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ENERGY EFFICIENT ROUTE IDENTIFICATION AND CLASSIFICAION USING Q-LEARNING BASED TECHNIQUES

Y. Deepika[1], Dr V. Raghunatha Reddy[2]

[1]Research Scholar, Department of Computer Science and Technology, Sri KrishnaDevaraya University, Anantapur

[2]Associate Professor , Department of Computer Science and Technology, Sri KrishnaDevaraya University, Anantapur.

ABSTRACT

As increased advancements in electronics and in communication technology rapidly evolved, the use of Wireless Sensor Networks (WSN) also increased in which vast number of tiny sensors is used for communication. Researchers are facing significant challenges in developing a robust and energy-efficient routing protocol for the WSN. These routing protocols are used in various applications for the benefit of everlasting and to bring vital importance on every communication task. The existing approaches and models are forecasting the clustering and node selection mechanism and dis-regarded the other important aspects of the routing protocols such as safe and maintaining energy-efficient data transfer in communications. To provide such efficient routing protocol services, the development of resilient and key issues of energy management systems is mandatory. In order to determine energy-efficient route for the data transmission from the base node to the destination node the hybrid algorithm (Ant Colony Optimization (ACO) algorithm integrated with Particle Swarm Optimization (PSO) algorithm) is used where the trust and fitness values are considered to find the optimal solutions for routing in WSN. As the sensor nodes are dynamic in nature with large data sets and also to provide robustness it is needed to implement Q- learning based algorithms for the data classifications into train and the test data. The proposed technique also uses Adaptive Boosting (Adaboost) and Random Forest(RF) techniques for the classification of prediction results. The overall model is evaluated using the performance metrics comprising the accuracy rates, precision, throughput, delay and the packet-delivery ratios.

Keywords: Ant Colony Optimization Algorithm (ACO), Particle Swarm Optimization Algorithm (PSO), Adaboost, Random Forest (RF) Wireless Sensor Networks (WSN), Optimization, Effective Routing protocol, the.

1. INTRODUCTION

WSN are one of the most researched and used area looks for an increased energy efficiency, and the usage rates. But the main challenge lies in the transmission of data [1]. Low cost and the optimal routing protocols are some of the key motives of the WSN [2]. In this case, the data processing, topology management, routing and also the appropriate device control plays a significant role in the optimization of the energy, resulting in enhanced lifetime of the network [3]. Methods such as Opportunistic Routing are done and are applied in the WSN for enhancing the energy levels and also lifetime of the network, to overcome the power-asymmetry problems in the WSN, which results in decreased QoS and the lifetime of the network. This will also deploy a weaker routing protocol for the data transfer from the base node to the destination node [4]. As these WSN are evolved in key technologies for a domain of interest and owing itself to extensive range of applications, the routing protocol of the WSN are leveraged in view of reducing the utilization of the energy and also in enhancing the lifespan of the respective network [5].

These WSN are self-configured, used in monitoring the physical and the environmental conditions such as temperature, vibration, and pressure to pass the data via network to the desired location or a destination [6]. In

WSN, the energy preservation at the time of node coverage plays a vital role in the detection of the node failure and also in the efficient with the symmetrical data transmission among the nodes in the WSN. By making use of the cluster methods, with effective localization techniques, the nodes are grouped to discover the precise location of the nodes, to establish a connectivity among the neighboring nodes, aims in avoiding the node failure. But these are devoid in making a complete data transfer from one region to the other, with energy transfer at higher rates. [7]. Though many such approaches for resolving issues such as energy efficiency, forward secrecy and the anonymity laidback in making a real-time authentication and in making the key agreement protocols, these methods also lagged in making a lighter and devoid in being an easier applicable model for the realization of the authentication in the WSN schemes [8]. The process of routing in the WSN are not easy as they become uncertain if the sensor node fails during the phase of data transmission and the routing protocol should meet the power demands of the WSN. Along with the development in the WSN, the Large Scale WSN have also been developed which are used in various settings, such as healthcare monitoring, and in surveillance systems, where these data are collected using the sensor nodes and are transferred to the head nodes and end users. The location of the sink node being a major task in the WSN, optimization is also a challenging task in the data transfer via WSN, as these eventually lowers the energy consumption ratios of the sensor as it receives and sends data from one sensor node to the other by the consumption of energy [9].

Thus, choosing the optimal and the best node for the transfer will save the levels of energy consumption of the complete network which in turn results in the enhancement of the lifetime of the WSN network [10]. As these WSN are with a core constrain of limited energy resource using powered battery devices, which absolutely results in the decreased lifetime of the WSN network, and also an increased levels of energy exhaustion by the nodes [11]. This enhances the efficient workloads of the network, resulting in the incomplete network topology control and reduced interference among the sensor nodes [12]. As the determination of the distance among the sensor node and the sink node are one of the vital factor in the criteria of the energy consumption [13], if the distance among the terminal node and the sink node are too far, from each other, the rate of energy consumption will result in a surge and the lifetime of the respective network shortens [14]. Thus, choosing and in the determination of the optimal and the energy efficient routing affecting system are more vital in alleviating the lesser energy consumption rates [15]. Despite of several algorithm such as ACO, Fuzzy are used in the energy optimization and in the effective routing protocol and in scheduling the data transmission in view of preventing the collision of the messages, but laid back in providing the sufficient QOS and minimum delay in providing the immediate response to the data transfer event [15].

Unlike the ad-hoc networks, the WSN are designed in order to meet up the effective needs of the energy management and also should serve the terms of security, QoS and in minimum delay resulting in the immediate response to the event [15]. Due to the network system being homogeneous, there are identical forms of complexity and the energy usage are high to meet up the requirements of the critical resource and in order to minimize the energy consumption at different levels of the network in the WSN for an effective data transfer from the base station to the destination node [16]. In view of these requirements, researchers face significant challenges in developing the energy-efficient routing protocols for the WSN without discarding any of the significant data and also by integrating several vital aspects of the routing by integrating several critical characteristics [17]. The proposed work uses ACOPSO algorithm, for the efficient energy routing in the WSN, and Reinforcement Learning based classification using the hybrid Adaboost and RF algorithm, for the classification of better and energy efficient path for the data transfer. The complete evaluation of the model is done using the performance metrics comprising the accuracy, Precision, Recall, Packet delivery ratio, Delay.

AIM AND OBJECTIVES

The main aim of the proposed work is to find the optimal and the energy efficient path in the WSN for the node transfer from the Base node to the destination node along with efficient determination of the path classification based on the Q-learning mechanism done using the AdaBoost and RF. The objectives of the proposed work are correlated with the aim as follows.

To classify the optimal path detection using the Q-learning (Reinforcement Learning) method for efficient routing protocol for the data transfer.

To evaluate the overall performance of the proposed model using the appropriate comprising the accuracy rates, precision rates, throughput, delay etc., for validating the performance of the proposed model in routing protocol and data classification.

PAPER ORGANIZATION

The complete paper is categorized into five separate sections, which includes the section I explains a brief introduction about the entire methodology and the approach followed. Section II briefs some of the existing models used in the same routing protocol for WSN. Section III deliberates the complete methodology of the entire study. Followed by the section IV explains the results and the outcomes obtained after the implementation. Finally, the section V briefing a conclusion for the proposed study.

2. REVIEW OF EXISTING WORKS

There are many related conventional and existing methods and procedures done for finding the best and the efficient route for the data transfer in the WSN and in decentralized IoT-based systems. The suggested study [18] has used a smooth path finding mechanism, using Incremental Grey Wolf Optimization (GWO) and Expanded GWO for finding the vital parameters for the data transfer in WSN but are not applicable in finding the routes using the heterogeneous nodes. The efficient cluster head selection results in enhancing the lifetime of the network and less energy consumption in the WSN [19] which are deployed in the specific WSN area, using effective load balancing techniques. But these methods are complex in the run time and in clustering for finding the route using Fixed Parameter Tractable (FPT) algorithm for the optimization process.

Defined and an adaptive strategy finding are essential in efficient routing mechanism in WSN [20] by the exploration and the exploitation phase, using the metaheuristic algorithm Sand Cat Optimization algorithm, but takes more of complex parameters and operations for the complete solution. The extension in the survival time of the nodes in the WSN, by efficient cluster based routing mechanism by the GA and the PSO [21], used in the optimized CH selection and optimized route for the mobility of sink are used in the suggested study, but the end-to-end delay and the cost efficiency lagged in the complete mechanism. The optimized CH selection using the GA in the heterogeneous WSN [22] for a multiple data sink done using the integration of various parameters, for the formulation if the fitness function, but are not applicable for applying them in hostile and reactive WSN applications and more of enhancement can be made in the moving sink scenarios. Several research works are done upon the survival time of the sensor node in the WSN, where PSO with Energy Efficient clustering Formation (EECF) with sink mobility parameters [23] are used in the heterogeneous WSN but can be made cost efficient and reduce the time delay by making a hybrid form of algorithm approach.

The optimization of the energy hole issues is associated in WSN, resulting in more of drained energy. This happens when the Base Station is far from the gateway. this can be reduced using the energy efficient clustering using the GWO [24], but these applications are not applicable when there is an intentional change in the location of the sensor or the gateway of the sensor nodes in WSN. The key parameters relied in the designing of WSN are the high reliability and the low cost with an easier maintenance [25]. For a large-range Multi-sink WSN, using simulated annealing methodology with GA as a hybrid approach [26] for performing clustered routing using a two-level heterogeneity approach in WSN. But these methods are not capable to make them use with the multi-level heterogeneous WSN networks. To enhance the data access mechanism and the reliability challenges of the mobility in the WSN which are endured with the information Centric, in the suggested study using Black Widow Optimization technique and the Optimized Bee Colony (OBC) algorithm [27] for the CH selection and path for WSN, which are less applicable to the vast WSN, but can be applied using the ML techniques. The limited energy resources and harsh properties of the WSN are making them more difficult in the tasks of routing [28].

The IoT based WSN are completely relied on the efficient routing mechanism where the occurrence of the faulty node results in increased energy consumption and the stability of the WSN [29]. To overcome these issues the suggested study used a centralized form of the clustering protocol which is a Low-Energy Dynamic Clustering [30] are developed for emending the query-based WSN. But this clustering mechanism will consume more of energy and results in increased workload in the CH selection in the WSN. To solve these approaches, the energy consumption and the residual energy of each nodes are found in the suggested study using the GWO and the dual-hop for the routing mechanism are used in the suggested study [31], for ensuring the minimal and a balanced consumption of energy, for the nodes which are far from the base station and the single-hop for the nodes near to the BS. But this protocol can be served with enhanced Quality of Service (QoS) in consideration to serve large WSN. The Cluster-Tree-based protocol for the routing in the WSN are introduced for reducing the

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rates of latency, and also for creating a cross communication systems, with the mobile-sink as the center for making the improvement in the utilization of the nodes in the WSN [32]. These approaches are meant for enhancing the lifetime and also decreases the number of transmission hops for reducing the latency in the data, where these approaches can be made hybrid to enhance the lifetime of the WSN.

The Enhanced Fuzzy Based protocol for the routing approach for the WSN are developed, used in the formation of the cluster, using the PSO algorithm and using the EFERP for the transmission of these data from BS, but these approaches are applicable only to smaller number of nodes and the data taking smaller number of iterations, but are less applicable to a large BS associated WSN [33]. Some of the limitation associated with the WSN [34] are the complexity of high configuration, capacity in the communication, lower speed in communication and limited computational which results in optimal energy usage systems in the WSN. This emerged CH-IoT-WSN which resulted in the decreased power consumption and the cost function, but also minimizes the performance of the network eventually and are also not capable to act with the sensors which changes the position in the real-time. The suggested study uses the "low-energy adaptive clustering hierarchy" (LEACH) based on the Trust-Management [35], which is used in increasing the size of network, and also the lifespan of the network, and also in maintaining the scalability of the network used in defending against the internal attacks occurring [36]. Several AI based routing protocols are used in the WSN for finding the optimal path of routing in the node transfer, using the TIDE approach [37] which is more time-relevant form of deep reinforcement learning method, taking the network as the input, results in the failure of the learned language. To overcome these drawbacks [38], [39] in the effective routing protocol in the WSN, such as the effective protocol for the heterogeneous nodes, complex node connectivity, increased run time for the node transfer from the base node to the destination are managed in the proposed study using the optimal path selection and the classification of the energy efficient route using the Reinforcement Learning protocol using the Adaboost with RF algorithm.

3. PROPOSED METHODOLOGY

The Wireless Sensor Networks known as the WSN, is actually less in infrastructure and are deployed in huge number of wireless sensors. Some of the existing approaches have taken only the concern of cluster head selection and also the security on the data transfers but have missed recognizing the energy efficient and optimal routing protocol for the data transfer. The proposed work for the effective routing mechanism or the protocol for the data transfer from the base to the destination node are initialized by finding the optimal and the effective routing path for the node to transfer. This work uses an ACOPSO algorithm, following both the Ant Colony Optimization and the Particle Swarm Optimization method, where both these algorithms are used in the optimization of the pheromones, finally used in finding the optimal fitness function value and is used in finding of optimal routing path for the node to transfer from the base station to the destination. This is first done by deploying the appropriate system model which are used in initializing the agents, of the node transfer. The complete protocol is shown in figure 1.

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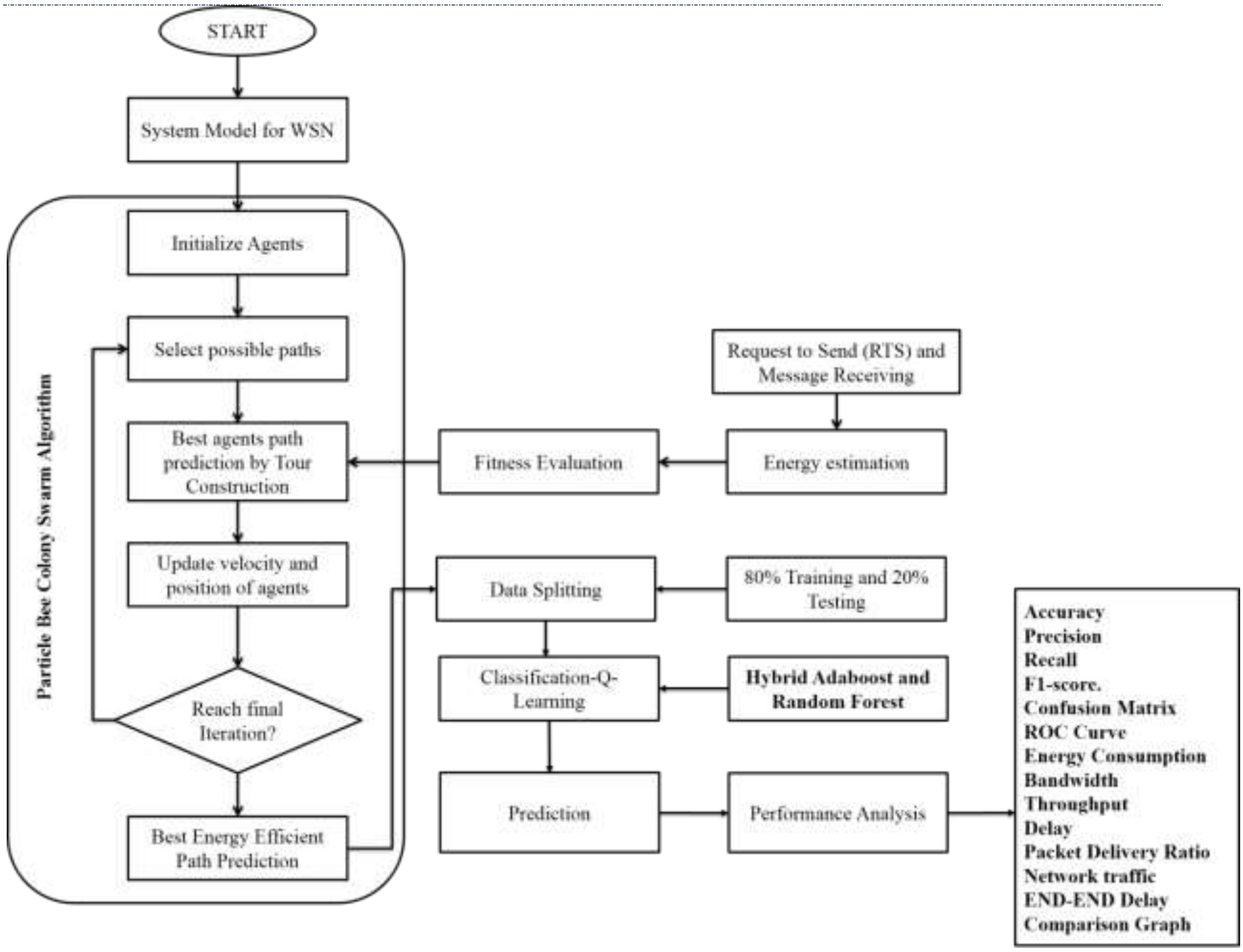

Figure 1 Overall Flow of the Proposed Methodology

These algorithms are used in the pheromone matrix update and also in the generation of the PSO particles. These are used in selecting the possible and the optimal path for the node transfer, by predicting the best agents, using the tour construction method. During this process, the fitness function value is evaluated by checking its optimal values of the energy consumption, occupied by the process of selecting the best agents for the optimal path selection via the Request to Send (RTS) and receiving process, where the data are transferred from the BS to the destination node via many interrupting nodes. Following this, the velocity and the positions of these agents are updated regularly. When the optimal and the efficient path is found and reached, the final iteration is reached.

Followed by this, the data are split into the train and the test data at the ratio of 80% to 20%, where the train data is used in training the model and the test data is used in testing and in evaluating the model efficiency. This classification of the data is done using the Reinforcement Learning (RL) comprising the hybrid model of both the Adaboost and the Random Forest (RF), which are used in the prior analysis of the future data which can be provided for the better classification of determining the efficient or the insufficient path for the data transfer. These are also used in solving the complex problems, which are devoid by the conventional algorithms, and can also achieve long-term results, these models can be applied to even large datasets, as they do not require more of labelled data. Also, these RL are capable of producing higher accuracy rates in the prediction and also in the classification providing a defiance to the minimal standard of performance. The behavior of the respective model using the RL is also increased visibly. Finally, the prediction of optimal routes using the proposed approach are evaluated for their performance using the appropriate performance metrics comprising the accuracy rates, precision values, delay, Packet delivery ratio and other suitable performance metrics.

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ACOPSO algorithm for optimal path selection

The ACOPSO algorithm in the respective study is used for the determination and in the selection of the optimal and the energy efficient path for the node transfer from the base node to the destination node via the optimal and the energy efficient path which has less energy consumption and also prevents the chances of data loss. The ACO algorithm, relies or works on the basis which mimics the act and the behavior of the ant, which always determines and selects the optimal and the shortest distance for the search of food to their destination. When the existing path seems unfit, the ant tries in creating and in optimizing the new and the efficient path for the travel by depositing some of the trail pheromones. These pheromones are operated among the other ants via efficient forms of communication, and return back to their destinations, in an efficient way. The complete algorithm is descripted in algorithm I.

ALGORITHM I :ACO- ANT COLONY OPTIMIZATION ALGORITHM

Set the base attractiveness, t_i , and visibility, η, for each edge;
for ii < IterationMax do:
for each ant do:
Choose randomly (based on equation) the next state to move in todd that move to the memory(tabu list)for each antadd that move to the memory(tabu list) for each ant;
repeat until each ant completed a path;
add that move to the memory(tabu list) for each ant;
repeat until each ant completed a path;
end;
for each ant that completed a path do:
update attractiveness t for each path(edge) that theant traversed;
end;
if (local best path better than global path)
save local best path as global path;
end;
end;

PSO algorithm is considered to be one of the most effective forms of meta-heuristic algorithm, used in the process of optimization, which are initiated by the behavior nature of swarm. This meta-heuristic algorithm takes a few or devoid of the assumptions, regarding the respective issue and are able to examine and optimize huge spaces of the candidate solution. These PSO has more of several other advantages, which has rapid convergence, more efficient and capable in solving various issues which are related to the optimization being an efficient form of global search algorithm. The complete algorithm is mentioned in the algorithm II.

ALGORITHM II: PSO – PARTICLE OPTIMIZATION ALGORITHM
Step 1: Particle is initialized: establish a population of particle spread over R_{iN} Here R is N_i dimensional Search space **Step 2**: Fitness value is calculated: compute position of each particle by considering objective function. **Step 3**: Detect the finest position Pbest (P_i): if a particle's existing location is considered to be better than the preceding best position, promote the position **Step 4**: Detect the superlative position globally Gbest (P_g): the particle's position is represented as Gbest **Step 5**: Apprise the position of the particle $Xid = Xid + V_i Id$ **Step 6**: Terminate the process, if conditions are fulfilled if not go to ii.

The existing methodology uses the hybrid form of ACO-PSO algorithm, for finding the optimal and the energy efficient path for the WSN. Unlike, the traditional form of ACO and PSO algorithm, the proposed hybrid ACO-PSO algorithm makes use of all the parameters in the algorithm. When the PSO and the ACO are made to the hybrid form, in view of reducing the attributes, the PSO still maintains the robustness of each of the particle.

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The implementation of the GA requires more of iterations for the proper functioning. Whereas the PSO algorithm requires only few and a simple form of primitive methods, and operators for the optimization function. Thus the proposed work considers the ACO-PSO algorithm for the determination and also in the selection of the optimal and energy efficient path for the WSN. The complete hybrid ACO-PSO algorithm is described in Algorithm III.

ALGORITHM III: ANT COLONY OPTIMISATION WITH THE PARTICLE SWARM OPTIMISATION ALGORITHM

Set the base attractiveness, t_i , and visibility, η, for each edge;
for ii < IterationMax do:
for each ant do:
Choose randomly (based on equation)the next state to move
intodd that move to the memory(tabu list) for each ant
add that move to the memory(tabu list) for each ant;
repeat until each ant completed a path;
add that move to the memory(tabu list) for each ant;
repeat until each ant completed a path;
end;
for each ant that completed a path do:
update attractiveness t for each path(edge) that theant traversed;
end;
if (local best path better than global path)l
save local best path as global path;
end;
end;
Initialization of particle:
organize a population of particle spread over R_{iN}
Here R is N_i dimensional Search space
Calculate the fitness value: calculate each particle's position with the help of objective function.
Find the best position Pbest (P_i): if a particle's present position is better than the previous best position, upgrade the position
Find the best position globally Gbest (P_g): the positionof particle denoted as Gbest (according to particles best position)
Update the particle position
$Xid = Xid + V_iId$
Stop if criteria are satisfied otherwise go to ii

Adaboost and Random Forest for classification based on Q-learning

Adaboost is one of the boosting technique. In the proposed study the respective algorithm is used in the classification by Reinforced Learning (RL) method, as they require only few of hyperparameters for tuning than the other conventional algorithms. Whereas, the adaboost enhances the accuracy of the weaker ML models and avoids the model from overfitting, as the input parameters are optimised individually. The accuracy levels of the weak classifiers are also enhanced using the adaboost algorithm. These RL based boosting algorithm can make more of accurate predictions, as this is one of the iterative form of ensemble method. As this method combines, multiple poor classifiers to obtain higher accurate and strong classifiers. As both the adaboost and the RF algorithm are based on the reinforcement learning mechnism, are capable of making more of curious and accurate classifications of the model by enabling the detection of optimal routes for effective data transfer The complete algorithm is presented in Algorithm IV.

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ALGORITHM IV: ADABOOST ALGORITHM
Given $(x_{i1}, y_{i1}) \ldots \ldots \ldots \ldots \ldots \ldots (x_{im}, y_{im}), x_{ii} \in X_i, y_{ii} \in Y_i = \{-1,1\}$ Initialize$D_{ii}(ii) = 1/m_i$ For $t_i = 1 \ldots \ldots \ldots . T_i$ Train Weak classifier using distribution D_i Get Weak hypothesis $h_{ii}: X_i \rightarrow \{-1,1\}$With error $\sum_{ii:h_{it}(x_{ii}) \neq y_{ii}} D_{it}(x_{ii})$ Choose $\alpha_{it} = \frac{1}{2} \log \left(1 - \frac{\varepsilon_{ti}}{\varepsilon_{ti}}\right)$ Update $S_{hi} := \sum_{i=1}^{n} X_{ii}.W_{ii} + b_i$ // calculate the sum of the inputs $(X_{i1}, X_{i2}, X_{i3} \ldots \ldots \ldots \ldots .. X_{in})$ multiplied with their $(W_{i1}, W_{i2}, W_{i3} \ldots \ldots \ldots \ldots .. W_{in})$ for hidden layer node output hidden $\leftarrow \emptyset(s_{hi})$ output for hidden layer node $S_{out} := \sum_{i=1}^{n} X_{ii}.W_{ii} + b_i$ // input for output layer nodes $D_{it+1}(ii) = \frac{S_{out}(ii)}{Z_t} = \{\frac{e^{-\propto t} \text{ if instance ii is correctly classified}}{e^{\propto t} \text{if instance ii is not correctly classified}}$ Where Z_{if} is a normalization factor (chosen so that $\sum_{ii=1}^{m_i} D_{it+1} = 1$ Output the Final hypothesis $H_i(x_i) = \text{sign}(\sum_{t_i-1}^{T} \propto_{it} h_{it}(x_{ii}))$

RF is able to perform both the regression and the classification tasks, which are able in bringing better predictions that are made for easier understanding. These algorithm are capable to handle large datasets efficient in terms of classification, and are able to produce higher levels of accuracy rates in predicting the outcomes. These are also capable in making the automated generation of the values in the data which are missing. The complete algorithm of the RF is presented in Algorithm V.

ALGORITHM :V- RANDOM FOREST ALGORITHM
Input : Training Examples Forward Pass: $W_{ii} = \text{Value}_{random}$ Initialize Weights by Random Values $S_{hi} := \sum_{i=1}^{n} X_{ii}.W_{ii} + b_i$ // calculate the sum of the inputs $(X_{i1}, X_{i2}, X_{i3} \ldots \ldots \ldots \ldots .. X_{in})$ multiplied with their $(W_{i1}, W_{i2}, W_{i3} \ldots \ldots \ldots \ldots .. W_{in})$ for hidden layer node output hidden $\leftarrow \emptyset(s_{hi})$ output for hidden layer node $S_{out} := \sum_{i=1}^{n} X_{ii}.W_{ii} + b_i$ // input for output layer nodes $\text{output}_{predict} \leftarrow \emptyset(S_{out})$ // At output nodes Compare Error $(\text{output}_{predict} - \text{output Actual})$ Find Error Rate // from hidden layer Hl to output layer nodes Find Error Rate // from hidden layer Il to output layer nodes Update network weight $(\text{output}_{predict} - \text{output Actual})$ Output Trained Neural Network

Both these algorithm (Adaboost) and (Random Forest) are based on the Q-learning mechanism, which are more applicable and are capable of making more accurate predicitions, in the proposed method. This makes the behaviour of the particular model to be increased as the previous model are stable and can be remembered from the previous learned samples and are also able to learn the new and the upcoming samples. When the data are split using the Q-learming, can make a precise divide in the space problem, which can make the model achive

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the respective goal on each of the corresponding sub-regions. The complete hybrid Q-based Adaboost and the RF are provided in Algorithm VI.

ALGORITHM VI: ADABOOST AND RANDOM FOREST
Input: WSN dataset Output: Prediction for path Attack or Non-Attack Step1. Procedure Initialize (θ_i) Step2. Grow initial forest θ_i with feature vector f_o Step 3: While $V_i \geq f_o$ Step 4 : do Step 5 : Compute mean μ_o and standard deviation σ_o of feature weights in T^o Step 6 : Find $F_{i1} = F_o - R_i$ Step 7 : Find $\nabla_{ui} = \#T_{i_{n+1}} - T_{i_n}$ $\nabla_{vi} = \#T_{i_{n+1}} - T_{i_n}$ Step 8 : Find Feature Vector $F_{in+1} = F_{n_i} - R_{n_i}$ Step 9: update feature $T_{i_{n+1}} = T_{i_n} + A_{i_n}$ $T_{i_{n+1}} = T_{i_n} - A_{i_n} - R_{i_n}$ Step 10: Training vector Step 11 end For Step 12 : Testing vector Step 13 : Update Classification result Step 14 : End procedure

4. RESULTS AND DISCUSSIONS

The complete section deals with the experimental results after the implementation of the proposed model, for finding the energy efficient and effective route for the data transfer in the WSN, by selecting the suitable and the possible path by predicting the best agents for the effective routing mechanism, and are also represented using the comparative analysis by comparing the proposed model with the existing models for the routing protocol in WSN.

PERFORMANCE METRICS

The respective section deliberates some of the performance metrics for the analysis of the performance of the proposed model using various metrics. The projected study is evaluated via the metrics like accuracy, precision, recall, packet delivery ratio and the overall delay.

a. Accuracy

This metric is used in giving the measure of the model proposed across all the classes.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (1)$$

b. Precision

This metric is used in the retrieval of the information, and the instances considered vital for the model performance. These are the ratio of the true positives to the total true positive and the total false positive rates.

$$Precision = TruePositives \,/\, (TruePositives + FalsePositives) \quad (2)$$

c. Recall

This metric is used in defining the model detecting the positive instances to the total number of true and the false incidents of the proposed approach.

$$\text{Recall} = \text{TruePositives} \,/\, (\text{TruePositives} + \text{FalseNegatives}) \quad (3)$$

d.F1-Score

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F1 score is denoted as the weighted harmonic-mean value of precision and recall, the F1 score is estimated with the following equation

$$F1 - score = 2 \times (Rc \times Pc)/(Rc + Pc) \quad (4)$$

Where, P is denoted as precision and R is denoted as recall.

B.EXPERIMENTAL RESULTS

This respective section is used in depicting the tangiable and also the intangiable outputs of the proposed model obtained that are generated using the provided model or the methodology used. The Figure 4. Depicts the communication network plot of the WSN obtained after the proposed model in finding the energy efficient route for the communication from the base station to the destination.

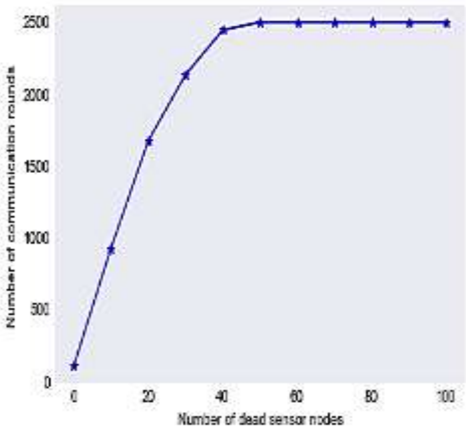

Figure 2 Communication network plot

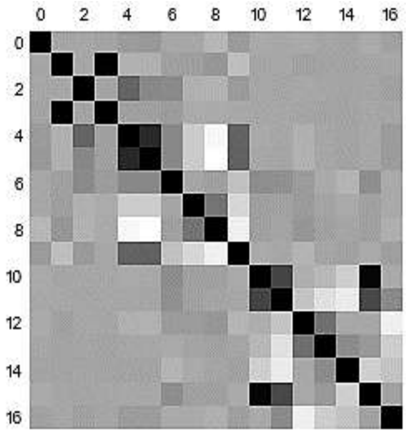

Figure 3 Correlation matrix

The figure 2 and 3 representing the communication network plot which is obtained after the implication of the efficient routing in the WSN, obtained after using the ACOPSO and hybrid AdaBoost and RF for the classification effective routing in the WSN. The communication network plot is represented in figure 2, which is used in defining the capability of the network, in transfering the node from the Base station to the destination node with higher efficiency rates, without any loss in energy value.

The correlation matrix in figure 5, is used in representing the correlation coefficients among the variables. This is also used in showing the possible pairs of the values which can be made from the table. This is one of a poweful tool in identifying and in visualising the patterns in the given data.

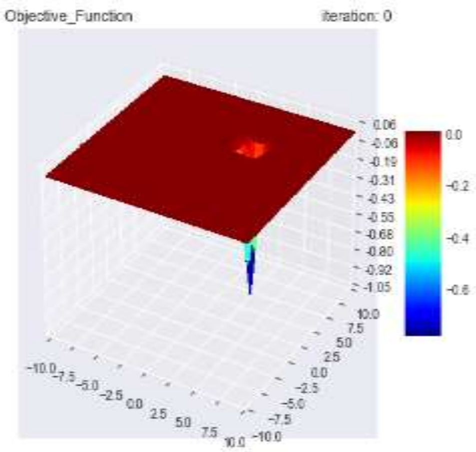

Figure 4 Representation of Objective function

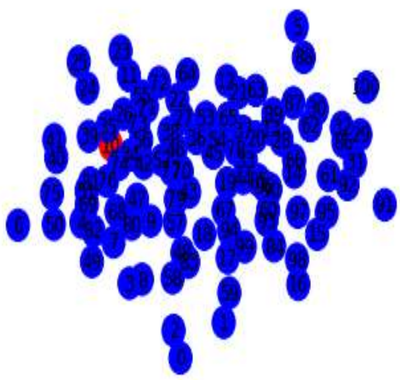

Figure 5 Representation of System model

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The Figure 4 representing the objective function, which can be either minimised or can be maximised which is a numeric form of value. This objective function is represented using the features (objective Function) obtained fronm the PSO in the rotation of where the node travels from the Base station to the destination and again to the base station. These are obtained in the form of 3D waves which are represents in the scale format in Figure 4.

These are real-valued function which can be set over a feasible alternatives. These are a linear function which are represented using the linear function as z=ax+by. The figure 5 representing the sysytem model which is deployed in the proposed system for finding the efficeint routing protocol in the WSN. Whereas the figure 5 representes the number of input nodes in the blue colour and the destination node in the Red colour. This represents the number of input node correclty reaches the destination node during each of the iteration.

C. PERFORMANCE ANALYSIS

The performance of the proposed system are analysed in the respective section, which is represented in emphasising the performance of the proposed model in the effective routing protocol in the WSN. This section is attributed to show the complete working of the proposed methodology in different aspects.

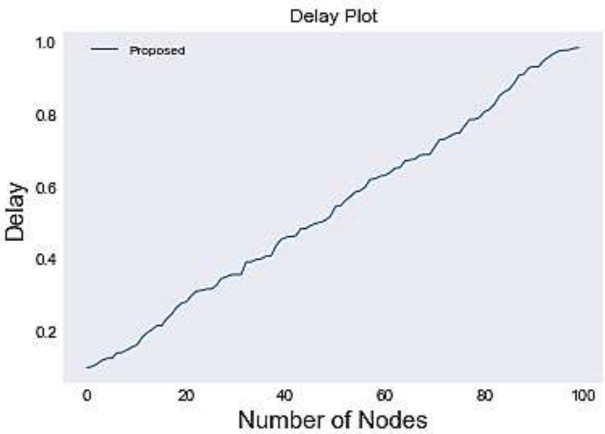

Figure 6 Delay plot

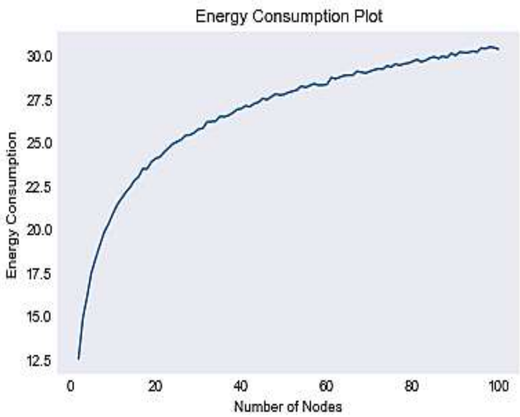

Figure 7 Energy consumption plot

The figure 6, represents the delay plot which is used in representing the time of delay taken for the packet to travel from the base station to the destination via WSN of the proposed ACOPSO and hybrid AdaBoost and RF algorithm for the Q-learning classification. The delay plot vitally represents the delay in the time to make reach the number of nodes, from the base station to the destination point. The delay time and the efficiency of the model are inversely proportional to each other. Where an efficient model takes a lesser delay time for the data transfer from the BS. Whereas, the figure 7 represents the levels of energy consumed by the proposed system for the data to travel from the Base Station to the destination. The energy consumption is directly proportional to the efficiency of the model, where less amount of energy consumed results the better operation of the model and more of energy consumption result

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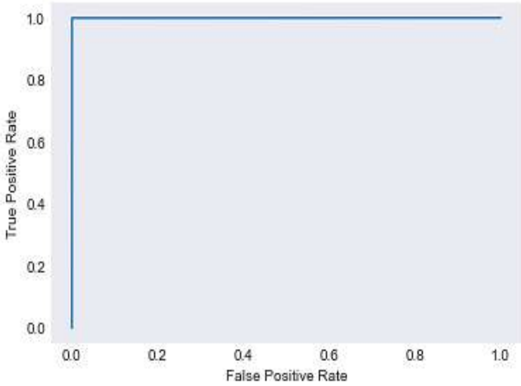

Figure 8 False Positive rate Plot

The Figure 8 represents the false positive rate, which depicts the models efficacy, where less false positive rate exhibits the higher efficiency of the proposed model. This is calculated using the number of negative events which are incorrectly categorised as the positive instead of negative is known as false positive, which shows the less effectiveness of the model.

D. COMPARATIVE ANALYSIS

The proposed model is compared with the exisitng models which are used in the WSN for evaluating their efficiency and to validate the proposed model outperformance with the existing models.

Table 1 Comparative analysis of the existing and proposed model under various parameters [40]

Topology	**Method**	**Total reward**	**Average file transmission time (s)**	**Average speedup**	**Average speedup**	**Action changes**
Fat-tree-structure	RL-Routing	542.33	88	0	0.28	7.4
	OSPF	383.21	222.6	2.52	0.14	0
	LL	477.54	168	1.9	0.17	35.7
Proposed	RL-Routing	642.56	69	0	0.18	3.2
	OSPF	451	124	0.1456	0.16	0
	LL	504.56	150	1.2	0.17	20.3

The table 1 shows the comparision with the existing model of Fat-tree, which is a three-layered structure being a 3D structure, consists of a core-switch, aggregation and also the edge switch [40]. This model consists of some of the protocols such as RL-Routing which is one of a SDN routing algorithm, completely based on the DL method. The Open Shortest Path First known as (OSPF) and the Least Loaded (LL) routing algorithm, which are some of the protocols which are evaluated for the efficiency of the proposed model in finding the efficeint path for enhanced data transfer. the effective Routing protocol mechanism, under various parameters, such as total reward, the total transmission time taken in an average, the average speed up levels and also the action changes occuring in the routing protocol. When, comapred the exisitng and the proposd model, the porposed model using the ACOPSO and the hybrid Adaboost with RF derived better results.

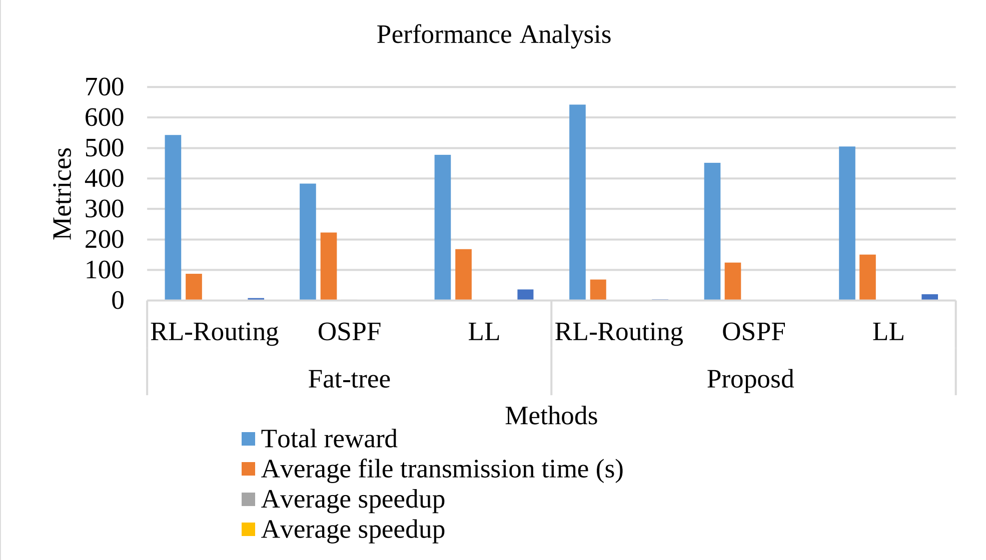

Figure 9 Comparative analysis of the existing and proposed model under various parameters

The figure 9, representing the comparision among the Reinforcement Learning for the routing protocol, with the proposed ACOPSO model in the effective routing protocol or a mechnism, the figure clearly depicts that the proposed model had outperformed than the existing routing protocol model.

Table 2 Comparative analysis of the existing and proposed model in terms of Precision values **[41]**

Precision	
CNN	82
F-CNN	92
Proposed	**99.9673**

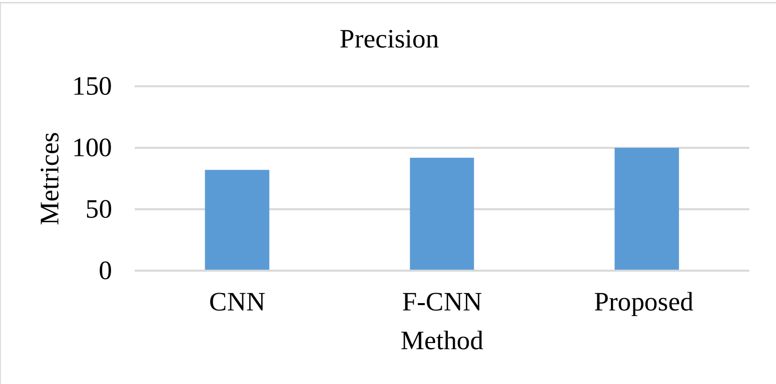

Figure 10 Comparative analysis of the existing and proposed model in terms of Precision values

The table 2 and figure 10 shows that when the proposed model is compared with the existing approaches **[41]**, shows that the proposed model had outperformed the existing Convolutional Neural Nwtwork (CNN) and the Fully Convolutional Neural Network (FCNN) models and had shown the precision rates with a value of 99.96%, better than the existing models showing the precision range of 82% and 92% respectively.

Table 3 Comparative analysis of the existing and proposed model in terms of Recall values [41]

	Recall
CNN	82
F-CNN	92
Proposed	**99.9673**

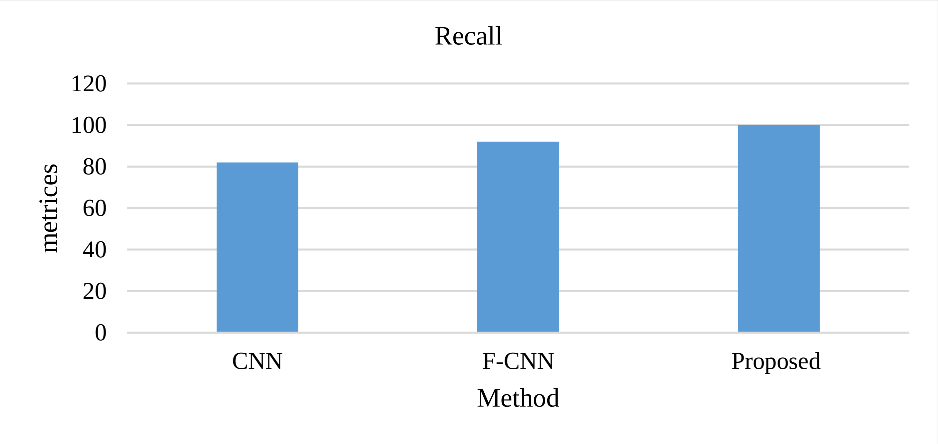

Figure 11 Comparative analysis of the existing and proposed model in terms of Recall values

The table 3 and figure 11 representing the comparision among the existing and the proposed model in terms of the recall values obtained for the efficient routing protocols for the data transfer in the WSN. The results when compared with the existing approach [41], shows that the proposed model had achieved higher levels of precision rates than the exisitng models achived only a precision rates of 82% and 92% where the proposed model had achieved an precision rate of 99.9673% .

Table 4 Comparative analysis of the existing and proposed model in terms of Accuracy rates

Existing [41]	**ACCURACY**
DT	80
RF	81
CNN	82
F-CNN	92
Proposed	**99.9673**

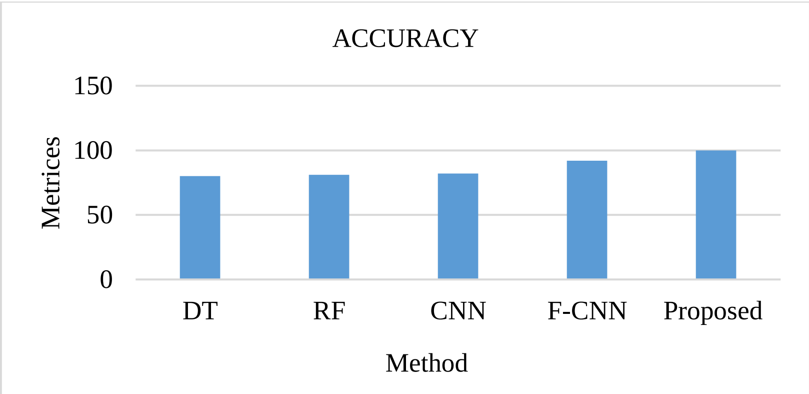

Figure 12 Comparative analysis of the existing and proposed model in terms of Accuracy values

The figure 12 and table 4, when compared with the existing models, [41] had achieved an accuracy rates of 80%, 81%, 82% and 92% which are obtained using the Decision Tree (DT), Random Forest (RF), Convolutional Neural Network (CNN) and the Fully Convolutional Neural Network (F-CNN) models in the existing approaches. The obtained results showed that the proposed model have achieved an accuracy rates of 99.96% which outperformed the existing models and approaches.

Table 5 Comparative analysis of the existing and proposed model in terms of Packet Delivery Ratio

Method	Packet Delivery Ratio [41]
O-LEACH	92
FRCSROD	94
DMCNN	95
ASNGSRA	97
Proposed	**99.9673**

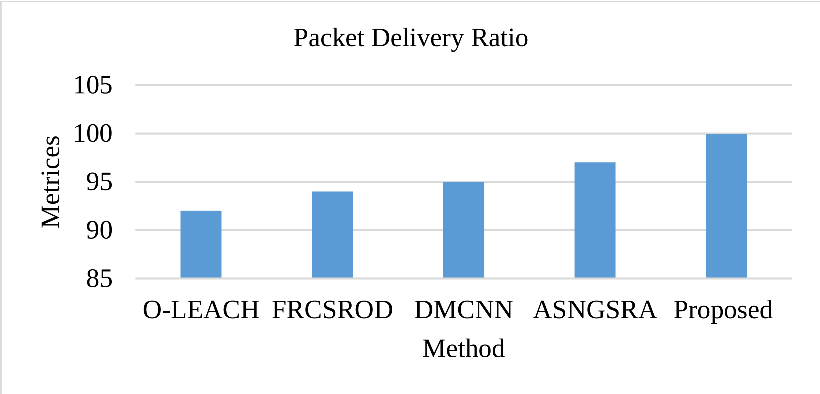

Figure 13 Comparative analysis of the existing and proposed model in terms of Packet Delivery Ratio

The proposed model when compared with the existing approach in terms of the packet delivery ratio, which is used in depicting the number of nodes which is sent from the base station to the destination node, without much of energy and the data loss during the transmission. On a comparision the proposed model had achieved higher levels of the packet delivery ratio than the existing models which comprises approahes such as O-LEACH, known as Low Energy Adaptive Clustering Hierarchy, Fuzzy Rule and Cluster based Secure Routing technique with Outlier Detection (FRCSROD), Method Based On Deep Multi-Scale CNN, A-Star Search Based Neuro-Genetic Secure Routing Algorithm (ASNGSRA) methodologies in [41], achiveing the ratio at a range of 99.96% which are more efficient than the existing approaches achieving only a range of 92% to 95%, wnich are represented in table 5 and in figure 13.

Table 6 Comparative analysis of the existing and proposed model in terrms of Delay rates

Method	Delay [41]
O-LEACH	30
FRCSROD	28
DMCNN	25
ASNGSRA	15
Proposed	**10.2**

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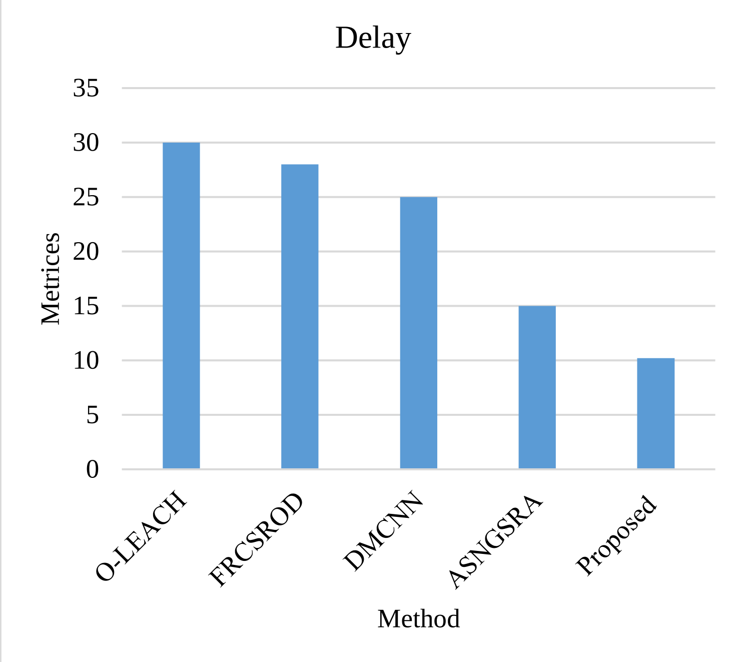
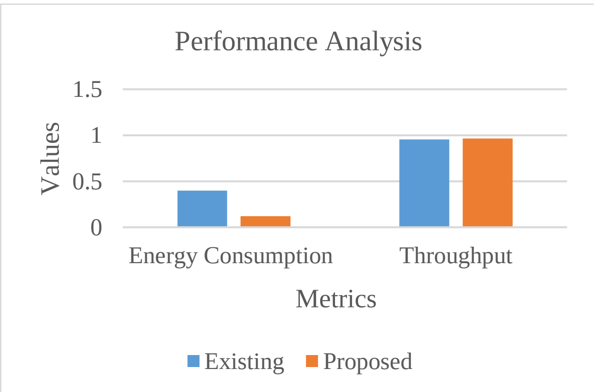


Figure 14 Comparative analysis of the existing and proposed model in terrms of Delay rates

The table 6 and figure 14 representing the delay in the roting protocol for making the packet reach from the BS node ot the destination node in ht eWSN. The incresed in the delay levels represent the less efficacy of the model. The results obtained clearly shows on a comparision with the existing models [41], which had achived higher rates of the delay in making the data transmission, where the proposed model have comparatively taken less time of delay in the data transmission.

Table7 Comparative analysis of the existing and proposed model in terrms of different vital parameters

	Energy Consumption	Network Life time	Throughput
Existing [42]	0.40	32320	0.9542
Proposed	**0.12**	**41000**	**0.9648**



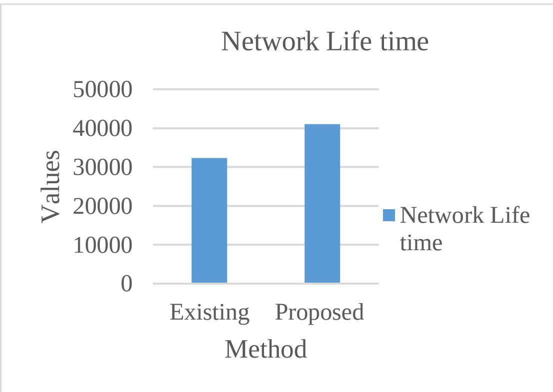


Figure 15a. Analysis with regard to vital metrics ***Figure 15b. Analysis with regard to network lifetime***

The figure 15a, figure 15b and table 7 represents the overall consumption of energy, the values of throughput and also the complete life-time of the network. On a comparative analysis [42], the outcomes have shown that the proposed model had outperformed all these parameters and hence shown its increased efficacy in the efficient routing protocol in WSN.

Table 8 Comparative analysis of the existing and proposed model in terrms of Recall values

Recall [43]	
SVM	0.9
MLP	0.92
Proposed	**0.996**

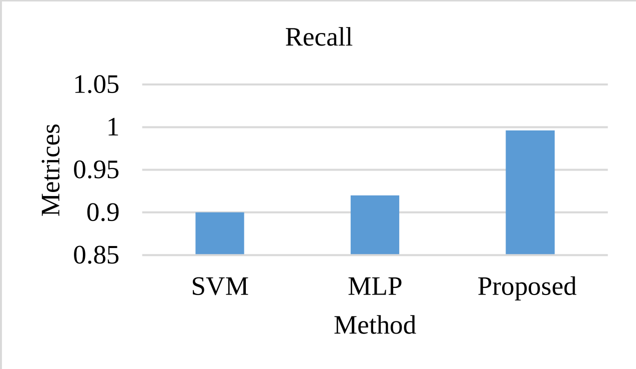


Figure 16 Comparative analysis of the existing and proposed model in terrms of Recall values

The figure and the table representing the overall recall values which are obtained for the proposed and the existing models [23], which have clearly showed that the proposed model had outperformed the exisitng models in terms of the recall values, where our proposed model have achieved recall rates of 0.99, which are comparitively more than the existing models which consisits approaches such as Support Vector Machine (SVM), Multi-Layer Perception (MLP). These are clearly explainded in figure 16 and in table 8.

5. CONCLUSION

The proposed model Q-learning based approach with Adaboost and Random Forest techniques provide a complete study over the energy effective routing for the data transfer in the WSN. In view of searching the optimal routing path, the consideration of the characteristics of the WSN, the probabilistic node state and the transition phase for the selection of path by the ACO and the optimal route determination using the PSO algorithm are deployed for effective routing protocol. In addition to this the Reinforcement Learning based approach, are used in the classification for finding the optimal and energy efficient route along with data transfer with more accurate predictions. The respective model is more stable in the predictions, and in classifications, which had achieved an accuracy and the precision rates in the levels of 99.96 and a less energy consumption rates with higher ratios of the packet delivery in a range of 10.2 and 0.84 respectively. In view of the future work, the respective model can be implemented to complex form of heterogeneous networks by simplifying the easier mathematical models for the development of the advanced and robust energy efficient WSN models

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