distance equation.

$$Distance = f(PathLossModel, SignalStrength, Interference) \quad (7)$$

Data Size (: The DP size moves through the path of source to destination. It may alter with the sizes of the packets.

Trust Aware (TA) Model

To obtain optimal communication routes within WSNs a TA framework is proposed that takes into consideration a mixture of QoS metrics as well as trust measures. Malicious nodes, poor link and impacts of external disturbances that affect the efficiency of the network can be reduced to a considerable level easily and that is achieved by applying trust information. WSN trust factors are needed to ensure reliability, safety of transmission channels. Trust factors can be determined by a list of factors such as node reputation, authentication methods, and history of previous behaviour.

Trust factor can be calculated by combining trustworthiness of previous communications, reputations of the nodes along the path and trustworthiness. The trust factor TF_i calculated across each path i based on following constituents :

$$TF_i = \sum^{m_i}(w_1 \cdot NT_{ij} + w_2 \cdot NR_{ij} + w_3 \cdot CR_{ij}) \tag{8}$$

In this case, w_1, w_2, w_3 are weighting factors which show the relativity of each component. So, the nodes number in path i can be represented as m i. Node j reputation in path i is named as NR_{ij}, communication reliability of node j in path i as CR_{ij}, and trustworthiness in path i by NT_{ij}. The specificities of the necessities and preferences of WSN application might demand modifying the values w_1 ,w_2 ,w_3. TF_i may also be altered based on real facts and contributions of other close nodes to concur with changing network situations as well as security demands.

TEAMR with Path Selection Using ASBO

An example of the distinctive multipath selection approach within the WSN is the ABSO algorithm.[27] A (SS) Search Space is able to address the problem and give it mathematical characterization that nodes members, or CMs, use to locate quasi-optimal paths so that ASBO can operate. ASBO also guides the members of the nodes to the most favourable destinations by making continuous transfer of information. The best and worst member performances difference and average statistics allow the node member position change at the same time because they are known simultaneously as well as average statistic.

An optimal approach to solve the optimization issue in WSNs needs each member of the nodes to represent only one CM utilizing ASBO algorithm. The mathematical expression of any ASBO member is a vector, according to mathematical dimensions of which are identical to the counts of the decision variables that concern CHS. The element in the vector that corresponds to each decision variable shows the chosen value of the variable. The members of the node in ASBO have a model which regulates their behaviour as they take part in the optimization process. With this framework, a systemic search and application of the solution space can be potentially conducted by ASBO, thereby leading to optimal path solutions which are determined using CHS criteria in a WSN.

The best and the worst members of ASBO are identified as the best CMs of path selection using this methodology.

- Phase 1: In phase 1 of ASBO, a CM needs to be established. This CM is required to update the ASBO node, and the best and the worst CM nodes are aggregated.
- Phase 2:- To refresh the CM places, considering the finest and poorest CMs within CM, the removal data which is acquired to be used as the ASBO means is adopted to WSN. The aim of this stage is to enhance the placing of the CM to optimise the SS even more to enhance the quality of the solution. Values attained by the objective functions will no longer be the same when new candidate values of the decision variables are considered due to the change of the status of the ASBO members. When the steps of the procedure are done, the algorithm takes up the next iteration based on the new values. After ASBO has been run to its fullest, then the solution that is provided after all repetitions of the algorithm is taken as the solution to the problem.

The TEAMR protocol also considers directional antenna radiation patterns in the process of selection of the path that is set to occur based on ASBO in addition to comparing the trust factors and energy (metric). Every sensor node shall be considered to use directional antenna of a predetermined beamwidth and orientation. In the process of optimization, candidate Cluster Members (CMs) evaluate potential neighbor nodes neither on the basis link reliability and residual energy alone, but also on the effective antenna gain along the direction of the link.

To this purpose, the antenna radiation pattern G(0) which represents the directional pattern of the antenna with the angular offset of 0 with respect to the direction of the antenna boresight is added as a multiplicative weight in the ASBO objective function. Directional gain alignment encourages links with high directional gain alignment that result in an increase in signal strength, a reduction in lateral interference as well as the boost in the spatial reuse factor, which is particularly critical in dense deployments.

Such propagation-aware, antenna-constrained selection mechanism makes path diversity and network robustness. By introducing antenna directionality, the communication range will not only be communicating based on the optimal axis, but also reducing those suboptimal links which would otherwise have a poor gain and also incur more consumption of power. Consequently, load distribution, and energy consumptions between the nodes of the network are more balanced with TEAMR and ASBO.

Data Aggregation Model

Figure 3 shows a schematic of the process that is recommended. Each kind of sensor possesses some sensing agenda that it employs to reduce the EC of sensing environment. It is continuously detecting the environs. When the sensing timeout is reached it collects environmental data and keeps the data in its ST queue. Each node can obtain any type of ST data transmitted by each of its neighbor by use of a transceiver and the succeeding storing of information in the corresponding sensor-type queue. In all kinds of sensor, we can also have a fixed wait time, whereby data is gathered in each node. Waiting time at queue can also be calculated based on the timing required on each ST.

The waiting timer rings after a reasonable time, and the data stored in the queue will be relayed to the aggregation module. The node calculates each raw data point of each kind of sensor and collects it at other nodes in the neighbour. Subsequently, any of the data is aggregated in a manner that involves aggregation model.

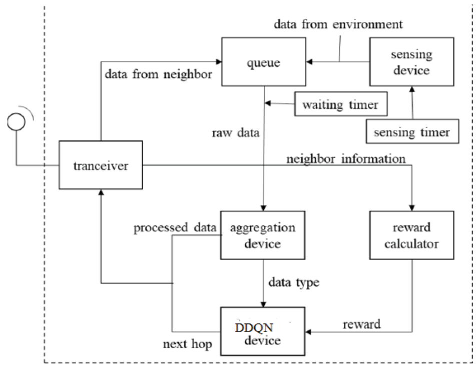

Fig. 3: Schematic of the Double Deep Q Network (DDQN) Based Data-Aggregation

To select the most appropriate neighbor node, the DDQN classifier is applied, the DA of each sensor type is sent to the neighbor node. Once the data is received the neighbor node acknowledges it by transmitting out ACK (acknowledgment) packets.

These packets include the information about the location of the node, parameters related to energy, HC to sink node and the status of the DA degree. In order to refresh the Q-table with regard to the applicable ST, the sending node will assess the R in accordance with the response.

The synchronization of the first time of sensing all nodes does not require synchronization in order to unlock the asynchronous sensing approach to work. With the asynchronous system, there is the possible latency involved in delivering packets as compared to the synchronous technique because it requires considerably a lot of overhead to determine wakeup schedules of the neighbouring nodes prior to sending packets to them.[28]

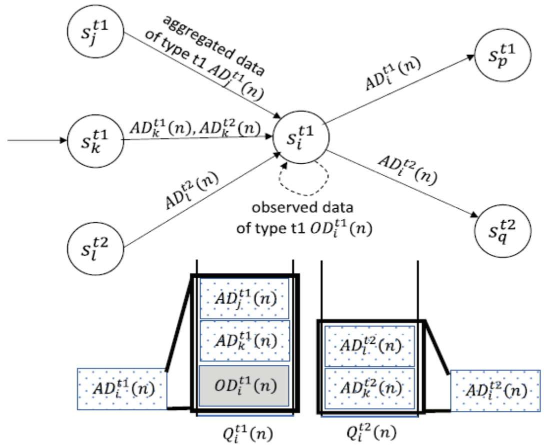

Fig. 4: DA and Transmission System Framework

Figure 4 is based on the assumption that each sensor node will only have one sensor attached to it. SN i whose type of sensor is t is denoted as, . denotes SN with more than one sensor type. There exist K different types of sensors in the WSN.

Each node contains K queues each of which stores data corresponding to a given sensor type independently. SN is expected to have K queues even in the case of a single sensor because it can also behave as a relay node irrespective of the contents of the data. The DA process along with the routing path to the SkN is illustrated in figure 4. The proceeding nodes designation included the node, as the next one was considered to be in the way to the SkN. SN receives sensing data of ST, and analyzes location at nth Time Step (TS) as shown in Figure 4.

It also receives aggregated data of the neighbouring nodes on each kind of sensor. The DA of type t 1 of j^{th} neighbor node at the n^{th} TS is given by .

Moreover, it receives aggregated information about each type of sensor on its neighbouring nodes. is the value of j^{th} neighbor node in t1-type of the DA at the n TS.

Data st1 i contains both the incoming and locally available data and all aggregated data at time slot t, at the nth TS in ST queues at time t.

At last, the node aggregates the recorded data into .This is then sent to the chosen neighborhood nodes that get the consolidated data of all the types.

The SNs in the WSN view the environment at the designated intervals in order to save energy instead of continuous monitoring. It is assumed that each sensor type t has a sensor time, denoted as well as sensor interval defined in the model as . Waiting time sensor type t DA is denoted by . is usually more than and adequately comprises several time steps during the sensing interval. Nodes are not subject to time synchronization; each node is free to initiate schedule at any time. The node will not receive DA of its neighbors until the waiting period is complete. The state of the que and the amount of SN DA at n^{th} TS are found by use of the following formulas:

$$Q_i^t(n) = OD_i^t(n) + \sum_{j \in N_i} AD_j^t(n) \tag{9}$$

$$AD_i^t(n) = DA\{Q_i^t(n)\} \tag{10}$$

In this DA{}is DA function. In the formula (8), when no due time is devoted to sensing of grade t at n^{th} TS then the value is (n).When it happens that the SN can manipulate the energy use in terms of transmission power, then the energy required as DT is always dependent on the size of the DA as well as distance between the receiver and transmitter. Then N_i denotes the neighbor nodes set of node i. The transmission amount of the data depends on size and decoding of data and the amount of reception energy required. The energy required by DA is dependent on the queue status at that juncture. The sum total of the energy that i^{th} node transmits is derived at:

$$E_i^{TX}(n) = \sum_{\forall t} \frac{AD_i^t(n)}{B} \left\{ P_{txElec} + P_{amp} \left(\frac{d_{i-n_*^t}}{d_{max}} \right)^{\beta} \right\} \tag{11}$$

In this case, d_{max} stands in the maximum distance of communication in every node.

As per the proposed routing protocol, the d between the node i and the next neighbor node t type, the formula indicates as $d_{i-n_*^t}$

Transmission power is and amplifier power is Pamp. The symbol rate could be referred as B.

The next is the sum of all receiving energy that node i will require during the course of nth TS:

$$E_i^{RX}(n) = \sum_{\forall t} \left\{ \frac{AD_i^t(n)}{B} P_{rxElec} + AD_i^t(n) E_{decBit} \right\} \tag{12}$$

In this, denotes the decoding power per bit and denotes the power of reception. The total EC by ithnode of DA at the n th time step is given by the following:

$$E_i^{DA}(n) = \sum_{\forall t} Q_i^t(n)\, E_{aggBit} \tag{13}$$

DA energy per bit is referred as . Since it has the ability to capture network dynamics and environmental parameters properly, the WSN routing issue includes each SN determining the next node to hand-over sensing data to the sink node. The WSN routing architecture proposed takes agent as data flow within the network. All the SNs are states. Upon expiry of DA type t waiting time, in order to receive the DA type t, SN i must select the next neighbor node.

In this, the neighbour node list along with the current state() depicts A in the current state(); ,, the node which the DA of type t is sent to is a node of the next state. States and actions are given as follows:

$$S = \{s_1, \ldots, s_N\},\ A = \{A_1, \ldots, A_N\},\ A_i = \{a_j = s_j | s_j \in N_{s_i}\} \tag{14}$$

In this N denotes the number of SN. N_{Si} will then refer to the set of neighbouring nodes at node S_i

If, the a = π(s). specific policy can be represented by the π. The agent in Q-learning then estimates the Q-value function Q (s, a). This system will act until the attainment of the successor state (the received SN of the DT) by following the action after which it will stop. The system was started in state s and was followed by action a (forwarding the DA of type t). $Q(s^t, a^t)$ can be given in a mathematical form as.[29]

$$Q^{\pi}(s^t, a^t) = \mathbb{E}_{\pi}\left[\sum_{k=t}^{T} \mu^{k-t} R^t | s^t, a^t \right] \tag{15}$$

Here, $D^t = \{ e^1 \ldots e^t \}$ the discount factor can be expressed as . In ST t, the reward (R) is achieved.

The agent just takes into account the current benefits if $\mu \leq 1$, but it also takes into account future rewards if . In essence, the long-term mathematical predicted returns produced by MDP are expressed as $Q^{\pi}*(s^t,a^t)$. To maximize the AV function of equation (13) and fulfil $Q^{\pi}*(s^t,a^t) > Q^{\pi}(s^t,a^t)$ for all Q-value functions, the optimal policy that is selected by A is, p* (s) = argmaxQ (s^{t+1} a^{t+1}) so that a^{t+1}. Bellman's equation allows us to express Q(st, at) as,[29]

$$Q(s^t, a^t) = Q(s^t, a^t) + \alpha \left[R_t + \mu \max_{a^{t+1}} Q(s^{t+1}, a^{t+1'} - Q(s^t, a^t) \right] \tag{16}$$

In data, $D^t = \{ e^1 \ldots e^t \}$ the DRL agent records its observations at every sensor type t, $e^t = (s^t, a^t. R^t, s^{t+1})$ The task of minimizing of loss function compared to the target value y^t was carried out with the help of the gradient descent of the mini-batch and could be aided with the combination of the samples accumulated in the data packets.[29]

In equation (14) R is the reward function of the given action and is obtained at the following state (at the next node) and quantifies the completeness of DA and EE at selecting the next node in the DA-aware EE routing. Upon receiving the DA, the next node acknowledges the sender with highest Q-values and the computed R. The definition of R within the prescribed routing approach is based on R of the DA degree, node energy situation and by the HC to the SkN. The DA reward vector (R_{DA}) is given in equation (16) to any data.

$$R_{DA} = \begin{bmatrix} r^t_{DA} = \dfrac{Q^t_{s'}(n)}{AD^t_{s'}(n)} \\ \vdots \\ \hat{r}^{t'}_{DA} = \dfrac{Q^t_{s'}(n^-)}{AD^t_{s'}(n^-)} \end{bmatrix} \tag{17}$$

In this , the node which conveys the data-type is referred to as t and r^t_{DA} is the reward of the DA type t. The last time period at which node s is calculated as $r^t_{DA'}$, and r - can be referred to as . Reward of energy status (R_E) is the following:

$$R_E = \frac{E^r_{s'}(n)}{E^r_{s'}(0)} - \left(\frac{d_{s-s'}}{d_{max}}\right)^{\beta} \tag{18}$$

The Maximum transmission range of SN can be represented by d_{max}. Then β=2, which is the path loss exponent and it is equal to two in free space.

In applying any distance estimation method on node s′, the estimated distance between nodes s and is parameterized on the value $d_{s\text{-}s'}$.

The R_E of the neighbouring node s′, is $E^r_S(n)$. at the n^{th} TS. In the 0^{th} time steps, R_E of next node s prime can be expressed by $E^r_S(0)$.

R should also be smaller than the maximum Q-value of the parent node of the hop counts so that the data could be relayed to SkN. When nodes that are not close to the SkN, are Backwarding and it is even likely when the fixed R is also applied to all the nodes in the network. An additional discount component (DF) of the R of the nodes must be used in order to prevent backwarding. The ultimate computation of R of A in S as below:

$$R = \begin{cases} \eta^{H_s} \times (R_{DA} + R_E \times \vec{1}) if\, s' is not a sink \\ R_s \times \vec{1} else \end{cases} \tag{19}$$

The sink node reward is R_s, the DF on the range of [0 ,1] is η. K-dimensional vector is the whole of 1s. The HC of node s is given by Depending on the R arrived at the nodes, it is obligatory to update the Q-table. It needs the following state nodes so that it can update its AV Q(s,a). DQN used DQN single max mathematical estimator in the selection and evaluation of action.

Therefore, learning agents will find it confusing at times when action may be chosen or assessed and this will result to over-optimistic action values. The max mathematical estimator which DQN employed in the updating of its Q-value function due to the cases of positive bias overestimation

The double Q-learning approach was proposed to solve the overestimation (AV) Action Value problem [30]. DDQN applies two independent estimators of the max function to both select action and to evaluate the action.

There are no overestimation AV due to the more reasonable value that this double estimator technique gives. The target value of the DDQN in equation (14) may be constructed,[30]

$$y^t = R^t + \mu Q\left(s', arg\max_{a^*} Q(s', a^*; \theta^t); \theta^{t'}\right) \tag{20}$$

In order to update for -greedy policy, 0 (a set of weighted parameters) was used at t ST. Other parameters . can be used to calculate the policy value.

The ϵ-greedy policy can describe the likelihood that an agent is going to play randomly due to the action that would help it to explore as opposed to playing in a way that would be described by the maximum Q-value of the immediate next state. During the i^{th} iteration of DDQN the DQN equation (13) to update the Q-value function will not update. Nonetheless, there is the value of target that varies as presented in.[25]

$$y^t = R^t + \left(s', arg\max_{a^*} Q(s', a^*; \theta_i); \theta_{i-1}\right) \tag{21}$$

Based on the prior iteration, the target network used the i−1 parameters on both DQN and DDQN. The target network however can use any of the previous iteration parameters $(i - k)^{th}$ in generalisation. Then, target network parameters are updated, periodically, with online copies of the network parameter.

Experimental Results and Discussion

The implementation of proposed systems is carried out based on the system specification in the MATLAB R2019a environment. Intel(R) Core (TM) i5 of 2.80 GHz and RAM of 16 GB is also an excellent selection working on Microsoft Windows 10. Then the concept is n bits of data that is conveyed via a d distance which is transited by transmitters and receivers in a free space network scheme of DT. Depending on the existing fitness, the solution with the minimum hop-counting is ideal CM to combine into one message and the method has picked the same. When the CHs continue to transmit the data which has been compressed to the BS through their radios and the Sluice between-cluster communication step. CSMA/CA would keep the CHs alive and utilizes the radio, CMs can go to a sleep mode in order to save energy when inter-cluster communication is to take place. Intra- and inter- cluster communications are made with the help of CSMA/CA. The BS is capable of traversing within the sensing zone and gaining access to the network info.

Table 1: Simulation Parameters

Parameters	Values
Network area size	200200
Number of nodes	100-500
Sink Location	(100,100), (100,50), (200,200)
Starting Energy	0.5, 2, 200 J
CHs percentage	10-15%
	50 nJpb
	0.0013 pJ/bitpm^2
	10 pJ/bitpm^2
	30 m
	100 m
HMCR	0.7
PAR	0.8
Packet Size	4000 bits

Performance analysis through the analysis program of the MATLAB R2019a is carried out based on a number of simulation tests. The parameters of the simulators are presented in Table 1. The parameters that our simulations in the current experiment use are some parameters like E_{elec}, E_{amp}, E_{fs}, d_0 *and* d_{max} which are normally associated with the radio energy. Following sections give the results of the test. The value of the parameters EE, NL, and QoS parameters are also simulated based on their value in the experiment in MATLAB R2019a.

Packet Delivery Ratio (PDR)

PDR is the number of the received data by dividing it with the entire amount of DT. PDR is calculated by using equation (21).

$$PDR = 100 - \frac{data\_received}{data\_transmitted} \times 100 \qquad (22)$$

Packet Loss Ratio (PLR):

The data losses during transmission and the data losses that are received at the destination node are also seen to be packet losses: this is between the source to the destination node. Proportion of DT to data received is the measurement in terms of 500 nodes. PLR is computed with the help of equation (22) in WSN.

$$PLR = 100 - \frac{data\_transmitted}{data\_received} \times 100 \qquad (23)$$

End-to-End (E2E) delay

The E2E delay is the process of transmitting and receiving the data in the same network so as to update the destination node. The equation (23) was used to find out E2E delay of the route.

$$End\ to\ End\ Delay = time_{taken_{data_{receiving}}} + time\_taken_{data\_transmitting} \qquad (24)$$

Throughput

Throughput measures the number of packet successfully transferred to the BS on each round. The throughput is the ratio between how many packets the receiver is getting per message the transmitter sends divided by the time it takes the transmitter to send the last packet. It is calculated based on equation (24).

$$Throughput = \frac{Datasize \times time\_taken_{data\_transmitting}}{Response\_time} \qquad (25)$$

Energy consumption

The EC of the node within the WSN plays a significant role in DT as well as efficiency of the network. Inefficiency can be used to explain the development of the node interference, in transmission. The DT of the amplifier to node where tamp is The EC to DT. The EC amount is . d is the distance between the nodes of the cluster and l^2 is the energy loss. Denote by el^2 the energy been lost in transmission of m bit of data. The energy is then calculated using, equation (25).

$$E_{tx}(m,d) = E_{con} \times m + t_{amp} \times m \times l^2 \qquad (26)$$

Network Lifetime (NL)

The important determinant parameter in a WSN is NL which is obtained by determining the time it takes the primary sensor energy to wear out. In a traditional WSN, every SN is set to communicate through multi hop so as to transfer data collected by it to the sink.

Impact of Antenna Type on Routing Performance

In order to investigate the effect of the antenna properties on the routing performance the simulations were performed on three different types of antennas under the same network configurations with 300 sensor nodes:

- **Omnidirectional (Dipole-type):** 0 dBi gain, 360° uniform radiation pattern
- **Directional (Patch Antenna):** 6 dBi gain, ~90° beamwidth
- **High-gain Directional (Yagi-Uda):** 9 dBi gain, ~40° beamwidth

These designs were tested in DDQNDA-TEAMR routing protocol to evaluate the performance changes on the basis of delivery reliability, energy efficiency, and network life.

Table 2: Routing Performance vs. Antenna Type (300 Nodes)

Antenna Type	PDR (%)	EC (J)	NL (Rounds)	E2E Delay (s)
Omnidirectional	88.4	0.52	4365	7.83
Patch (6 dBi)	93.7	0.44	4892	5.58
Yagi-Uda (9 dBi)	95.1	0.39	5116	4.96

Table 2 Simulation results in table 2 the results show that use of directional antennas would greatly improve PDR, limit energy consumption and increase network lifetime. There is further interference reduction as well as enhanced transmission efficiency with the Yagi-Uda antenna, which has a broader gain and narrow-beam-width. This identifying sends the notification that antenna patterns choices play a significant role in determining such energy consciousness and QoS-constrained WSN routing.

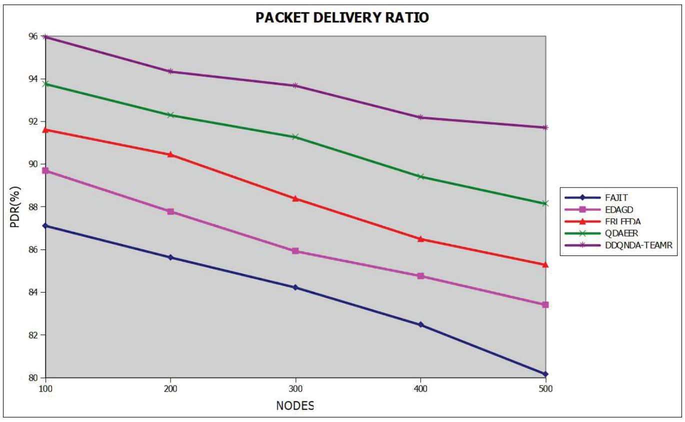

Fig. 5. PDR Evaluation Vs. Data Aggregation Methods

Table 3 and Figure 5 indicate the evaluation of PDR against DA methods. In case 100 sensors will be used initially, then it will be increased step by step to 500 with 100 additional ones. In this simulation, it is proven that the lesser the PDR, the bigger the number of nodes. With the proposed system exhibiting better efficiency than the existing systems utilizing the FAJIIT, EDAGD, FRLEEDA and QDAEER algorithms, it does much more with less, hence its efficiency. The PDR of 100 SN stands at 87.11%, 89.69%, 91.61%, 93.75, 95.95 in terms of FAJIIT, EDAGD, FRLEEDA, QDAEER and the recommended system respectively.

Table 4 indicates the amount of nodes and assessment of PLR with regard to DA techniques.

Table 3: Packet Delivery Ration Comparison

No. of Nodes	Packet Delivery Ratio (%)				
	FAJIT	EDAGD	FRLEEDA	QDAEER	DDQNDA-TEAMR
100	87.11	89.69	91.61	93.75	95.95
200	85.63	87.78	90.44	92.29	94.33
300	84.22	85.92	88.38	91.26	93.67
400	82.47	84.76	86.49	89.41	92.18
500	80.16	83.41	85.28	88.14	91.71

Table 4: Packet Loss Ratio Comparison

No. of Nodes	Packet Loss Ratio (%)				
	FAJIT	EDAGD	FRLEEDA	QDAEER	DDQNDA-TEAMR
100	12.89	10.31	8.39	6.25	4.05
200	14.37	12.22	9.56	7.71	5.67
300	15.78	14.08	11.62	8.74	6.33
400	17.53	15.24	13.51	10.59	7.82
500	19.84	16.59	14.72	11.86	8.29

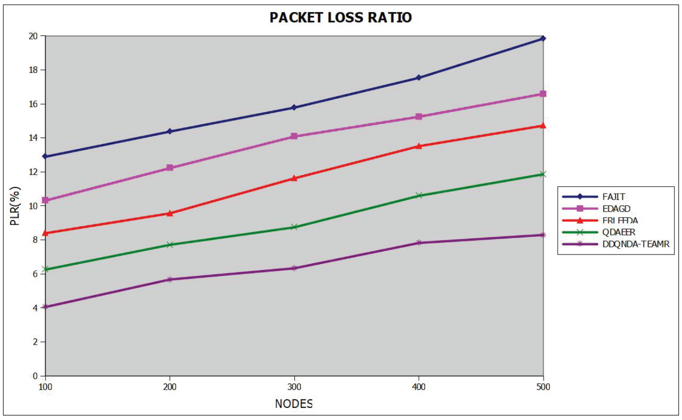

Fig. 6: Plr Evaluation Vs. Data Aggregation Methods

Figure 6 shows the number of nodes and the evaluation of PLR concerning DA techniques. The PLR is being computed by taking a 2-step escalation of 0 to 20. The proposed system is less time-intensive than other systems as this simulation shows. The loss ratio of the recommended system is less as compared to the present systems. With the increase in the loss rate, there will be increased nodes. The FAJIIT, EDAGD, FRLEEDA, QDAEER, and proposed method have the PLR of 12.89%, 10.31%, 8.39%, 6.25%, and 4.05%, respectively. The proposed solution has a reduced stream of packet loss because every DA node can be used only to cover a small region, and therefore it collects data accordingly through the DDQN.

As shown in Table 5, variations in data aggregation methods assess E2E latency that is compared to other existing systems; the proposed system shows the shortest delay.

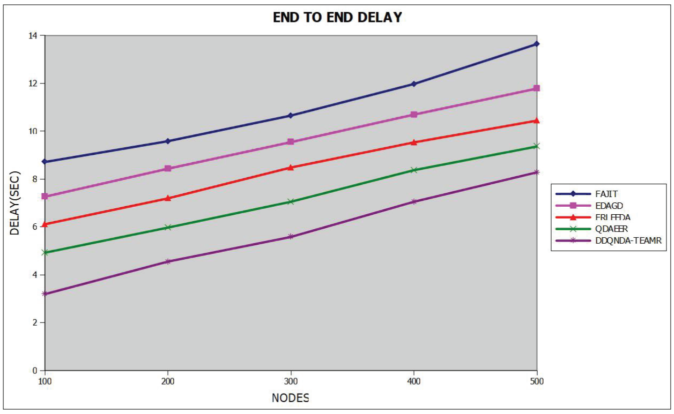

Figure 7. E2E Delay Evaluation Vs. Data Aggregation Methods

Figure 7 demonstrates the evaluation of the E2E latency done by various data aggregation methods. The suggested system has the minimum delay as compared to other existing systems. E2E delay of the proposed (100 nodes) system is given as 3.19 s, of QDAEER is 4.92 s, of FRLEEDA is 6.11 s, of EDAGD is 7.26 s and of the FAJIT is 8.71 s. The advised approach is superior to others owing to existence of DDQN, optimum routing and optimum CHS. Confirmed through figure 8, the proposed system is superior to the similar techniques on the aspect of throughput, irrespective of whether the BS is at the centre or not. The recommended system also provides a higher rate of throughput when compared to the other existing systems and factoring in the 100 nodes.

Table 6 illustrates the comparison of throughput allocation of the proposed and the existing approaches. The proposed system comes with a throughput of 0.9512 in 100 nodes; QDAEER system comes with 0.9125;

Table 5. E2E Delay Comparison

No. of Nodes	E2E Delay (sec)				
	FAJIT	EDAGD	FRLEEDA	QDAEER	DDQNDA-TEAMR
100	8.71	7.26	6.11	4.92	3.19
200	9.58	8.43	7.19	5.97	4.55
300	10.65	9.54	8.48	7.05	5.58
400	11.97	10.69	9.53	8.37	7.05
500	13.64	11.78	10.44	9.36	8.28

Table 6. Throughput Comparison

No. of Nodes	Throughput (kbps)				
	FAJIT	EDAGD	FRLEEDA	QDAEER	DDQNDA-TEAMR
100	0.7952	0.8236	0.8717	0.9125	0.9512
200	0.7467	0.7824	0.8249	0.8758	0.9165
300	0.6921	0.7365	0.7716	0.8243	0.8694
400	0.6546	0.6898	0.7244	0.7751	0.8153
500	0.6014	0.63214	0.6763	0.7216	0.7569

FRLEEDA comes with 0.8717; EDAGD comes with 0.8236; and FAJIT comes with 0.7952.

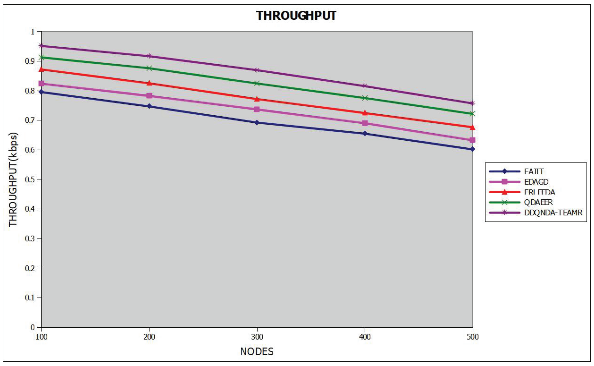

Fig. 8: Throughput Evaluation Vs. Data Aggregation Methods

The figure 8 illustrates that throughput will decrease with increase of node. In consideration of 500 nodes, the throughput falls and the proposed system is the maximum. The throughput of the proposed system is 0.9512 using 100 nodes; that of QDAEER system is 0.9125, FRLEEDA is 0.8717, EDAGD, 0.8236 and FAJIT, 0.7952. The improved DDQN aggregation, best routing, and CHS, explain performance improvement mainly.

Table 7 illustrates NL evaluation as one of the DA techniques. Compared to the existing algorithms, the proposed system contains a widespread NL as compared to the others.

Table 7: Network Lifetime Comparison

No. of Nodes	Network Lifetime (rounds)				
	FAJIT	EDAGD	FRLEEDA	QDAEER	DDQN-DA-TEAMR
100	4336	4742	5165	5448	5789
200	4154	4426	4813	5125	5467
300	3915	4239	4564	4892	5178
400	3726	4047	4347	4648	4915
500	3457	3898	4205	4451	4763

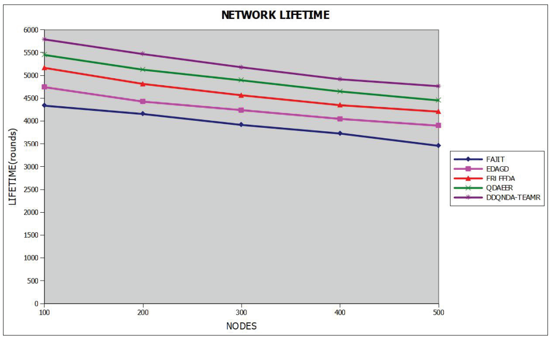

Fig. 9: Network Lifetime Vs. Data Aggregation Methods

Figure 9 shows the NL evaluation of the simulation of the DA techniques. The key aim of the system is to improve the NL. In comparison to the existing algorithms, the proposed one possesses a bigger NL than others. The FAJIT system has a shorter NL as compared to these current systems. The nodes are increased in order to reduce the NL. The respective NL of FAJIIT, EDAGD and FRLEEDA, QDAEER and the proposed system is 3457, 3898, 4205, 4451, and 4763 rounds of 500 nodes respectively.

Conclusion And Future Work

To minimize total EC and improve the lifetime of the WSN network this research proposes the DDQNDA with TEAMR protocol. The TEAMR algorithm aims at determining the optimal route of communications in the WSNs by considering both the trust aspects as well as the QoS parameters. Background continuously gets measured by sensors according to a predetermined detecting time of each ST since DDQNDA reduces the EC of environment sensing. The nodes will measure the raw values of an individual type of sensor and will accumulate the results of adjoining nodes with the help of the process of aggregation. DDQNDA is taken as a network-wide data flow agent.

In the quantum-decision-based DDQN, two different max function estimators are applied in order to decouple action selection and evaluation processes. Path is the optimum path offering maximum improvement in R to each SN and DDQNDA considers sensor type of the adjacent node, energy, distance and HC to sink. It is capable of reducing the overall DT load and extend the lifetime of the WSN. Finally, the results of the DA methods are measured by such criteria as PDR, PLR, E2E delay, EC, throughput, and NL. The suggested model of aggregating data produces better results on each criteria as compared to various other methods. The future development of the suggested model can be applied to enhance performance with relation to connection and coverage issues. Proposed future research The proposed research will focus on enhancing the NL in WSN by considering the mobility of the BS.

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