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PAPER

Analysis of ANN Routing Method on Integrated IOT with WSN

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ABSTRACT

Internet of Things (IoT) in recent times offers a greater amount of flexible design during the deployment of it in the form of network. The interfacing of IoT with a wireless sensor network (WSN) requires an optimal solution to preserve the consumption of energy while the data has been transmitted via nodes. In this paper, we develop machine learning (ML)-assisted routing to route the data packets of IoT sensors from the real-time environment over WSN. In this study, we use three different planes for optimal routing of packets from the source node to the destination node. The source node is the IoT sensors that involve data collection, and the intermediate nodes are the WSN sensor nodes that route the packets. Optimal routing decisions based on the pre-trained data in an artificial neural network (ANN) stabilize the routing of data packets without congestion. The simulation is conducted to test the efficacy of the ANN routing in the integrated network, and the results show that the ANN-based routing achieves higher energy efficiency and throughput than other models.

KEYWORDS

machine learning (ML), routing, wireless sensor network (WSN), Internet of Things (IoT), energy efficiency

1 INTRODUCTION

Emerging services from the Internet of Things (IoT) allow various devices connected to the internet to seamlessly operate on an integrated infrastructure. Several studies have been conducted by various researchers to reduce the problems associated with the fastest routing [1]. As an emerging technology, IoT is gaining more attention and benefits from various applications that include sensors in industries and healthcare systems. Sensors and wireless sensor network (WSN) interface devices are required for the sensing of industrial WSN. The sensor data is acquired. It also helps us better understand our surroundings. To meet the requirements of data acquisition by IoT devices in the industrial environment, more accurate routing of data by the WSN is needed.

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As an emerging technology, IoT gains more attention and benefits various applications, including sensors in industries and healthcare systems. Sensors and WSN interface devices are required for the sensing of industrial WSN. The sensor data is acquired. It also helps us better understand our surroundings. To meet the requirements of data acquisition by IoT devices in the industrial environment more accurate routing of data by the WSN is needed.

However, WSN diversity tends to increase the complexity of defining the task due to its complex hardware or software specifications. Moreover, hardware or software needs to be selected based on the requirements of an application and its corresponding environmental conditions [3].

The interface for data acquisition can collect the IoT sensor data to meet the long-term requirements of data collection in the industrial environment of IoT devices. IoT devices can collect diverse and accurate data [4–8]. Maintenance and reliability of WSN are negatively impacted by these ad hoc alterations, which lowers their applicability in IoT applications [2]. To handle such a vast number of nodes, an effective, scalable algorithm is needed. Due to external factors or device designers, the WSN can be dynamically re-created. There are several ways in which it might affect location, network routing, cross-section design, and delay. It can also affect QoS and the quality of the link. WSNs are designed to work in a dynamic network environment, so it makes sense to reduce the network reorientation that results from conventional techniques.

A major problem associated with the interfacing of these two technologies is the matching of speed between IoT sensors and WSN sensors. If the speeds are not matching, the computational burden tends to increase, creating congestion in network traffic. It is hence essential for the protocols of the network to establish optimal network balancing with proper route establishment.

Machine learning (ML) [10–14] is a non-specific automated method of enhancement or learning. Our computing processes improved in terms of performance, reliability, and efficiency thanks to ML. By analyzing increasingly complex data, ML generates models that are autonomous and reliable. Through a performance enhancement architecture, ML can deliver detailed solutions. Its interdisciplinary character makes it relevant in many fields, such as engineering, medicine, and so forth. Many WSN issues have been solved recently thanks to ML. WSN performance is enhanced and human intervention is prevented by using ML, but without ML, it is difficult to access large amounts of sensor data to extract usable information from it. Thus, using an ML-assisted approach, it is possible to address WSN-related concerns in this paper [15–25]. A neural network is a type of ML algorithm that is modeled in the form of a human neuron. The neural network works like the way the brain processes information. Artificial neural networks (ANNs) involve many interconnected units that process together to obtain information.

The contribution involves the following:

- The ANN [9] enables high-speed data packet routing from the source IoT onto intermediate nodes of WSN and finally into the cloud.
- IoT sensors are used for data acquisition, and the ANN routing algorithm is designed to match the speed of the input data acquisition rate.
- The authors also aim to balance the data collection rate and packet delivery rate to reduce the delay between acquisition and transmission.

The outline of the paper is given below: Section 2 provides the related works. Section 3 discusses the proposed method. Section 4 evaluates the entire work. Section 5 concludes the entire work with possible directions for future scope.

2 LITERATURE REVIEW

A traffic flow prediction approach for the intelligent transport system that utilizes quantum particle swarm optimization was proposed in [26]. A suitable model is developed that focuses on the traffic flow data characteristics. Genetic annealing is used for the optimized initial cluster center of the quantum particle swarm optimization and to optimize the radial neural network parameter.

The problem of multi-user offloading using evolutionary models is investigated [27]. The study examines the evolutionary mechanism of IoT systems using replicator dynamics. The study shows that the evolutionary stability approach for multi-user computing offloading.

A multi-path on-demand distance routing protocol using energy consumption and link lifetime prediction on edge computing [28] uses the energy grading strategy followed in the route discovery process. When the energy is less than the threshold, the nodes are removed from the routing path.

The channel interference issues and multi-user time slot collisions arising from radio transmitting information during WMNs are investigated [29]. A multi-strategy channel allotment algorithm for edge computing is used for the development of data cache models and channel node segregation.

A fuzzy neural Network for the development of a data-missing estimation method was used in [30]. Also, we proposed a mobile learning paradigm that follows the user dynamically without the user's understanding or interference by active service from place to place and from computer to machine. This potential can be achieved by an intelligent part system and a migration process dependent on agents.

A TCP-Quick Start congestion control model with an optimal slow starting step is discussed in [31]. The *cwnd* parameter value is set at the beginning of the link as the higher value, depending on the bandwidth of the detected network, to shorten the time during the sluggish beginning stage and to dynamically modify the value of the ss_{thresh} parameter due to network adjustment. When the failure of packets happens, different approaches are used for various purposes.

A weighted topology solution to WSNs based on IoT theory follows a uniform clustering of weighted emerging WSN [32] models based on local-world theory. Sensor capacity, transmission distance, and flow are considered in the meanings of edge weight and vertex power.

A multicast routing system for minimal data transmission was suggested in [33]. Due to random load, information fusion studied the causes of unknown information in WSN for industrial use. In random circumstances, the study creates an industrial application transmission model and uses a heuristic distributed minimal transmission algorithm for multicast routing.

A protocol on media access control based on the authenticity of interpreted data and spatial correlation was developed in [34]. This protocol establishes a paradigm of ring-shaped spatial correlation. To successfully send the high-quality data to the sink node and improve data transmission reliability, the nodes near the data source are given high importance in the access channel.

Liu, S., et al. [35] proposed a temporally ordered routing algorithms (TORA) routing protocol for flood control. First, the self-repair using a directed acyclic graph transforms the optimal search problem for the optimum node selection according to the uniform node deployment. The search results are shown to be the optimal search solution, as in the Ray-algorithm. A conditional algorithm is used to decide the mechanism of self-repair and the conditional threshold to start the process.

Table 1. Conventional energy conservation IoT models

Author(s)	Reference	Method	Results
Zhang, D., et al.	[26]	Quantum Particle Swarm Optimization (QPSO) with Genetic Annealing for traffic flow prediction	Developed an optimized model for traffic flow prediction; improved accuracy by focusing on traffic flow data characteristics.
Cui, Y., et al.	[27]	Evolutionary model using replicator dynamics for multi-user offloading in IoT systems	Demonstrated evolutionary stability approach for multi-user computing offloading in IoT systems.
Zhang, D. G., et al.	[28]	Multi-path on-demand distance routing protocol considering energy consumption and link lifetime prediction	Implemented an energy grading strategy; nodes with energy below a threshold are removed from routing paths.
Zhang, D., et al.	[29]	Multi-strategy channel allotment algorithm addressing channel interference and multi-user time slot collisions in WMNs	Developed a data cache model and channel node segregation to reduce interference and collisions.
Zhang, T., et al.	[30]	Fuzzy Neural Network for data missing estimation	Provided a method for estimating missing data with improved accuracy.
Zhang, D. G.	[31]	Mobile learning paradigm with intelligent part system and agent-based migration process	Enabled dynamic user-following mobile learning without user interference.
Zhang, D. G., et al.	[32]	TCP-Quick Start congestion control model with optimal slow start step	Shortened slow start phase and dynamically adjusted ssthresh parameter for better congestion control.
Zhang, D. G., et al.	[33]	Weighted topology solution for WSNs based on IoT theory	Developed uniform clustering for WSN models considering sensor capacity, transmission distance, and flow.
Zhang, D. G., et al.	[34]	Heuristic distributed minimal transmission algorithm for multicast routing in WSNs for industrial use	Created a transmission model to minimize data transmission with high efficiency in industrial WSNs.

The studies in Table 1 explore various optimization and routing techniques in intelligent transport, IoT systems, and wireless networks. Techniques include quantum particle swarm optimization for traffic prediction, evolutionary models for IoT offloading, energy-efficient routing protocols, and multi-strategy channel allotment to reduce interference. Additional contributions involve fuzzy neural networks for data estimation, mobile learning paradigms, congestion control models, weighted topology solutions for WSNs, and heuristic multicast routing algorithms.

3 SYSTEM MODEL

In this section, the study considers a two-dimensional network model with sensor nodes, considering the assumptions given below:

- The study considers one sink node or gateway.
- The sensor nodes are considered homogeneous, with similar processing and communication capabilities.
- The two neighboring sensor nodes are estimated using the Euclidean distance.
- The IoT nodes collet temperature and humidity data from the surrounding area, where the data is sent to the WSN network and routed directly to the sink node and then to the gateway to be uploaded to the cloud.

3.1 Cluster formation

After network deployment, cluster formation is considered predeterminable during the start of an operation. Nodes are initially deployed at random, with no set locations within clusters, and their membership within clusters is determined by their original position. Each cluster contains non-fixed nodes. Each node in the cluster is aware of the other nodes.

To reduce communication delay and energy consumption, the cluster head selection technique is employed. The sensor node weight W is computed by taking into consideration information such as residual energy status, node density, and proximity to sensor nodes. The energy efficiency is accomplished by the weight $W(i)$ of the node.

Using node beaconing, this information can be obtained. The members of a cluster send messages to each other to elect and re-elect a leader at regular intervals, say γ. Data broadcasting of the control messages involves the measurement of QoS, where the sensor nodes are notified of the presence of sensor nodes. After receiving this message, a CH or other nodes compute the weights based on Equation (1).

$$W(i) = \frac{cN_i E_i}{D_i} + \frac{(1-c)k}{\sum_{j=1}^{k} H(i,a_j)} \tag{1}$$

Where,
E_i – residual node energy i,
D_i – average distance between the sensor nodes,
N_i – neighboring nodes,
k – actuator nodes and
$\sum_{j=1}^{k} H(i,a_j)$ – total distances between the nodes.

The coefficient value $c \in [0,1]$ is made low for the cluster head selection. Increasing the coefficient value c places greater emphasis on energy conservation and network connectivity.

3.2 Energy model

The homogenous sensor nodes are considered energy-dissipating modules for radio communication. This model shows the estimation of the transmitting rate *r* of the entire transmitting or receding sensor nodes. The energy consumed during n-bit data transmission is then sent to the receiver node, which is located at *d* and is estimated as in Equation (2):

$$E_{tx}(d) = n\phi_{amp}\, d^{x} + nr\phi_{cir} \tag{2}$$

Where,

ϕ_{cir} – Energy dissipation during the transmitter circuit operation, and

ϕ_{amp} – Distance factor representing the transmitter amplifier.

α – exponent representing the path loss component

The study considers $\alpha = 4$ for multi-path fading and $\alpha = 2$ is assigned for 180 free spaces.

The energy consumption at rate *r*, which is represented as below:

$$E_{rx} = nr\phi_{cir}$$

The consumption of energy E_i for reception over the distance *d* is:

$$E_i = E_{tx} + E_{rx} = nr(2\phi_{amp}\, d^{\alpha} + 2\phi_{cir}) \tag{3}$$

3.3 Routing using artificial neural network

The IoT nodes are used only for data collection that uses temperature and humidity sensors. It is connected to the wireless nodes, where the nodes are used for routing the data packets to the sink nodes. The algorithm of the proposed methods is shown below.

Step 1: Start
Step 2: Collect data via IoT sensor nodes
Step 3: Transmit the collected node from the source IoT node to the WSN network.
Step 4: Collect the data packets based on the directions from the control plane.
Step 5: The control plane initiates the process of routing.
Step 6: ANN finds the optimal routes based on various metrics like the energy level of sensor nodes and the distance between the neighborhood sensors.
Step 7: Allot the sensor nodes for optimal routing of packets.
Step 8: Ensure acknowledgment is received from the sink node to the base station by the control plane.
Step 9: Check if the sink node offloads the data to the gateway and then to the cloud.
Step 10: End

The protocol in Figure 1 consists of three phases:

WSN-IoT integration uses opportunistic routing that depends on a single hop and low-speed broadcast. The cluster formation protocol is reactively initiated by any WSN to route the IoT data.

The study uses three-phased models: The sensing *plane* collects IoT devices, and the data collected is supplied directly to the WSN nodes for optimal routing.

The control *plane* involves decision-making by the ML algorithm that considers the input traffic data from the WSN sensor nodes and the data collection speed from the IoT devices. *Data plane* implements the process of data packet routing from IoT nodes for optimal data packets to the cloud.

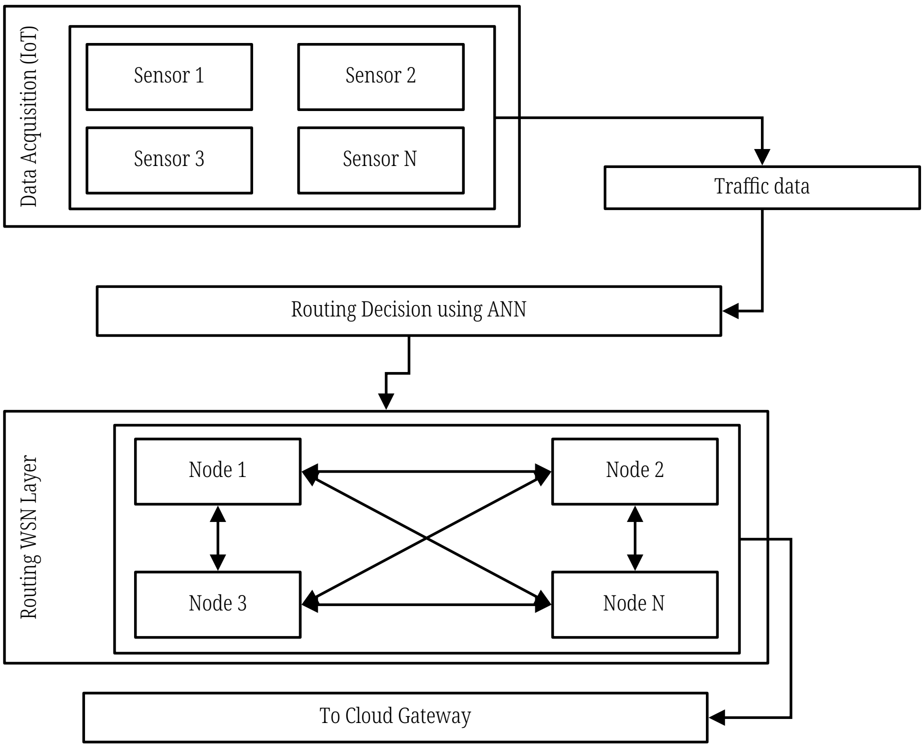

Fig. 1. Proposed flow diagram

In the initial phase, a CH removes the IoT node that routes the packets and broadcasts a request from the additional nodes to join a cluster. WSN communicates with IoT nodes to send the packets, and other sensor nodes join the cluster in the second phase of the process.

In the second step, the nodes of WSN receive the join request. WSN nodes connect with CH after entering the cluster. When the CH receives a response from a cluster node, it decides to leave the node. CH finds the messages from all cluster nodes.

Collection of training data

Prior to the model training, the study requires larger training data, which contains the data rate, generate rate, data flow rate, congestion flag, and allocated path for routing.

Artificial neural network model training

The study uses a back propagation neural network as the ANN model that gets trained to create a routing path based on the labels obtained from all the feature inputs. A weighted threshold value $W(i)$ is used to compare the weights $W(i)$. Beacon messages carrying the weights of nearby sensor nodes are disseminated when $W(i)$ exceeds the W_t. The beacon message is received by the sensor nodes and stored locally. because each member of the cluster is represented by a weight. After sorting sensor node weights, the nodes with the highest weights are selected as cluster leaders.

To determine which sensor node will lead a cluster, the former value is replaced with present values of a WSN node. If the weights of the CH $W_{CH}(n)$ are fewer than its prior weights, $W_{CH}(n)$, then the cluster head re-election is performed $W_{CH}(n-1)$. If $W(i) < W_t$, the node is discarded from the cluster.

The QoS metrics show the frequency of packet reliability, network strength, and network longevity. Even in a dispersed control system, the proposed schema QoS information improves performance. By avoiding misdirected packets, the QoS metric information helps to improve the delivery ratio and reduce total delay. Furthermore, in mobile ad hoc networks, similar QoS metrics are used to analyze energy usage and packet delay measurement.

4 RESULTS AND DISCUSSIONS

The ANN model for optimizing the routing paths is validated in terms of various performance metrics, including average delay, packet delivery ratio (PDR), routing payload, and network lifetime of IoT data collection and WSN routing. The ANN model on IoT-WSN is compared with other ML algorithms that include, SVM and decision tree (DT) [16] and [17]. The model is simulated in the NS2 simulator on a Windows 10 platform with a high-end computing system.

4.1 Performance metrics

The metrics for validating the performance are given below:

Packet delivery ratio (PDR): PDR is the ratio of the total packets received at BS to the total packets generated by the source IoT nodes.

Delay: Delay is the time taken for successful packet transmission between the source IoT nodes and destination gateway nodes via WSN intermediate nodes. The delay accounts for cache delay, buffer delay, and retransmission delay, propagation delay by ANN for forming a route for transmission.

Normalized routing payload (NRP): NRP is the total control packets transmitted to the WSN gateway upon successful delivery of packets.

Normalized MAC payload (NMP): NMP is the sum of total number of routing packets, address resolution packets, overhead, and control packets between the source IoT nodes and WSN gateway.

Network lifetime: The lifetime of a network is the total time taken by a sensor node to transmit data until its energy is null.

4.2 Parametric setting

This section provides the details of the simulation parameters carried out to deploy the ANN for routing in carrying out the packets by WSN. The design consideration includes the selection of robust sensor nodes for transmitting the packets between the source IoT nodes and destination gateway in regular instances. The 10 Mbps bandwidth is the LTE communication channel bandwidth that carries the data packets via gateway to the cloud. The nodes used belong to the dynamic topology, and hence they are designed between 0 and 30 m/s. The entire simulation time is 1000s, and the pause time varies between 10 and 1000 s. The entire simulation is conducted in the Network Simulator Tool (NS-2). The ANN algorithm is performed in MATLAB using mobility traces obtained from ns-2 simulations. The data rate of the wireless sensor node is 250 kbps. The data rate of IoT temperature and humidity nodes lies between 100 and 200 kbps, and the entire parameters are given in Table 2.

Table 2. Parameters for simulation

Parameters	Value
WSN nodes	100
WSN node distribution	Random
Range	1000 m × 1000 m
IoT nodes	10 (fixed)
Simulation time	1000 s
Transmission rate	54 Mbps
Routing Protocol	ANN
Mobility model	Gauss-Markov Model [16]
Channel Bandwidth	10 Mbps
Pause times	10–1000s
Tx power	20 dBm
WSN Node Velocity	0–30m/s
Transport protocol	TCP
Modulation	OFDM

4.3 Simulation results and discussions

Figure 2 shows the results of PDR between the proposed model and existing models in terms of various sessions for transmitting the data packets. The simulation results show that when using reduced pause time, the PDR is lower, and vice versa. However, the results show that the PDR of ANN is higher than that of the existing methods. The computation of efficient paths by the ANN enables optimal data transmission compared to SVM and DT. On the other hand, the existing methods fail to match the speeds of the input data rate and the allocation of paths in forming a buffer less the transmission. With a stable path, the ANN performs better in transmission of data with minimal link failure.

Table 1 shows the results of packet delivery rates using various numbers of nodes between the proposed method and existing SVM and DT methods. The result of the simulation is compared with various network sessions.

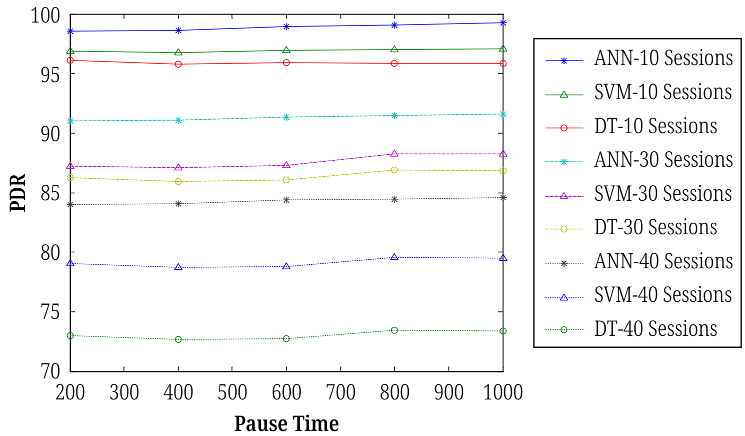

Fig. 2. Packet delivery rate

Figure 3 shows the results of the delay between the proposed model and existing models in terms of various sessions for transmitting the data packets. The simulation results show that when using reduced pause time, the delay is higher and vice versa. However, the results show that the delay of ANN is less than that of SVM and DT. The faster computation of efficient paths by the ANN enables optimal data transmission compared to SVM and DT. On the other hand, the existing methods fail to match the speed of the input data rate, which increases the delay in transmitting the packets.

Table 2 shows the results of the delay using various numbers of nodes between the proposed method and the existing SVM and DT. The result of the simulation is compared with various network sessions. The results show that the proposed method obtains a reduced rate of delay compared to existing methods.

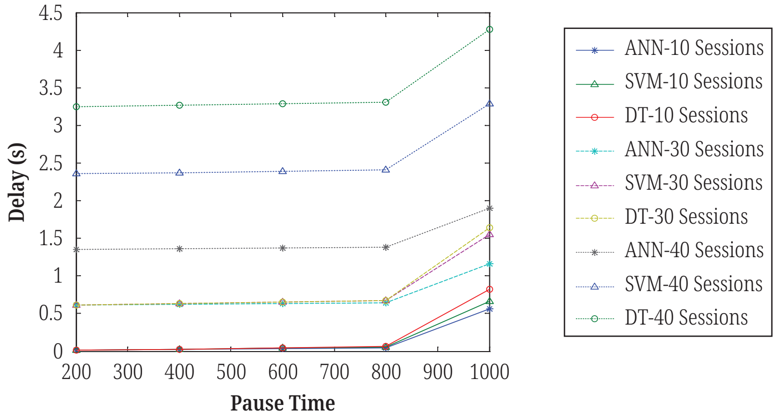

Fig. 3. Average end-to-end delay (s)

Figure 4 shows the results of NRP between the proposed model and existing models in terms of various sessions for transmitting the data packets. The simulation results show that when using reduced pause time, the NRP is higher and vice versa. However, the results show that the NRP of ANN is lower than that of SVM and DT. The faster rate of routing path computation by the ANN enables optimal data transmission compared to SVM and DT.

Figure 5 shows the results of normalized the routing payload using various numbers of nodes between the proposed method and existing SVM and DT methods. The result of the simulation is compared with various network sessions. The results show that the proposed method obtains a higher normalized routing payload than existing methods.

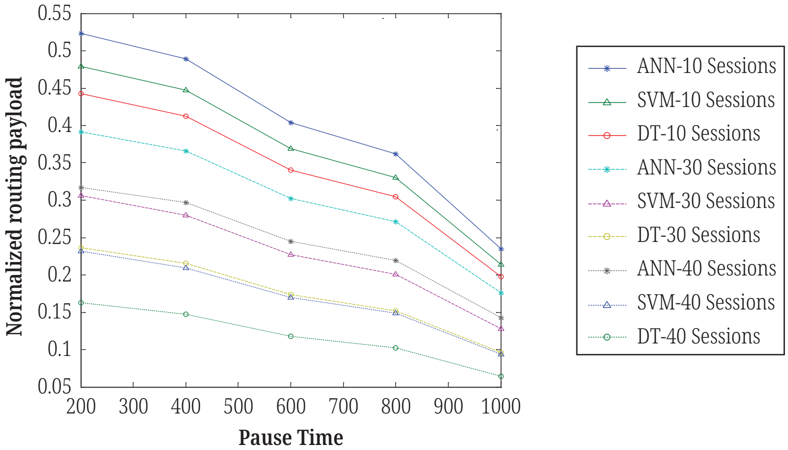

Fig. 4. Normalized routing payload

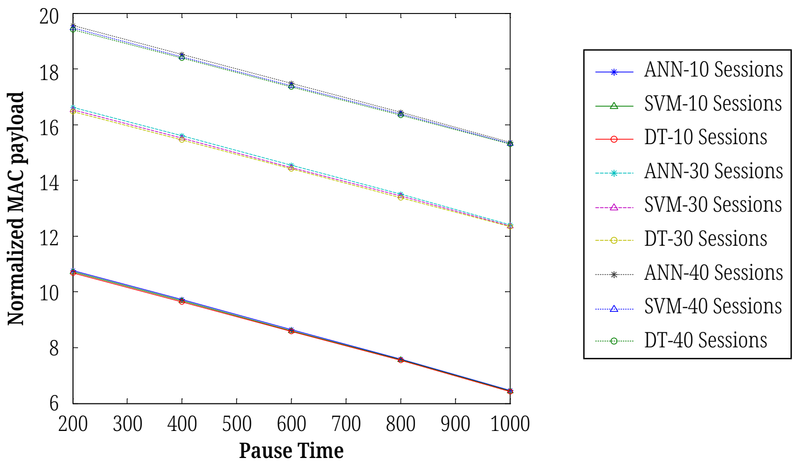

Fig. 5. Normalized MAC payload

Figure 5 also portrays the results of NMP between the proposed model and existing models in terms of various sessions for transmitting the data packets. The simulation results show that at the time of using reduced pause time, the NMP is higher and vice versa. However, the results show that the NMP of ANN is less than that of SVM and DT. The faster rate of routing path computation by the ANN enables optimal data transmission compared to SVM and DT. The MAC payload is estimated to determine the QoS of the entire network. The data collected via IoT devices and sent to the cloud environment shows better delivery of packets from the source nodes to the destination and to the users.

Thus, the problem of interfacing to match the data rates of IoT and WSN sensors is handled well in this study, as the latency in delivering the data to the cloud is reduced as per the above claims. The data speeds are maintained in a queue-less manner with efforts to create congestion and less traffic in the network.

5 CONCLUSIONS

In this paper, various control planes are used to establish optimal routing of high-speed data packets from the source node to the destination node. The source IoT sensors involve effective data collection, and the intermediate nodes enable the fastest routing mechanism via ANN decisions. The optimal routing decisions stabilize the routing of data packets without congestion. The simulation is conducted to test the efficacy of the ANN routing in the integrated network, and the results show that the ANN-based routing achieves higher energy efficiency and throughput than other models. The increasing data rate of the IoT node may lead to network congestion, which may affect the optimal route selection. In the future, the proposed method can be elaborated by identifying the key parameters associated with the Internet of Things. Also, the need for deep learning to route the packets can be identified for better allocation of resources.

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