A Priority based Self-Organised MAC Protocol for Real Time Wireless Sensor Network Applications

Archana R. Raut
CSE Department, G H Raisoni College of Engineering, Nagpur, India
archana.kakade5@gmail.com (corresponding author)

Sunanda Khandait
IT Department, K D K College of Engineering, Nagpur, India
sunanda.khandait@kdkce.edu.in

Dipti Theng
CSE Department, Symbiosis Institute of Technology, Pune, India
deepti.theng@gmail.com

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ABSTRACT

Wireless Sensor Networks (WSNs) are expressively utilized in various real-time control and monitoring applications. WSNs have been expanded considering the necessities in industrial time-bounded applications to support the dependable and time-bound delivery of data. Recently, Machine Learning (ML) algorithms have been used to address various WSN-related issues. The use of ML techniques supports dynamically modifying MAC settings based on traffic patterns and network conditions. In WSNs to control the communication between a large numbers of tiny, low-power sensor nodes while preserving energy and reducing latency, effective MAC protocols are essential. This paper addresses the ML centered priority-based self-organized MAC (ML-MAC) protocol to provide a priority-based transmission system to ensure the timely delivery of critical data packets. In this research, depending upon the predictions of the ML model, the MAC parameters are dynamically adjusted to find priority-based channel access and the optimal routing path to meet the deadline of critical data packets. From the result analysis, the average throughput and delay of the proposed ML-MAC algorithm outperforms the existing I-MAC protocol.

Keywords-adaptive learning; MAC; ML; real-time; priority; WSNs

I. INTRODUCTION

A Wireless Sensor Network (WSN) accommodatingly observes the physical or environmental conditions. Initially, WSNs were mostly planned for applications like military area observation and environmental and industrial control and monitoring. In these applications, increasing the energy efficiency and network lifetime were the primary design objectives. Providing the best-effort data transmission with improved network lifetime is critical in such situations. Currently, WSNs are used in various real-time control and monitoring applications, like object tracking, environmental monitoring, home monitoring, localization, personal health monitoring, industrial control and monitoring, etc. [1-3]. WSNs offer several applications that contribute to a smart, economical, and comfortable lifestyle. In [2], current research methodologies and key aspects of real-time communications in wireless sensor networks are discussed. Some of the most important problems with WSNs from applications to technological difficulties are covered in [3]. In order to accomplish continuous logistics optimization, decision-making is based on the information processing and communication capabilities offered by a sensor network [4]. Most of the applications stated above require minimum end-to-end delay with reduced packet losses while data transmissions. These rising applications are revealed by requirements concerning Quality of Service (QoS) fulfillment such as time-bound and reliable data transmission based on the criticality of data packets [5]. Every application has unique QOS needs. Additionally, information may seek different QoS processing (e.g. alarm messages vs. normal monitoring messages etc.) depending on the application. However, ensuring QoS in WSN-based applications continues to be a difficult challenge due to the unreliability of the wireless medium and the hardware restrictions of devices [6]. Recent advancements demonstrate their effective application in QoS providing. In time-critical applications, whenever critical data packets arrive, they must be transmitted within specific time bounds. Excessive delay in such cases may result in system uncertainty, financial harm, or life risk in the employed zone.

Many studies and improvements have been passed out in designing new architectures and protocols for minimizing the energy depletion of the WSN [4-6]. However, very few researches have been carried out to increase the WSN performance in terms of provisioning QoS. In real-time monitoring applications, a WSN is supposed to be an operational, useful and highly probable tool. Some predominant Real-Time (RT) application areas in WSNs, where provisioning QoS is an important concern are exhibited in Figure 1.

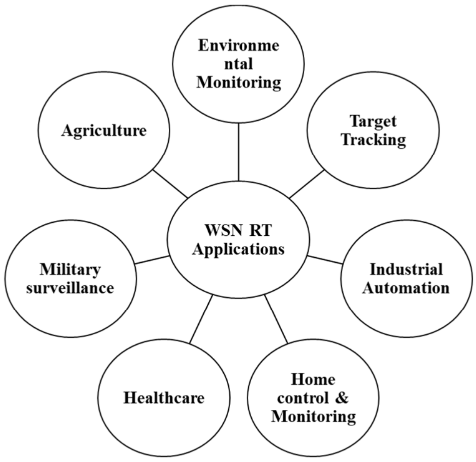

Fig. 1. WSN RT applications.

II. LITERATURE SURVEY

To support the time-bounded performance of the network when developing time-bounded applications for WSNs, it is also needed to analyze the resource constraints and node-to-node transmission reliability. Numerous MAC and routing protocols with a focus on QoS have recently been made available in wireless sensor networks [7]. Since most present protocols consider energy to be a valuable resource in sensors, they focus on increasing energy efficiency [8]. Additionally, a few other challenges arise as a result of the RT time-constrained data delivery applications that demand new routing protocols to effectively utilize the sensor nodes and gather data in a short amount of time [4, 5, 7]. The network layer is accountable for routing data packets to the destination node within bounded time limits, while the MAC layer is accountable for ensuring the delay when accessing the channel.

While designing traditional network layer protocol parameters such as end-to-end route detection, resource reservation is mainly considered. But even if having similar characteristics, it may not be appropriate for WSN for various causes. Spending time in optimal route detection is not tolerable for critical non-periodic packets. Also, reserving the resources for such irregular non-periodic packets is again inconvenient. Even if the traffic is periodic and continuous, still these methods are not concrete in dynamically changing WSN environment due to disturbances in service while path recovery increases the delay in data transfer which is unacceptable in time bounded emergency applications. Guaranteeing the QoS in varied traffic types is a challenging problem at the network layer in WSNs [5, 9, 10] due to the following features of the WSN:

- Dynamic topology changes: Topology changes in the network are caused by the failure of nodes or due to node mobility.
- Large-scale sensor nodes.
- Generation of periodical and unperiodical traffic in the network having diverse urgencies and different RT application requirements.
- Data redundancy can be formed by simultaneous working sensor nodes.

A. *Machine Learning Algorithms in WSNs*

In the ML approach, the system obtains the information from the analysis of the existing data which is updated timely. Utilizing ML-based systems, real-time decisions can be taken dynamically without being explicitly programmed [9, 11, 12]. Authors in [13] provide a statistical comparison of several ML approaches utilized for the QoS parameters from 2013 to 2023. Using ML techniques also makes the computations reliable, more dominant, and efficient even in the case of complex data. Figure 2 presents various ML approaches and their associated methods. The appeal of ML algorithms lies in their use of architecture to learn and improve performance to offer generic solutions. Due to its interdisciplinary character, ML is essential in several disciplines, including engineering, medicine, and computers. The vast volume of sensor data can be simply gathered and analyzed using an ML-based approach to excerpt relevant evidence from the sensor data.

The three primary types of ML algorithms are supervised, unsupervised, and reinforcement learning. Currently, ML techniques are utilized to resolve issues and find optimized solutions for real-time data communication applications in WSNs. Various ML-based techniques and algorithms are used in WSNs to fulfill the QoS requirements of various RT applications [9, 14-22]:

- Tracking throughout for rapid dynamic changes in the ecosystems.
- Calibrating a WSN to get new environmental information.
- Modeling complicated systems, which are challenging for mathematicians to model.
- Extracting important information from sensor data and suggesting system improvements in advance.
- Developing wise decision and self-governing control systems.

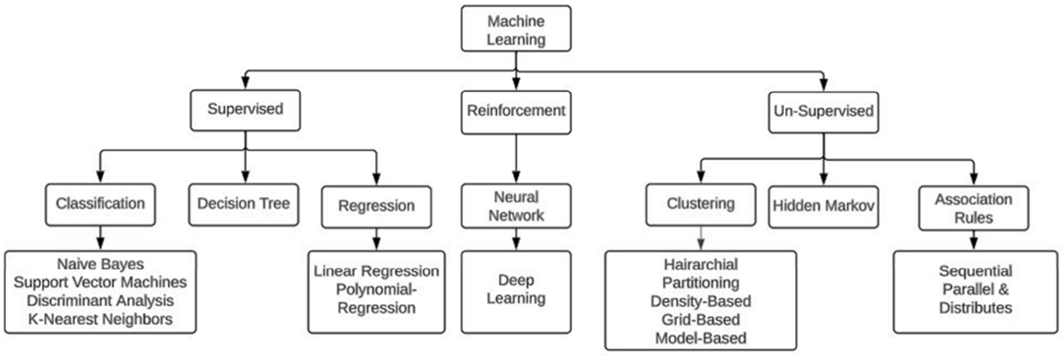

Fig. 2. ML approaches and methods.

The use of ML increases the effectiveness of WSNs and reduces the need for human intervention or reprogramming. To tackle the QoS issues in WSNs, we firstly reviewed earlier work. Additionally, we analyzed ML-based methods already used to solve various problems in WSNs in more recent times [8, [23-26]. Figure 1 gives different aspects of current methodologies used in various application domains. Many researchers have developed energy and latency-efficient communication protocols using ML-based techniques [15]. To improve the performance of WSNs, a few deep learning techniques were proposed in [15, 25]. This extra intelligence aids in identifying the network topology and link settings variations so that the network can update its situational awareness and adjust the protocol parameters appropriately.

Time Division Multiple Access (TDMA), allots a specific time slot for transmission to each node by dividing the available time into fixed-size slots. TDMA lowers contention and collisions by ensuring that transmissions are planned ahead of time and is appropriate dor time-sensitive applications where exact timing is crucial. A MAC layer protocol called TSCH (Time-Slotted Channel Hopping) combines channel hopping and TDMA [23]. Nodes synchronize their schedules to send and receive within the time windows that are allocated for this purpose. Channel hopping increases dependability and reduces interference. A routing protocol called RPL was created specifically for lossy and low-power WSNs [24]. It supports two different routing data modes: storing mode and non-storing mode. RPL can assist in ensuring that time-sensitive data is delivered on schedule by effectively routing data across the network. In queuing based on the priorities method, the criticality or temporal sensitivity of each packet determines its priority [19, 27, 28]. High-priority packets are transmitted by nodes ahead of the low-priority ones. This guarantees that, even in the event of congestion or contention, time-sensitive data gets sent promptly. Using this method, the criticality or temporal sensitivity of each packet determines its priority. Accordingly, the prioritizing for accessing the medium will be accomplished by the MAC layer [28].

Based on the above survey, several MAC protocols have been created expressly to reduce data transfer latency. These protocols frequently use techniques like shortened contention windows and quick acknowledgment schemes, giving priority to time-sensitive traffic over non-essential traffic.

ML-based I-MAC (Intelligent MAC protocol) was suggested in [29]. This approach helps the network nodes choose the MAC protocol that best fits the existing network conditions by combining competitive and non-competitive protocols. Based on the characteristics of the data packets, an intelligent choice system selects either a TDMA-based or CSMA/CA-based MAC. The impact of both inherent and external parameters is taken into consideration to address the application restriction problem experienced in one MAC protocol. Because competitive and non-competitive MAC protocols function differently, the author describes an ML strategy for identifying the most appropriate protocol model.

As stated above, dynamic TDMA as well as CSMA/CA, are the two main MAC protocols discussed in [29] to support RT applications. Authors in [30] used self-adaptation techniques to reduce the energy consumption with the help of a prediction-based adaptive duty cycling scheme. Recently, many novel protocols have been proposed to handle RT communication in WSNs [31].

Adaptive ML, as its name suggests, can adjust to quickly changing data sets, which increases its applicability to real-world scenarios. Compared to classic ML, adaptive ML is more reliable and effective and integrates agility, improved accuracy, and higher sustainability. Large amounts of data may be processed by adaptive ML, and its operational parameters can be more easily changed as the requirements of the firm using it change. Adaptive ML can quickly adjust to new information and offer in-the-moment insight into the potential applications of that data.

In the proposed system, adaptive-based ML model is used. Some of the benefits of such a protocol are:

- Better Performance: The protocol may optimize network performance in RT, resulting in higher throughput, lower latency, and increased energy efficiency by dynamically adjusting MAC parameters.
- Robustness: The protocol is more resistant to oscillations and interference since it can adjust to shifting network circumstances and traffic patterns.
- Energy Efficiency: The protocol can extend the life of the network by preserving energy by intelligently controlling transmission power and communication schedules.

III. PROPOSED METHODOLOGY

In the suggested approach, we have employed an ML-based methodology to achieve the service quality requirements in WSNs. Figure 3 gives the system model of the proposed approach. Firstly, the data packets collected by the sensor nodes are classified based on their criticality after comparing them with the benchmark value called a threshold value (Th). The threshold value is decided based on application requirements and sensor node data. Different threshold values can be assigned for different sensors, grounded on the values of data captured at the sensor node for transmission to the base station and critical condition benchmarks. For example, in industrial applications such as monitoring and controlling temperature in an oven or a boiler, the set reference temperature can be considered as a threshold value. The temperature above the reference temperature needs to be controlled to avoid damages and system failures. In such applications, the current temperature is matched with the reference temperature and if it is larger, appropriate measures are taken to control it. Thus, based on the application necessities, the threshold condition can be changed and data can be classified and forwarded to the sink accordingly. Sensor node data are categorized considering the criticality of data packets. When an emergency data packet is identified, the communication is carried out using a proposed ML-MAC algorithm. The proposed algorithm finds the optimal routing path for the transmission of critical data packets which ensures that the closest and least energy-intensive route will be chosen at that moment based on the current network situation.

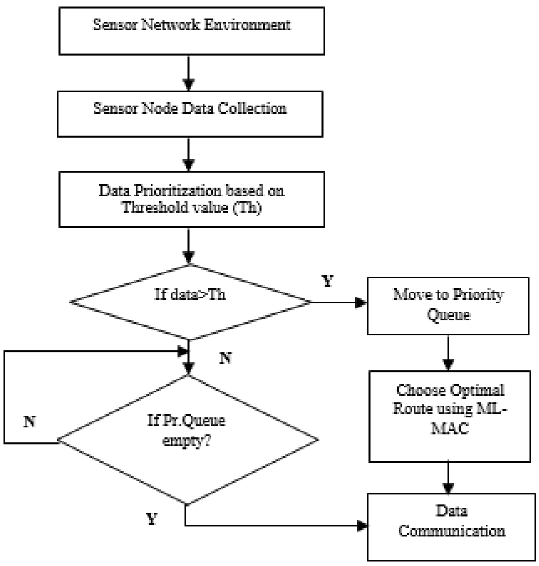

Fig. 3. Proposed system model.

When multiple packets with the same priority emerge at once, a queue is maintained to broadcast packets according to the FIFO principle. The normal data packets in this scheme must wait until all the time-critical packets have successfully reached their destinations. This technique is estimated to rise the end-to-end delay of regular data packets, however it decreases the delay in time bounded packets. Figure 4 shows the critical data transmission model.

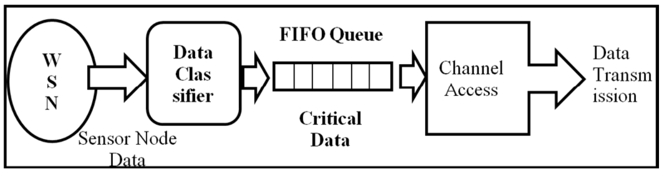

Fig. 4. Critical data transmission model.

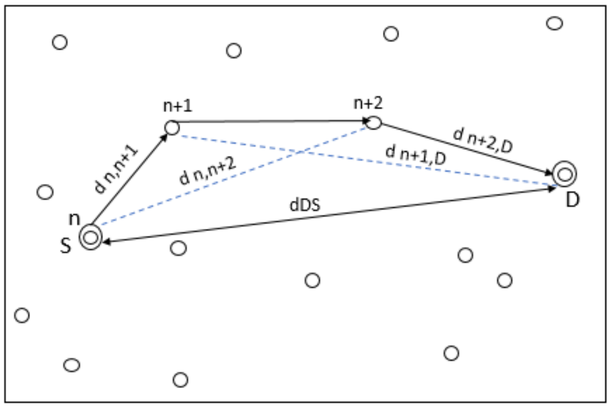

Fig. 5. The proposed system.

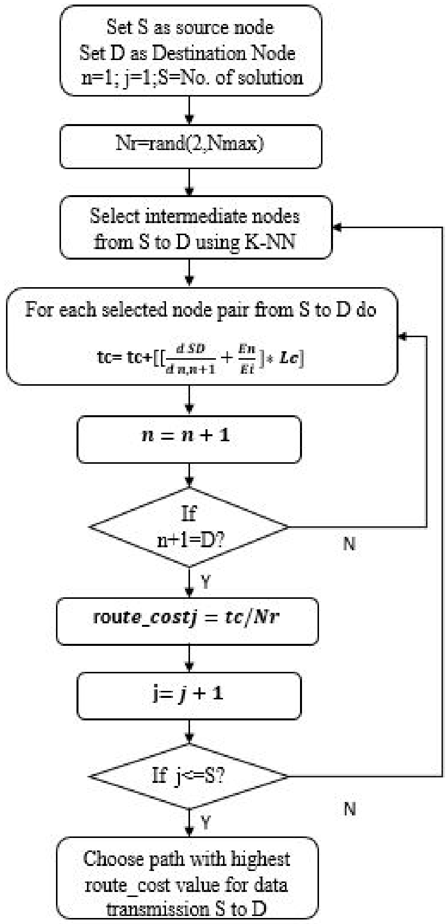

Fig. 6. Proposed system flowchart.

The ideal routing path for the delivery of crucial data packets is modified in the suggested algorithm to account for changes in wireless network settings. This gives the network an edge in recognizing the changes in the network and deviations in link settings so that required parameters can be adjusted dynamically. In the proposed methodology, an intermediate node is selected based on the K-nearest neighbor (KNN) classification algorithm. The distance between each node pair is determined using Euclidean distance from the source node to the destination node. The detailed scenario is shown in Figure 5.

Assume S is the sender and D is the receiver node. For all the intermediate nodes, the distance is calculated using the Euclidean distance formula i.e. distance between $S(x_1,y_1)$ and $D(x_2,y_2)$ can be calculated as:

$$dSD=\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}$$

Figure 6 shows the system flow chart of the proposed model. The selection of intermediate nodes for data transmission from the source node (S) to the destination node (D) follows.

Any node between S and D can be selected as an intermediate or relay node if it satisfies the following conditions:

1. $d(S,D) < d(S,n+1)+d(n+1,S)$
2. $d(n+1,D) < d(S,D)$

Nodes satisfying both conditions ensure that they lie in the path between source to destination. After the selection of intermediate nodes, the total cost of the route is calculated considering the distance, residual energy of the nodes, and link quality in the selected route as:

$$\text{totalroutecost (tc)} = tc + [(dDS/d(n, n + 1)) + (En/Ei)] * Lc$$

where, dSD is the Euclidean distance between S and D, d(n,n+1) is the direct distance between nodes n and n+1, En, Ei are the residual and initial energy of a node n respectively, and Lc is the link quality of the selected channel c. Link quality (Lc) is a considered to be a significant element during the transmission path selection. Seeing the fluctuating features of sensor nodes, the hardware-based metric of Link Quality Indicator (LQI) is considered which distinguishes the link quality as 3, 2, 1 respectively, for good, medium and bad links. The value of tc is calculated considering multiple attributes like distance, energy, link quality of specific channel etc. so, it is accountable for finding the optimal path value. The total route cost (tc) is calculated as the summation of the tc values for the complete path from S to D. The final route_cost value of the selected route is calculated as:

$$\text{route\_cost} = tc/Nr$$

where Nr is the number of routing nodes in the transmission path. In the end, the number of solutions are generated as shown in Table I. The path having the highest route_cost value is considered to be the optimal routing path and is selected for packet transmission. Table I shows the path identified based on source node 5 and destination node 41.

TABLE I. ML-MAC-BASED ROUTING TABLE

S	D	Solution No. (Ns)	Relay Nodes	Total route_ cost	route_cost
5	41	0	15, 37	10.98	5.49
5	41	1	8, 39	37.316	18.658
5	41	2	2	5.91	5.91
5	41	3	15, 38	8.81	4.405
5	41	4	16	5.94	5.94
5	41	6	40, 35	7.29	3.645
5	41	7	13, 20	7.76	3.88
5	41	8	8	5.811	5.811
5	41	9	2, 47, 32	8.76	2.92
5	41	10	13	5.88	5.88
5	41	11	38, 39	7.95	3.975
5	41	12	38	5.9	5.9
5	41	14	18, 20	7.31	3.655
5	41	15	1, 13, 25	9.49	3.16333
5	41	16	15, 19	9.19	4.595
5	41	17	19	5.64	5.64
5	41	19	16, 31	7.54	3.77

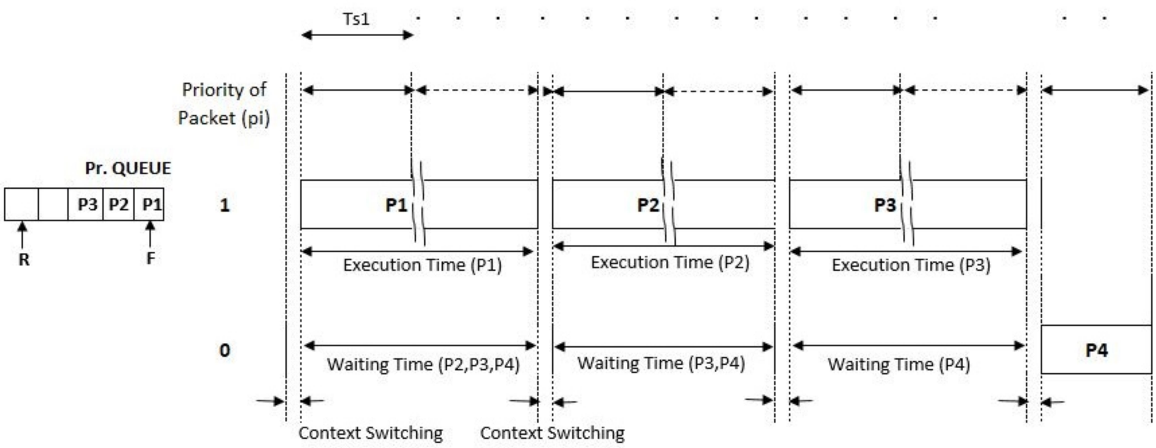

Fig. 7. Timing diagram of the proposed protocol.

As shown in Table I, a total of 19 paths were identified after the last iteration. The route_cost value is calculated at every iteration and the final path for transmission is selected based on the highest route_cost value. In the end, each solution has a calculated route_cost value. To choose the best path, the path with the highest route_cost values is taken into account. The ultimate best path for data transmission is selected depending on the results of all iterations. In the previously discussed example, the optimal data transmission route from source node 5 to destination 41 was chosen as 5 → 8 → 39 → 41. Normal data packets will now have a longer end-to-end latency because of this method. Lower energy usage and a higher packet delivery ratio increase the system's overall performance. As a result, it is quite beneficial for applications utilizing wireless networks that are sophisticated and smart. Packet scheduling for different types of data is shown in Figure 7: If 4 packets P1, P2, P3, and P4 arrive with P1, P2, and P3 as priority data packets and P4 as a normal data packet. Based on the arrival time of priority data packets a priority queue (Pr. QUEUE) is maintained and packets are transmitted one after another until the queue becomes empty. The normal packets will be transmitted after successful transmission of all the critical data packets. Here, priority 1 is considered high priority and 0 is considered low priority or normal data.

IV. RESULTS AND DISCUSSION

The proposed protocol (ML-MAC) was implemented in network simulator NS-2. The simulation environment settings used for confirming and calculating the performance of the proposed scheme are given below.

- Routing Protocol: AODV
- Number of nodes: 60
- MAC: TDMA
- PHY: 802.11
- Packet size: 1000 bytes
- Simulation time: 500 s
- Packet interval: 0.01 s
- Map Size: 1000 × 1000 m

Figure 8, shows the implementation of the proposed protocol on network simulator NS2. Grounded on the existing literature, we compared the performance of the proposed algorithm with the existing ML-based MAC protocol taking into account some performance metrics delay and throughput for quality of service assurance. The proposed system is equated with I-MAC considering TDMA MAC taken into account parameters such as throughput and transmission delay.

Figure 9 shows the comparison between protocols I-MAC and ML-MAC considering the metric transmission delay. Delay is evaluated as the time gap between the time the packet was sent and the time it reached the target node. Figure 10 shows the comparison between protocols I-MAC and ML-MAC considering the average throughput. Throughput is calculated as the total information the network is able to manage and administered by the system within a specific time period. It helps evaluate the overall network performance based on the number of successful communications in the network. From the result analysis, it is clear that the average throughput and delay of the proposed algorithm outperforms the existing I-MAC protocol. It shows that under varying network environments, the proposed algorithm performs better in terms of transmission delay and throughput over existing schemes.

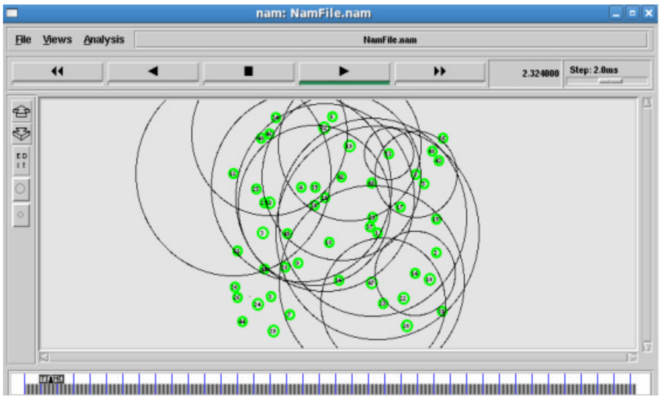

Fig. 8. Communication amongst sensor nodes.

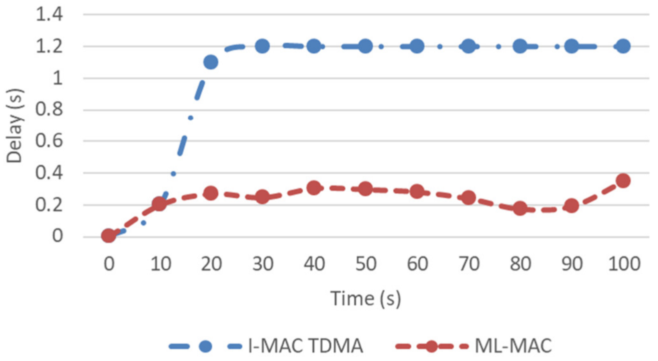

Fig. 9. Average delay: I-MAC vs. ML-MAC.

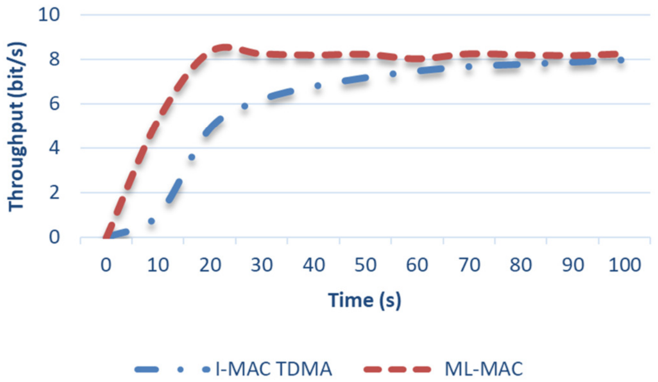

Fig. 10. Average throughput: I-MAC vs. ML-MAC.

V. CONCLUSION

With the growing and fast developments in wireless sensor networks, a widespread range of real time applications demand time-restricted data transportation. To address this issue, in this paper, a priority-based adaptive MAC protocol called ML-

MAC is proposed. The proposed algorithm uses an adaptive learning approach for channel allocation and optimal routing path selection to support mission-critical data transfer in WSNs. A machine learning approach is employed to select the most efficient and optimal routing path for the transmission of emergency data packets specifically based on the existing situation. In addition, ML-MAC proposes a multi-priority based adaptive mechanism constructed considering elements such as data priority, node's residual energy and link quality. The performance of the proposed protocol was tested with the existing machine learning-based I-MAC protocol. Based on the experimental findings, the average throughput of ML-MAC is 22% more than that of I-MAC. Similarly, the average transmission delay of the proposed ML-MAC algorithm is 75% less than that of the I-MAC. This shows that under varying network environments, the proposed algorithm achieves improvement in terms of transmission delay and throughput over the existing I-MAC. The suggested ML-MAC technique is very advantageous in smart wireless sensor network management. ML-MAC has been designed considering the static sensor nodes in the network and numerical data collected from sensor nodes. In the future, it can be extended to work in dynamic sensor node networks with image data classification and transmission to the destination grounded on a priority of data packets.

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