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IRDFPR-CMDNN: An energy efficient and reliable routing protocol for improved data transmission in MANET

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Abstract
Mobile Ad hoc Networks (MANET) are structure less, autonomous wireless networks with mobile nodes that dynamically establish data transmission connections. Due to dynamic topological change, MANET routes are unbalanced and break repeatedly. Hence, providing efficient and reliable data delivery with effective utilization of network resources is a challenging issue to be considered in MANET. This paper proposes an instant-runoff Ranked Decision Forests Probit Regression-based Connectionist Multilayer Deep Neural Network (IRDFPR-CMDNN) for efficient data transmission and higher data delivery with a minimum end-to-end delay. This IRDFPR-CMDNN method performs route identification, data delivery, and route maintenance with more than three layers. Then the mobile nodes are sent to the input layer of the Connectionist Multilayer Deep Neural Network. In hidden layer 1, the Instant-runoff Ranked Decision Forests algorithm is applied for classifying the mobile nodes depending on the residual energy and load capacity. With selected mobile nodes, the Probit Regression is applied for finding the nearest neighboring nodes in the second hidden layer based on the link quality and received signal strength for route path establishment. Then multiple paths for routing are established from source to destination node and start to perform the data transmission. If link failure occurs during the data transmission, another alternative route with better link quality is selected for routing. In this way, energy-efficient data transmission is performed from source to destination with a higher data delivery rate and minimal time consumption. Experimental evaluation is carried out on energy consumption, packet delivery ratio, packet drop rate, throughput, and end-to-end delay with varying numbers of mobile nodes and data packets. Simulation results show that the IRDFPR-CMDNN technique effectively enhances data delivery, throughput and minimizes energy consumption, packet loss rate, delay with respect to conventional methods.

Keywords
routing and data delivery, connectionist multilayer deep neural network, instant-runoff ranked decision forests algorithm, probit regression

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УДК 004.89

IRDFPR-CMDNN: энергоэффективный и надежный протокол маршрутизации для улучшенной передачи данных в MANET

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Аннотация

Мобильные одноранговые сети (Mobile Ad hoc NETworks, MANET) — бесструктурные автономные беспроводные сети с мобильными узлами, которые динамически устанавливают соединения для передачи данных. Из-за динамических топологических изменений маршруты MANET оказываются несбалансированными и постоянно прерываются. Следовательно, обеспечение эффективной и надежной доставки данных с эффективным использованием сетевых ресурсов является сложной задачей, которую необходимо в MANET учитывать. Предложена многослойная глубокая искусственная нейронная сеть на основе пробит-регрессии с ранжированными решениями (IRDFPR-CMDNN) для эффективной передачи данных и более быстрой доставки данных с минимальной сквозной задержкой. Метод IRDFPR-CMDNN выполняет идентификацию и обслуживание маршрута, а также доставку данных более чем на трех уровнях. Затем мобильные узлы отправляются на входной уровень многослойной глубокой искусственной нейронной сети. На первом скрытом уровне применен алгоритм ранжированных лесов решений с мгновенным стоком для классификации мобильных узлов в зависимости от остаточной энергии и нагрузочной способности. К выбранным мобильным узлам применена пробит-регрессия для поиска во втором скрытом слое ближайших соседних узлов. Поиск выполнен на основе оценки качества канала и уровня принимаемого сигнала для получения пути маршрута. Далее установлено несколько путей маршрутизации от узла-источника к узлу-получателю и произведена передача данных. При отказе канала для маршрутизации выбирается альтернативный маршрут с лучшим качеством канала. В результате осуществлена энергоэффективная передача данных от источника к получателю с высокой скоростью доставки данных и минимальными временными затратами. Выполнена экспериментальная оценка энергопотребления, коэффициента доставки пакетов, скорости отбрасывания пакетов, пропускной способности и сквозной задержки с различным количеством мобильных узлов и пакетов данных. Результаты моделирования показали, что метод IRDFPR-CMDNN эффективно улучшает доставку данных, пропускную способность и минимизирует потребление энергии, уменьшает потери пакетов и задержки по сравнению с обычными методами.

Ключевые слова

маршрутизация и доставка данных, многослойная глубокая искусственная нейронная сеть, алгоритм ранжированного леса с мгновенным стоком, пробит-регрессия

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Introduction

Mobile Ad hoc Networks (MANET), an infrastructure-less, multi-hop remote network, include several distributed and independent mobile devices that generate a short-term network. It has a dynamically changing topology because every node moves arbitrarily in different directions. The node mobility and resource limitations are critical factors that affect MANET performance. Also, link stability is affected by node mobility. So, it is necessary to design an efficient technique to perform routing in MANET to improve reliable data delivery.

Related works

The decentralized context-adaptive topology control protocol is introduced in [1] which enables mobile nodes for connecting and communicating reliably with changing energy and density of nodes. However, the data delivery capacity with minimum time delay was not analyzed. A QoE (quality of experience)-driven multipath TCP (MPTCP)-based data delivery model was introduced in [2] for enhancing load-balanced routing with minimum delay. But designed model failed to achieve energy-efficient routing and data delivery.

A Topological change Adaptive Ad hoc On-demand Multipath Distance Vector (TA-AOMDV) routing protocol was designed in [3] for choosing a stable path, it depends on link stability and residual energy. But it failed to develop an efficient route that considers path stability and node density. Zone Assisted Mobility Aware Multipath Routing (ZM2R) technique was designed in [4] for performing optimal Quality of Service and minimum energy cost in MANET. But higher packet delivery ratio is not achieved.

Energy-aware on-demand routing protocol was designed in [5] for enhancing packet delivery and lesser packet delay. However, energy-efficient neighborhoods nodes selection was not improved. A novel and efficient routing method was introduced in [6] that depends on a hybrid method to increase network lifetime with a decrease in route failures problem. But link quality estimation was not performed to improve the data delivery.

A cross-layer routing protocol is designed in [7] using particle-swarm optimization (PSO) algorithm to create stable and energy-efficient paths. The designed protocol increases the packet delivery with minimum consumption of energy. However, higher throughput was not achieved. A Dynamic Energy Ad-Hoc on-Demand Distance Vector routing protocol (DE-AODV) is developed in [8] for reducing packet delay and extend network lifetime. But designed DE-AODV failed to improve residual battery power.

The deep Reinforcement Learning (DRL) technique was introduced in [9] to increase the packet delivery and throughput. But the designed technique failed to efficiently improve the lifetime of the MANET. Decision Tree-based Routing Protocol (DTRP) was designed in [10] for performing route selection process from source to destination via neighboring nodes. The designed protocol failed to ensure the reliability of the link and to address the problem of link breakage.

An efficient and reliable routing method was introduced in [11] using deep reinforcement learning for increasing packet delivery rate. But efficient routes were not generated with lesser time consumption. Mobility, Residual energy, and Link quality Aware Multipath (MRLAM) routing technique were developed in [12] for finding the best route and energy-efficient nodes. The designed MRLAM scheme failed to extend the other large-scale network deployments.

Machine learning (ML) techniques were developed in [13] for selecting the adequate routing parameter to ensure optimal performance. However, the designed techniques failed to apply efficient classification methods to further improving the optimal performance. A stable and more reliable multipath quality of service multicast routing protocol (SR-MQMR) is designed in [14] for MANET. But the designed protocol failed to provide more precise results with higher density. In [15], different routing protocol analyses were performed to improve the performance of MANET.

The particle Swarm based Routing method is implemented in [16] for increasing resource optimization and network lifetime. However, the performance of throughput remained unaddressed. An Energy-Aware Location-Aided Routing (EALAR) method is developed in [17] for integrating particle swarm optimization to reduce the required energy consumption. But the method failed to minimize delay and enhancing the performance of the entire network.

An RPS (Reliable Path Selection) based LEACH protocol is developed in [18] for selecting an efficient path to better data transmission. This system failed to use the efficient routing mechanism for enhancing data delivery and lesser delay.

A Markov chain framework was introduced in [19] for increasing the packet delivery ratio and decrease energy consumption. But it failed to deliver packets accurately to all nodes in the transmission range due to dynamic network topology. A multipath routing was designed in [20] to improve the efficiency and reliability of routing with lesser overhead. But the performance of this protocol was not minimized the delay tolerance in routing.

From the above discussion, it is evident that the existing methods suffer from high energy consumption, end-to-end delay and failed to choose the energy-efficient neighborhoods nodes, lesser throughput. In order to overcome such inefficiencies, the IRDFPR-CMDNN method is presented in this paper to downtrodden the two main challenges such as energy efficiency and reliable data delivery. The scientific novelty of the proposed work is the application of ML techniques to achieve energy efficient data delivery in MANET. To date, The ML techniques gains greater attention in the field of Mobile Ad hoc Networks. The prime objective of this technique is to automatically learn such environment quickly, predict accurately and provide optimized results.

The novelty and key contributions of the IRDFPR-CMDNN technique is illustrated as given below:

— To increase the performance of routing and data delivery in MANET, the IRDFPR-CMDNN technique is introduced. This technique is designed with the implementation of Connectionist Multilayer Deep Neural Network, instant-runoff Ranked Decision Forests algorithm, and Probit Regression.
— For identifying the mobile nodes with higher residual energy and better load capacity, the instant-runoff Ranked Decision Forests algorithm is used with Connectionist Deep Neural network architectural design.
— A Fuzzy decision stump regression tree as a weak learner is incorporated in the Decision Forests ensemble algorithm to find the better node.
— We rank the classification results with a minimum error rate, and Instant-runoff voting scheme is used in the proposed technique.
— In contrast to existing works, the proposed technique is introduced with the probit regression function which is used to find the nearest neighboring node for measuring the link quality between the two mobile nodes and received signal strength.
— To discover an efficient route with the better link quality, the Route maintenance process is carried out for increasing the throughput and minimizing the end-to-end delay.
— Finally, the simulation is carried out to estimate the performance of the IRDFPR-CMDNN technique and other related routing approaches with different metrics. The result and discussion shows that the IRDFPR-CMDNN technique is highly efficient in energy efficiency and data delivery as compared with the other methods.

Methodology

In MANET. ML techniques provide ample scope for addressing various problems including network optimization, routing, resource management, and security [21, 22]. These techniques learn the dynamic environmental changes and act accordingly for producing optimized result with high prediction accuracy. The proposed IRDFPR-CMDNN technique is designed with ensemble learning method which is a ML technique that combines the result of multiple models to produce optimal predictive performance result. Bagging and Boosting are the two most commonly used ensemble models. Our proposed work applies random forest (a kind of bagging method) as learning method and decision tree as individual mode1. Also it employs instant runoff voting method (Majority voting) to make final prediction.

The design of MANET is given in graphical model $G(V, E)$ where V is the number of mobile nodes $MN = MN_1$, MN_2, …, MN_n deployed in squared area ($X \times Y$) within the communication range (r), and E is connections between the nodes. The number of data packets $DP = DP_1$, DP_2, DP_3 …, DP_n is forwarded from source to destination node. Depending on motivation, the proposed IRDFPR-CMDNN technique is developed in MANET.

Fig. 1 illustrates the architecture of the proposed IRDFPR-CMDNN for achieving energy-efficient routing and data transmission using connectionist deep multilayer perceptive neural networks in MANET. First, set of mobile nodes $MN = MN_1$, MN_2, …, MN_n is deployed in the network and is given to the deep layer.

Fig. 2 illustrates the schematic illustration of a connectionist multilayer artificial deep neural network

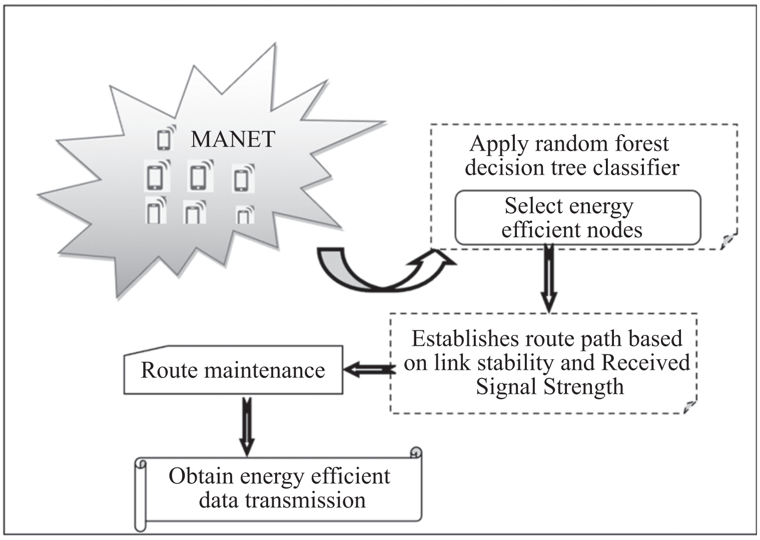

Fig. 1. Block diagram of proposed IRDFPR-CMDNN Technique

which includes the neuron-like nodes positioned into various layers. In the connectionist method, the nodes are interconnected from one layer to another and form the entire network with simple, consistent units. The structure of the connections and the units are different from design to design. The unit represents neurons, and the connections symbolize synapses in the human brain. The synapses in the neural network allow transferring of a signal (i.e., input) to another neuron in the next layer. The input from one layer to another is transferred in the forward direction. Hence it is called a feed-forward network.

In the input layer, the number of mobile nodes $MN = MN_1, MN_2, \ldots, MN_n$ is considered as input. Then the input is transferred into the first hidden layer where the classification is performed using random decision forests algorithm. The random decision forests algorithm is a machine learning ensemble method that converts weak learner results into strong classification. The weak learner is difficult to establish accurate classification results. But weak learner is a base classifier that converts weak classification results into strong ones.

Fig. 3 represents the structural process of the random decision forests algorithm to obtain final ensemble classification results. Let us consider the training samples, i.e., number of mobile nodes $MN = MN_1, MN_2, \ldots, MN_n$ as an input. The Ensemble technique uses a set of weak

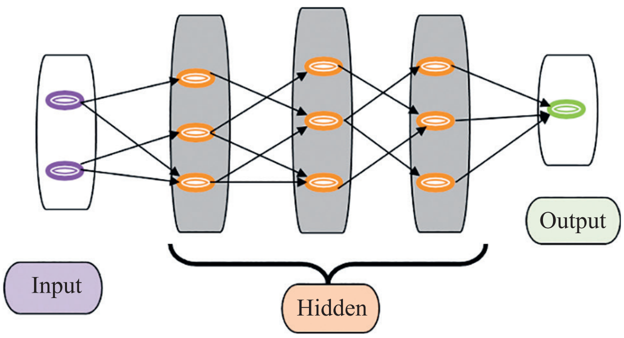

Fig. 2. Schematic diagram of the Connectionist Multilayer Deep Neural Network

learners $\beta_i \in \beta_1, \beta_2, \beta_3, \ldots, \beta_k$ as a fuzzy decision stump tree; a fuzzy decision stump is a one-level decision tree. The weak decision stump includes a decision tree that has one root node which is linked to terminal nodes (leave node). The weak decision stump creates classification results depending on residual energy and load.

The mobile node's initial energy is predicted to be depended on transmission and reception.

$$MN_{TE}(t) = E_T(t) + E_R(t). \quad (1)$$

In (1), $MN_{TE}(t)$ is the total energy of the mobile nodes, transmission; $E_T(t)$ is an energy transmission, and $E_R(t)$ is an energy reception at a time moment t respectively. Then the residual energy of mobile nodes is estimated as,

$$E_{Res}(t) = E_{Res}(t-1) - MN_{TE}(t). \quad (2)$$

In (2), $E_{Res}(t)$ is an estimated residual energy, based on residual energy of a mobile node at a time moment $t-1$; and $MN_{TE}(t)$ is the total energy consumed by a node at a time moment t respectively. The load on each mobile node is estimated as given below:

$$\varphi_{\tau i} = \frac{n_{\tau i}}{T_{\tau i}}. \quad (3)$$

In (3), $T_{\tau i}$ represents the total load capacity of the mobile node and $n_{\tau i}$ indicates the number of data packets being carried by anode. The residual capacity of a node is then estimated as following:

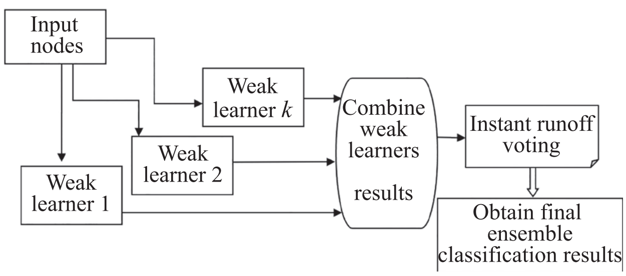

Fig. 3. Structural design of random decision forests algorithm

$$R\varphi_{\tau i} = T_{\tau i} - C_{\tau i}. \quad (4)$$

In (4), $R\varphi_{\tau i}$ is a residual load of a node; $T_{\tau i}$ is the total load capacity of the mobile node; $C_{\tau i}$ is a capacity of load carried by the node. Then the Fuzzy decision stump regression tree is applied to analyze the mobile node's residual energy and load and load capacity.

Fig. 4 illustrates the process of the Fuzzy decision stump tree which includes the root node and leaf node. In the root node, residual energy and residual load are verified with the threshold using the fuzzy rule. The fuzzy rule is applied to link inputs with outputs. By employing algorithmic formalism as (condition) and (conclusion), rules are defined. The condition part validates energy and residual load with threshold and the conclusion part provides the classification outcomes.

$$W = \begin{cases} [E_{Res}(t) > \delta_{th}] \ and \ [R\varphi_{\tau i} > \rho_{th}] & ;better\ nodes \\ otherwise & ;node\ not\ selected \end{cases}. \quad (5)$$

In (5), W is an output of weak classifier; δ_{th} indicates the threshold for residual energy; and ρ_{th} indicates the threshold for residual load capacity. The weak classification results are not efficient to provide accurate results. The weak classifiers are combined for acquiring accurate classification.

$$Y = \sum_{i=1}^{k} W_i. \quad (6)$$

In (6), Y is an ensemble classification, W_i indicates predicted classification results. The generalization error is estimated as a difference between the expected and observed errors for every weak learner. The error is formulated in (7) as,

$$Error = [expectedresults] - [observed\ results]. \quad (7)$$

After (7), the Instant-runoff voting scheme is applied to rank the classification results based on the error rate. The classification results with the most last-place rankings are removed rather than the ones with the fewest first-place ranking. The results having lesser error are ranked first than the other results.

Finally, the majority votes must be chosen as a final classification.

$$Y = \underset{k}{\operatorname{argmax}}\ v(W). \quad (8)$$

In (8), Y is the strong ensemble classification results, argmax corresponds to the argument of maximum function for determining majority vote (v) of classification results whose conclusion is identified to the k^{th} results. In this way, efficient nodes are selected for route identification.

Route path identification

After finding the efficient nodes, the nearest neighboring node with better link stability and higher Received Signal Strength Indicator is selected in the second hidden layer, for providing a route path from source to destination. The nearest neighboring node is identified by using the probit regression function. The probit regression function is a machine learning technique that helps to analyze link stability and the Received Signal Strength of mobile nodes. After the analysis, the regression function returns the probability outcomes either 0 or 1. The probit regression aims to estimate the probability with link stability, and the Received Signal Strength falls into specific one of the categories.

Fig. 5 illustrates the probit regression-based neighboring node selections. Then the regression function first estimates the link quality between the nodes,

$$LQ(MN_i \rightarrow MN_j) = \frac{Prob[R_{DP}(t)]}{Prob[ER_{DP}(t)]}, \quad (9)$$

where $LQ(MN_i \rightarrow MN_j)$ is a link quality LQ between two mobile nodes MN_i and MN_j; $Prob[R_{DP}]$ is a probability of received data packets; and the $Prob[ER_{DP}(t)]$ is an expected data packets to be received by $Prob[ER_{DP}]$ at a time moment t. Based on the result in (9), the link quality between mobile nodes MN_i and MN_j is obtained.

The signal strength of mobile node is calculated in (10) as follows:

$$SS = \left[\frac{g_t g_r h_t^2 h_r^2}{D^4}\right] p_t. \quad (10)$$

In (10), S is the received signal strength of mobile node; g_t and g_r are transmitter and receiver gain; h_t^2 indicates the height of transmitter; h_r^2 indicates the height of receiver; D is a point to the distance among sender and receiver, and p_t indicates transmitted signal power. The node with better link quality and higher signal strength is

$$R = \begin{cases} Better\ LQ(MN_i \rightarrow MN_j)\ and\ SS, & return\ 1 \\ otherwise, & return\ 0 \end{cases}. \quad (11)$$

In (11), R denotes an output of the regression function that returns 1 and the mobile node is chosen as the neighbor node; the regression function returns 0 and the node is not chosen as the neighbor node. After selecting neighboring nodes, the route path between the source and destination is established.

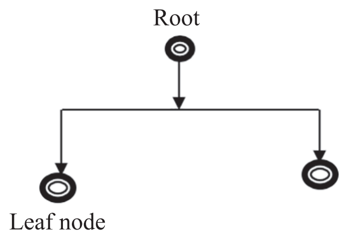

Fig. 4. Fuzzy decision stump tree

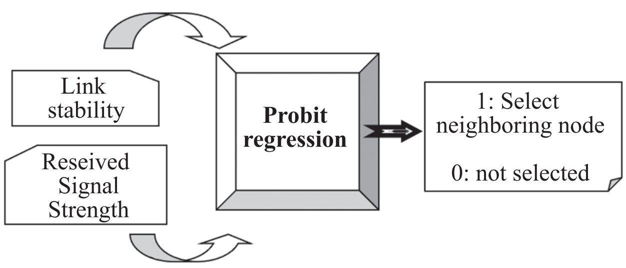

Fig. 5. Probit regression-based neighboring node selection

Data delivery and route maintenance

After establishing the route paths between source and destination, the data is transmitted along the route path. If any link failure occurs, the alternate route having better link quality is selected to increase data delivery from source to destination. Therefore, the IRDFPR-CMDNN technique performs route maintenance at the third hidden layer.

As shown in Fig. 6, route maintenance is carried out during the data delivery to improve the data communication from source (S) to destination (D) via neighboring nodes N_1, N_2, N_3, N_4, N_5, N_6, N_7. As shown in Fig. 6, during the data transmission, whenever the link break occurs along the active route, the particular node selects an alternative link with better quality to forward the data packets. In this way, efficient routing and data delivery are performed from source to destination at the output layer. The algorithmic process of the proposed IRDFPR-CMDNN technique is described as given below.

// Algorithm 1: *Instant-runoff Ranked Decision Forests Probit Regression-based Connectionist Multilayer Deep Neural Network*

Input: Number of mobile nodes $MN = MN_1, MN_2, \ldots, MN_n$, $DP = DP_1, DP_2, DP_3, \ldots, DP_n$
Output: Increase data transmission
Begin
Step 1: Number of mobile nodes taken as input in the input layer
Step 2: Transform the input into the hidden layer
Step 3: **for each** mobile node MN
Step 4: **Apply random decision forests algorithm**
Step 5: Construct k number of weak learners $\beta_i \in \beta_1, \beta_2, \beta_3, \ldots, \beta_k$
Step 6: Measure residual energy $E_{Res}(t)$ and load capacity $R\varphi_{\tau i}$
Step 7: **if** $((E_{Res}(t) > \delta_{th})$ *and* $[R\varphi_{\tau i} > \rho_{th}])$**then**
Step 8: Node is selected for routing
Step 9: **else**
Step 10: Node is not selected for routing
Step 11: **end if**
Step 12: **end for**
Step 13: Combine all weak learner results $Y = \sum_{i=1}^{k} W_i$
Step 14: **for each** W_i
Step 15: Compute the generalization error
Step 16: Apply Instant-runoff voting
Step 17: Rank the weak classification results
Step 18: Select the weak learners with minimum error for further processing
Step 19: Find majority votes of the output $\operatorname{argmax}_k v(W)$
Step 20: Obtain strong classification results
Step 21: **end for**
Step 22: **for each selected mobile node**
Step 23: Compute link quality and received signal strength
Step 24: **if** (*Better* $LQ(MN_i \rightarrow MN_j)$ *and SS*) **then**
Step 25: R returns 1
Step 26: select neighboring node
Step 27: **else**
Step 28: R returns 0
Step 29: Node is not selected as the neighboring node
Step 30: **end if**
Step 31: **Send** data packets $DP = DP_1, DP_2, DP_3, \ldots, DP_n$ to destination
Step 32: **if** any link failure occurs
Step 33: Select another alternative route with better link quality
Step 34: **end if**
Step 35: end for
End

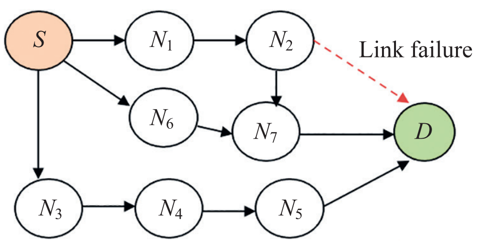

Fig. 6. Route Maintenance

Algorithm 1 explains deep learning algorithms for improving data delivery in MANET. Initially, numbers of mobile nodes are given as input to the input layer. Then the input is transferred to the first hidden layer, where an ensemble classification algorithm is utilized. The ensemble technique constructs k number of weak classifiers for identifying the better nodes having higher residual energy and load capacity. Then the weak classification results are combined and the generalization error is estimated. After that, the Instant-runoff voting scheme is applied for ranking the weak classification results based on the error. Then the higher-ranked classification results with a minimum error are selected for further processing. Finally, the majority votes of the output are selected as final classification results. As a result, the better nodes are picked out for further processing. After that, the nearest neighboring nodes are selected by applying the probit regression. The node with the better link quality and higher signal strength is chosen for data delivery. With selected neighboring nodes, data packets are transmitted from source to destination. If any route failure occurs, then an alternative route is taken for increasing data transmission and lesser delay.

Simulation scenario setup

The simulation of the proposed IRDFPR-CMDNN and two existing methods, namely Decentralized Context-adaptive topology control protocol [1], QoE-driven multipath TCP (MPTCP)-based data delivery model [2], are carried out in the NS2.34 simulator. In order to perform the simulation, 500 mobile nodes are located in a squared area of A^2 (1500 × 1500 m^2) with node's speed of 0–20 m/s. The Random Waypoint is used as a node mobility model, and DSR protocol is performing energy-efficient routing with data delivery. Table describes simulation parameters.

Performance results and discussion

The performance results of IRDFPR-CMDNN and existing methods, namely Decentralized Context-adaptive topology control protocol [1], QoE-driven MPTCP-based data delivery model [2] are discussed with various factors: energy consumption, data delivery rate, packet loss rate, throughput, and end-to-end delay with the help of graphical representations.

Table. Simulation parameter settings

S. No	Parameters	Values
1	Number of nodes	50, 100, 150, 200, 250, 300, 350, 400, 450, 500
2	Area size, m^2	1500 × 1500
3	Transmission range, m	250
4	Simulation time, s	10–50
5	Data Packet size, bytes	1024
6	Rate, kbps	50
7	Simulation runs	10
8	Network simulator	NS2.34
9	Protocol	DSR
10	Data packets	25, 50, 75, 100, 125, 150, 175, 200, 225, 250
11	Speed ranges, m/s	0–20

Energy consumption

It is measured as the amount of power consumed by the total number of mobile nodes. Energy consumption is calculated as,

$$EC = \sum_{i=1}^{n} E_{tot} \times MN^{i}\ . \qquad (12)$$

In (12), EC is energy consumption; i is a mobile node; and E_{tot} is the energy consumed at each node E_{tot}. The energy consumption is expressed in joule (J).

Fig. 7 demonstrates the energy consumption with mobile nodes that are varied from 50 to 500. The obtained results indicate that the IRDFPR-CMDNN reduces the energy consumption significantly compared to the existing methods. By considering the 50 nodes, the energy consumption of the IRDFPR-CMDNN technique is J, and the energy consumption of the nodes using Decentralized Context-adaptive topology control protocol [1], QoE-driven MPTCP-based data delivery model [2] is 3 J and 2.7 J correspondingly. At last, the average of ten comparison results is considered for identifying the overall performance. The result reveals that the overall energy consumption of IRDFPR-CMDNN is significantly reduced by 31 % and 22 % compared to the existing methods.

As shown in the plot, the energy consumption of the three methods increases with an increase in the number of mobile nodes. If compared to all three existing methods, the IRDFPR-CMDNN method reduces energy utilization. The lower energy consumption, when using the IRDFPR-CMDNN technique, is due to the instant-runoff Ranked Decision Forests algorithm implemented in Connectionist Multilayer Deep Neural Network. The Ranked Decision Forests algorithm finds the higher residual energy-efficient nodes for data delivery. This reduces energy consumption.

Data delivery rate

Data delivery rate is measured as the ratio of the number of data packets that are rightly received to the total number of data packets. It is expressed as,

$$DDR = \left[\frac{DP_R}{DP_t}\right] \times 100. \qquad (13)$$

In (13), DDR is the data delivery rate; DP_R is data packets received; and DP_t is data packets transmitted. It is calculated in percentage (%).

Fig. 8 demonstrates the comparison of data delivery ratio of three different methods IRDFPR-CMDNN and existing methods Decentralized Context-adaptive topology control protocol [1], QoE-driven MPTCP-based data delivery model [2]. The overall performance of the data delivery rate for three methods with data packets ranges from 25 to 250. Consider 25 data packets being sent from the source node. By applying the IRDFPR-CMDNN technique, 96 % of the data delivery ratio is obtained. Similarly, the data delivery ratio of existing [1, 2] is obtained as 88 %. For different kinds of input, various performance results are obtained. The average result using three different methods indicates that the IRDFPR-CMDNN method enhances packet delivery ratio by 7 % and 5 % compared to [1] and [2], respectively.

The overall packet delivery ratio of the proposed IRDFPR-CMDNN is considerably increased compared to

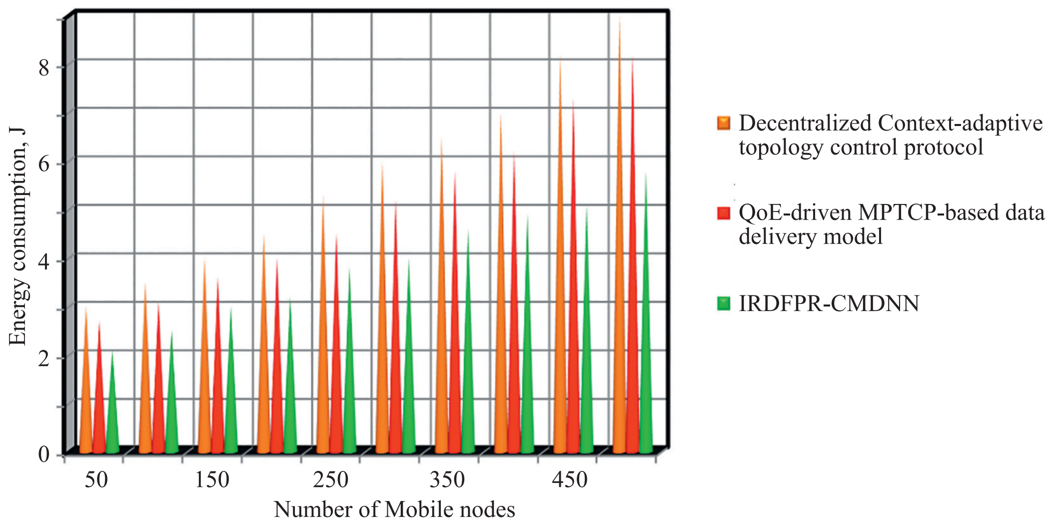

Fig. 7. Performance results of energy consumption

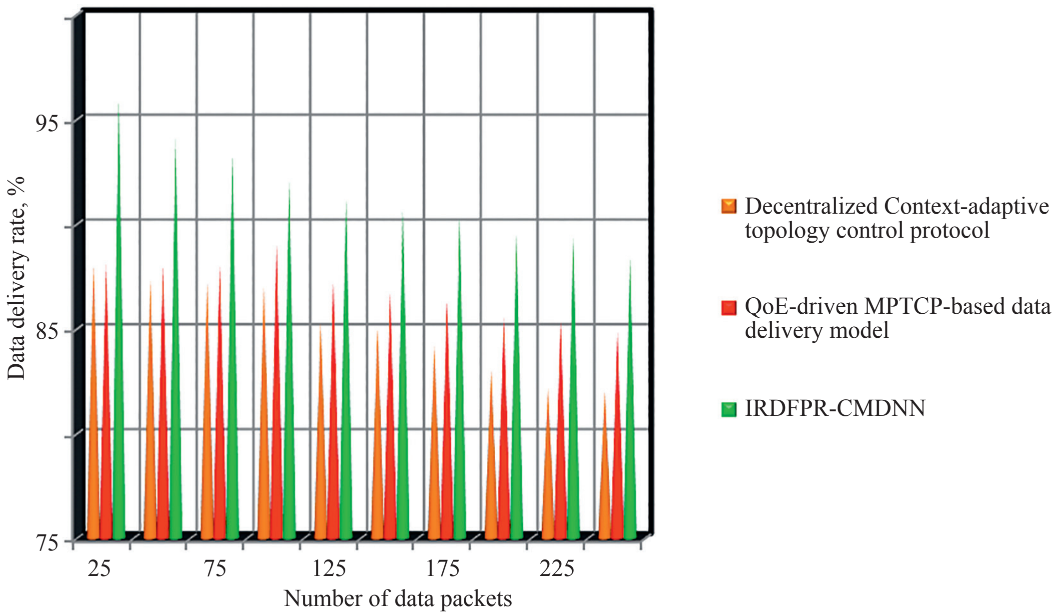

Fig. 8. Performance results of data delivery ratio

the others. The significant reason for the IRDFPR-CMDNN technique is to apply the Bagging Ensemble classification and regression technique. This enhances data delivery from the source to the destination node.

Packet loss rate

It is defined as the ratio between the number of data packets lost and the total number of data packets sent. It is estimated as

$$PLR = \left[\frac{DP_L}{DP_t}\right] \times 100. \tag{14}$$

In (14), PLR is the packet loss rate, DP_L is the data packet lost, and DP_t is data packet transmitted. It is expressed in percentage (%).

Fig. 9 depicts the performance of packet loss rate versus data packets ranging from 25 to 250, respectively. Consider 25 data packets for calculating packet loss rate. By utilizing IRDFPR-CMDNN, the packet loss rate is 4 %. Therefore, the packet loss rate of existing methods is 12 %. Ten iterations results are attained with respect to various counts of input data packets. The obtained comparison results of the IRDFPR-CMDNN technique are compared to the existing methods. The average of ten results indicates that the IRDFPR-CMDNN reduced the packet loss rate by 44 % when compared to [1] and 36 % when compared to [2].

It shows that the packet loss rate of the IRDFPR-CMDNN method is significantly reduced when compared to the existing methods. This is due to the selection of energy-efficient and minimum load capacity nodes that minimize the packet drop. In addition, the higher signal strength of the node enhances data packet delivery and lesser packet drop.

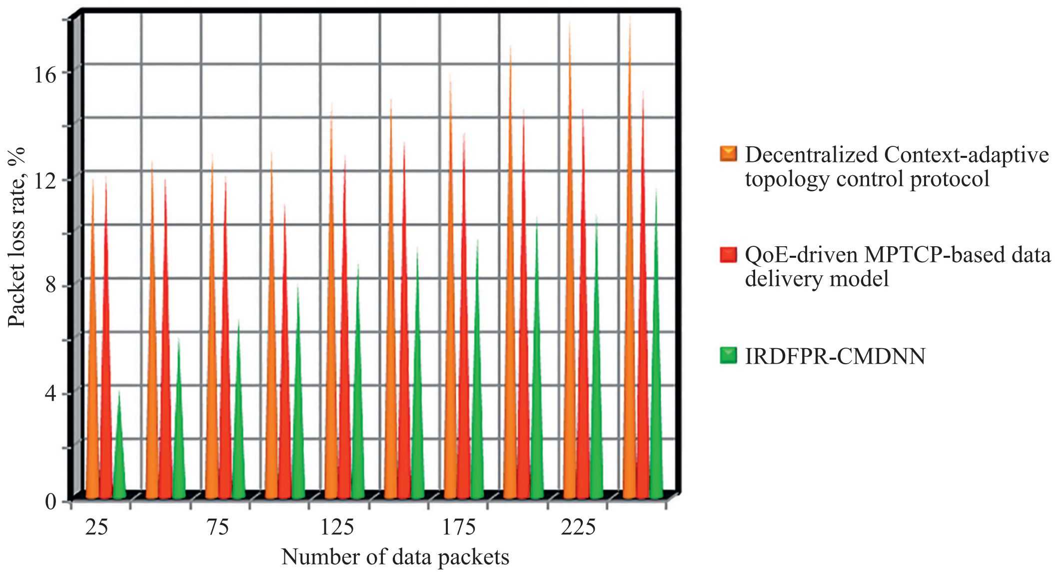

Fig. 9. Performance results of packet loss rate

Throughput

It is defined as the number of data packets that successfully reached the destination node in a particular time. It is estimated as follows

$$Throughput = \left[\frac{Number\ of\ DP\ successfully\ reached}{time}\right]. \quad (15)$$

In (15), DP is the number of data packets. It is calculated in packets per second (pps).

As shown in Fig. 10, the throughput of all three methods gets increased as number of data packets increases. Among the three methods, the IRDFPR-CMDNN technique outperforms well compared to the existing methods. In other words, the throughput of IRDFPR-CMDNN is considerably increased compared to the other methods, i.e., in the first iteration, 25 data packets are transmitted. By applying the IRDFPR-CMDNN technique, 20 data packets are successfully received at a particular time. Similarly, 14 and 16 data packets are successfully received by applying Decentralized Context-adaptive topology control protocol [1], QoE-driven MPTCP-based data delivery model [2]. The different results are obtained with various inputs. The overall performance of the ten results indicates that the throughput of IRDFPR-CMDNN is increased by 26 % and 12 % when compared to [1, 2], respectively.

End-to-End Delay

It is defined as the time difference between packet arrival time and sending time. It is estimated as

$$End - to - End\ Delay = Time_{arr} - Time_{send}. \quad (16)$$

In (16), $Time_{arr}$ is an arrival time of data packets, $Time_{send}$ is a sending time of data packets.

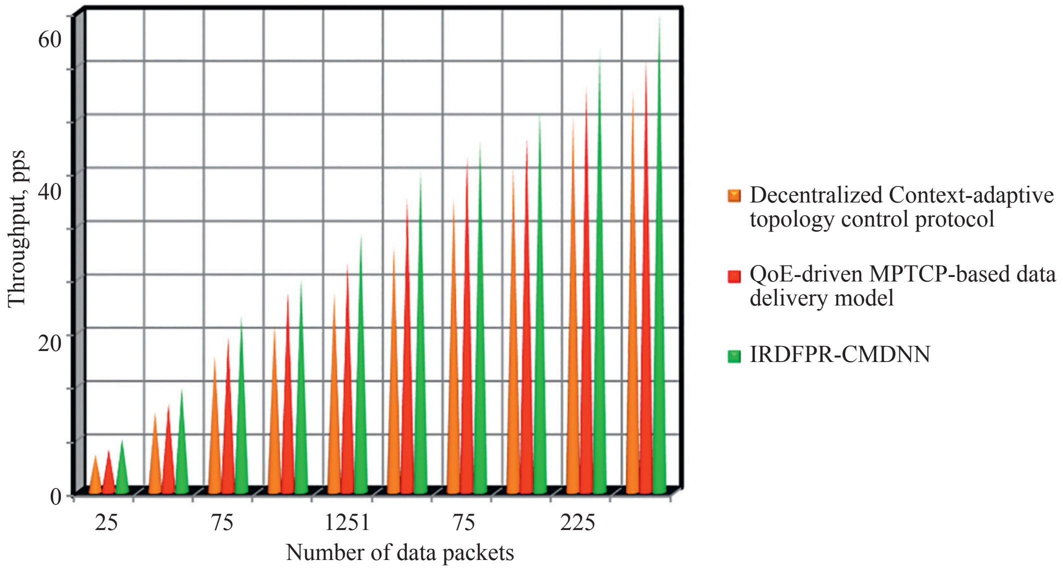

Fig. 10. Performance results of throughput

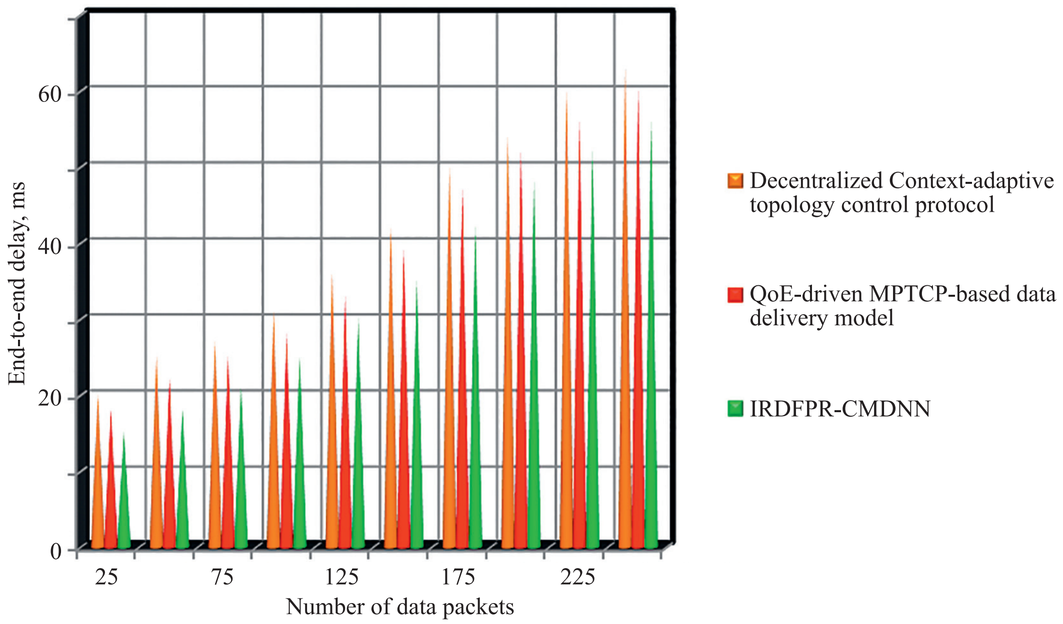

Fig. 11. Performance results of end-to-end delay

Fig. 11 illustrates the simulation analysis of end-to-end delay from source to destination. As revealed from Fig. 10, the end-to-end delay of the three methods gets increased as the number of data packets increases. But comparatively, the delay is found to be lesser using the IRDFPR-CMDNN method than other existing methods. This is proved using statistical estimation. In the first run, the simulation is conducted with 25 data packets, delay of data delivery from source to destination using proposed IRDFPR-CMDNN technique is 15 ms where the overall delay of Decentralized Context-adaptive topology control protocol [1], QoE-driven MPTCP-based data delivery model [2] are 20 ms and 18 ms, respectively.

The average of ten comparison results shows that the proposed IRDFPR-CMDNN technique enhances overall end-to-end delay by 22 % when compared to Decentralized Context-adaptive topology control protocol [1], and 11 % when compared to QoE-driven MPTCP-based data delivery model [2], respectively. This significant improvement is achieved by performing route maintenance. The advantage of proposed IRDFPR-CMDNN method is that it finds the nearest neighboring node with a lesser delay. If any link failure occurs during the data transmission, an **alternative route** with better link quality is selected for continuous data delivery from source to destination with minimum delay.

Discussion

In this section, the proposed IRDFPR-CMDNN and existing Decentralized Context-adaptive topology control protocol [1], QoE-driven MPTCP-based data delivery model [2] are discussed. Since the objective of the proposed method is to minimize energy utilization thereby increasing network life time, the performance metrics used in this work are: energy consumption, data delivery rate, packet loss rate, throughput, and end-to-end delay. The proposed technique has been implemented in NS2 simulation tools. Fig. 7 shows the energy consumption of the three methods. The reason for the attaining lesser energy consumption is discovering the maximum residual energy-efficient nodes. It is clear that, the energy consumption of proposed technique is minimized by 27 % compared to the existing methods. From Fig. 8, the data delivery rate of three different methods is identified. By the application of Bagging Ensemble classification and regression technique, the packet delivery ratio of proposed scheme is improved by 6 % as compared to the traditional methods. Fig. 9 demonstrates the packet loss rate by using three dissimilar methods. Obviously, the packet loss rate is minimized using the proposed technique with probit regression function by 40 % when compared to the existing methods. Similarly Fig. 10 proves that the throughput is considerably enhanced in the proposed technique by 19 % compared to the existing methods. Finally, Fig. 11 confirms the end-to-end delay of the three methods. The route maintenance activity in the proposed technique minimizes the end-to-end delay by 17 % compared to the state of artworks. To conclude, the proposed IRDFPR-CMDNN method exhibits better performance than works under consideration.

Conclusion

This paper presents an energy-aware routing and data delivery technique called IRDFPR-CMDNN. The IRDFPR-CMDNN technique uses the ensemble technique, and regression is implemented in the Connectionist Multilayer Deep Neural Network. First, the instant-runoff Ranked Decision Forests algorithm is applied for finding the energy-efficient mobile node with better load capacity nodes. After the classification, the source node finds the nearest neighboring nodes based on link quality and received signal strength through the probit regression. Finally, data transmission is performed via selected neighboring nodes. The route maintenance is carried out for enhancing data delivery and reducing the delay. The simulation is conducted with various performance parameters: energy consumption, data delivery ratio, packet loss rate, throughput, and end-to-end delay by varying numbers of mobile nodes and data packets. The proposed IRDFPR-CMDNN technique has performed much better than both energy-efficient routing and data delivery over other existing schemes.

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