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Design and Implementation of Resource Management Optimization Algorithm to improve QoS performance

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Abstract

In wireless communication, the physical layer handles radio propagation and other challenges unique to a wireless channel. Whereas, Media access control layer coordinates the access to the shared medium. This work carried out deliberates on physical as well as medium access control layers respectively. It aims to develop the algorithm to improve Quality of Service (QoS) for recommendation as well as allocation of a good channel in the presence of congestion in a dense environment. The performance of the algorithm is evaluated using network simulator NS2. The investigated algorithm focuses on improving the QoS performance of the network by throughput gain of 22.22 %, reducing packet dropping ratio by 4 %, and recommending a good channel based on the fitness function. The simulation result shows that the algorithm provides a 15% better packet delivery ratio in congestion and dense scenarios. In this paper, required QoS aimed at channel recommendation for communication using machine learning technique is achieved.

Keywords: ML, NS2, QoS, and QoE

1. Introduction

Wireless communication made revolutionary advancements in recent decades. Global System for Mobile cellular standard espoused for voice communications in 1992. A packet data network has shepherded a demand for pervasive data admittance. Successive generations of wireless standards

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support the humorous data package to users. Further, 3G is said to be operator-centric. Whereas 4G is considered service-centric and 5G is user-centric. Resource management consists of three steps. The first step is resource allocation. It supports utilizing existing network resources. The second step is resource-leveling. It helps to realize unproductive resources. The third step is resource Forecasting. It allows predicting future resource requirements.

The key network QoS parameters are throughput, latency, jitter, packet loss, availability, and reliability. The data rate is expressed in bits/second. The tiniest throughput is guaranteed for specific services as well as applications. Whereas latency defines the delay between the data sent and received. On the other hand, jitter characterizes delay variation. Packet loss epitomizes data loss. This is a result of congestion. Availability assists to deliver services to the users with reliability.

This paper comprises five sections and contributes to the enhancement of QoS performance by proposing a resource optimization algorithm using a machine learning approach. Section two explicates the literature adopted for enhancing the performance of the 5G network. The third section presents the design of the proposed algorithm. The fourth section elaborates the result and discussion. Finally, the last section presents the conclusion followed by references.

2. Literature Survey

Currently, 3G and 4G have control of smart technology. With the increasing market demand for smart wireless technology, 5G will most likely become leaders in providing connectivity for various types of smart devices. Therefore, for today's wireless mobile communication systems, resource management is required based on fitness functions to enhance network performance.

In [1] the massive growth in mobile data traffic requires rigorous QoS requirements for 5G networks. Here, Radio Resource Management and innovative packet scheduling are proposed for bandwidth-hungry applications under dynamic network conditions. Further, reinforcement learning, as well as neural networks, is presented. It finds appropriate scheduling decisions. Smart cities are designed to adopt modern communication technology. Here, the role of various cognitive domains is explored in [2] to assure the best services of 5G and beyond 5G communications. In [3], a network slicing design is presented. It uses a fusion learning algorithm. A blend classifier to optimize deep belief and neural networks are proposed. It uses the glow-worm swarm method. In [4] a deep learning approach is proposed to replace the channel estimator. Here, links are scheduled for communication with the help of topographical locations. The reason is that the channel forte is a function of the path loss. A sum-rate optimal scheduling algorithm that provides fairness is suggested in [5]. This approach shows viable network efficacy results. A deep learning technique for a wireless network to achieve significant performance gain is offered in [5]. It reduces computations by 50%. Hence, it can solve network optimization complications effectually.

Optimization of QoS in wireless networks requires well-organized channel allocation schemes. A modified Erlang-B dynamic channel allocation scheme is explained in [7]. It can expand network performance. This approach improved capacity as well as the quality of experience. In the present pandemic situation, data demand, as well as plans, is improved with various broadband networks for smartphones [8]. But industry and researchers are adopting 5G network. It provides services with diverging and technically stimulating user necessities. However, the network configuration, management, and planning have tremendously become thought-provoking. In [9], a bioinspired solution is demonstrated that achieves optimality in computations.

Currently, resource management techniques using machine learning emerged as a boisterous way to achieve QoS performance. A work proposed in [11] with learning to optimize as well as manage available resources. An analysis of machine learning (ML) to enhance network performance and achieve acceptable QoS/QoE is defined in [12]. Machine learning is useful to extract as well as predict trends. In universal, interference is evaluated at the physical layer. Further, link superiority is predicted at the data-link layer. Whereas, traffic demand is estimated at the network layer. The utility of training and learning in communication is gaged in [13].

It finds applications in clustering, routing as well as base-station switching control. In the end, 5G in [15] purposes efficacy of network optimization. It helps to make use of the resources. This resulted in achieving better capacity and QoS. This paper aims in developing an algorithm to improve QoS for the allocation of a good channel using machine learning techniques in the presence of congestion in a dense environment. In this work, performance metrics considered are throughput, packet dropping ratio, and packet delivery ratio.

3. Design and Implementation of Resource optimization Algorithm

A mobile unit is called a node that communicates with the central station. This center station is located at the upper corner called a router or Data collector. The router is connected to the outer network through wireless or Fiber. A channel recommendation algorithm runs inside the wireless router. The application targeted is a Smart Factory as shown in Fig. 1 For a particular node, one channel is assigned for communications. Further, the router decides which channel is to be recommended for every node. The channel with the highest fitness i.e. having very good QoS is assigned first, followed in descending order. Data give and take policy happens with the recommended channel. This entire record is maintained to build the data when the channel is released. This record is useful next time for channel recommendation to build up a data log. The work regarding channel recommendation with and without machine learning techniques is proposed

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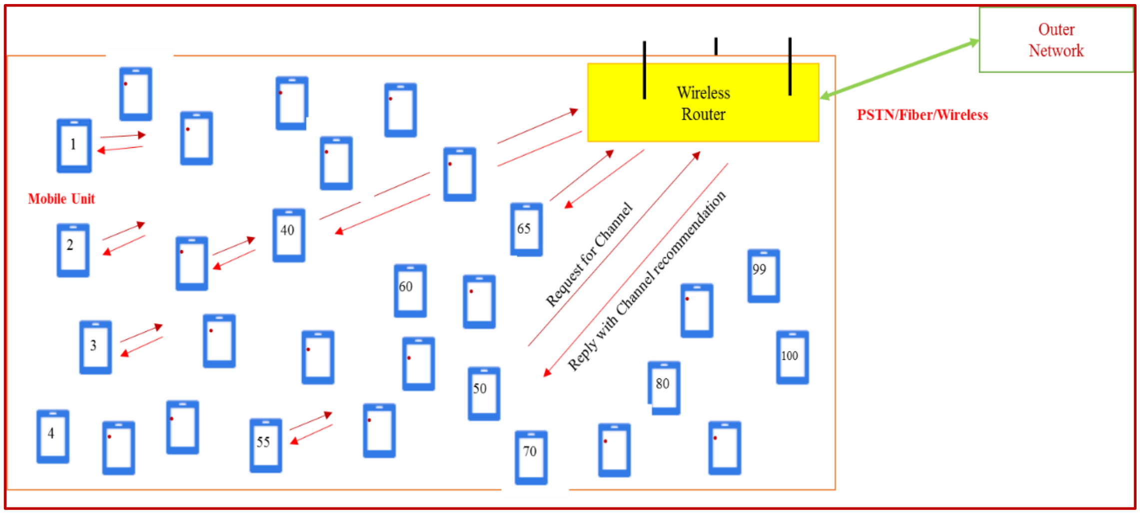

Fig. 1 Simulation Scenario for Smart Factory

. Simulations are carried out as per the settings shown in Table 1. The proposed algorithm is simulated using NS2.

Table 1. Simulation Parameters

Parameters	Particulars
Node Density	250
Node Speed	3 m/sec
Reporting Rate	50 packets/sec
Queue Length	100 packets
Energy	10 Joules
Packet Size	250 bytes
Simulation Area	1000 cm x 1500 cm
Simulation Time	50 sec
Channel Type	Mobile Nodes

Packet dropping ratio, packet delivery ratio, and throughput are used as performance metrics. They are observed against the changing size, the number of interfering nodes, and simulation time. Further, the effect of network congestion is studied. The metric evaluated is packet dropping ratio as well as throughput. The packet size, simulation time, and node density are rehabilitated in this simulation scenario.

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4. Results and discussions

The general flow chart for Resource Management Optimization Approach to improve 5G Network performance is given in Fig. 2.

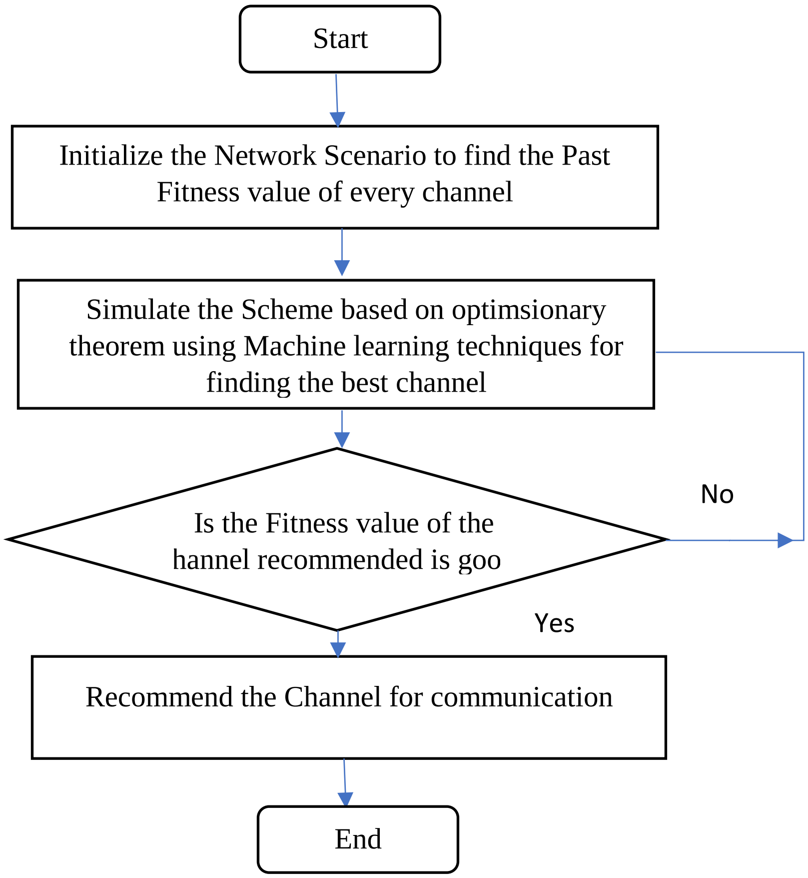

Fig. 2 Flowchart to evaluate network performance

The scheduling component is important at the access layer. It determines which users are active in a specified stint slot. Whereas, resource allocation is another mechanism at the physical layer of the wireless network. It assigns bandwidth as well as the power to the users. In this work, the experiment is to be done for channel selection based on QoS factors such as throughput, packet drop ratio, and Packet loss ratio.

A machine learning technique is designed and investigated for a 5G network. Packet dropping ratio and throughput are used as performance metrics. They are observed against the change in packet size, the number of nodes, and simulation time. Here, the size of the packet is altered in discrete steps. Fig. 3 and Fig. 4 illustrate the result of a change in packet size on considered performance metrics. A configuration of the algorithm and network setting is kept specifically for this experimentation. It is observed that changing the packet size is crucial in determining the

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packet dropping ratio. The algorithm updates the channel recommendation table for subsequent channel allocation. This results to maintain a packet dropping ratio generally steady in the range of 7 to 18 %.

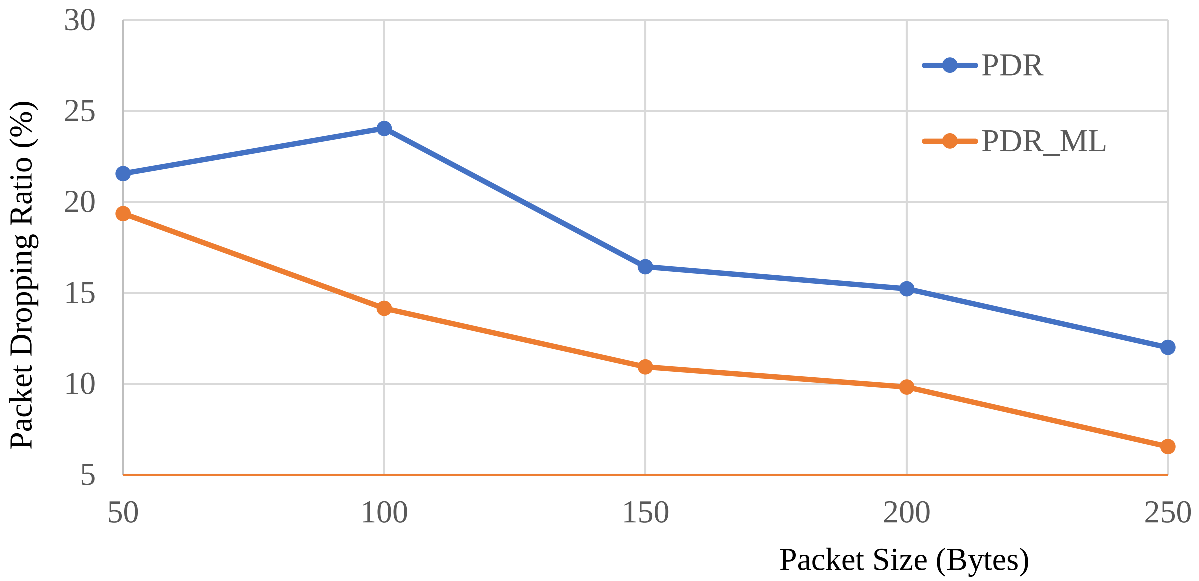

Fig. 3 Packet Dropping Ratio vs Packet Size

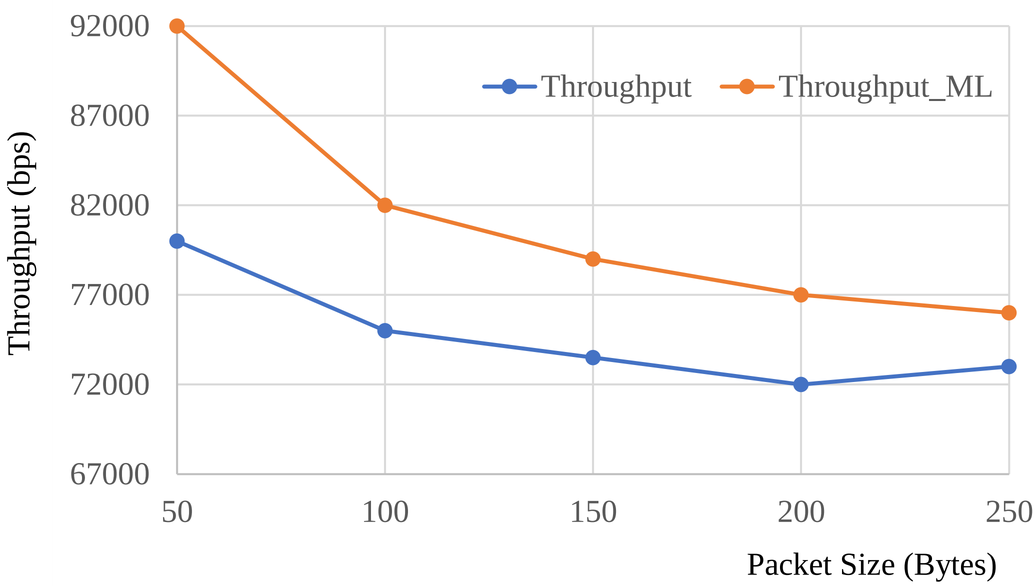

Fig. 4 Throughput vs Packet Size

Fig. 4 compares throughput with and without training the network for varying packet sizes. It is changed in distinct steps in the range of 50 to 250 bytes. The universal inclination is that an increase in the size of the packet decreases throughput. Thus, the proposed algorithm provides a

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well-adjusted decrease in packet dropping ratio as well as throughput. It achieves a maximum 13.04 % improvement as compared with the network without training the network. A total of 65, 000 frames were transmitted. Thereafter, the packet loss ratio is evaluated. It is pragmatic that as the size of packet increases in distinct step in the range 50 to 250 bytes, decreases the total count of efficacious delivered packets. The algorithm had a total of 62,100 packets delivered at a packet size of 50 bytes as revealed in Fig. 5. The least gain achieved over with training is 9.73 %.

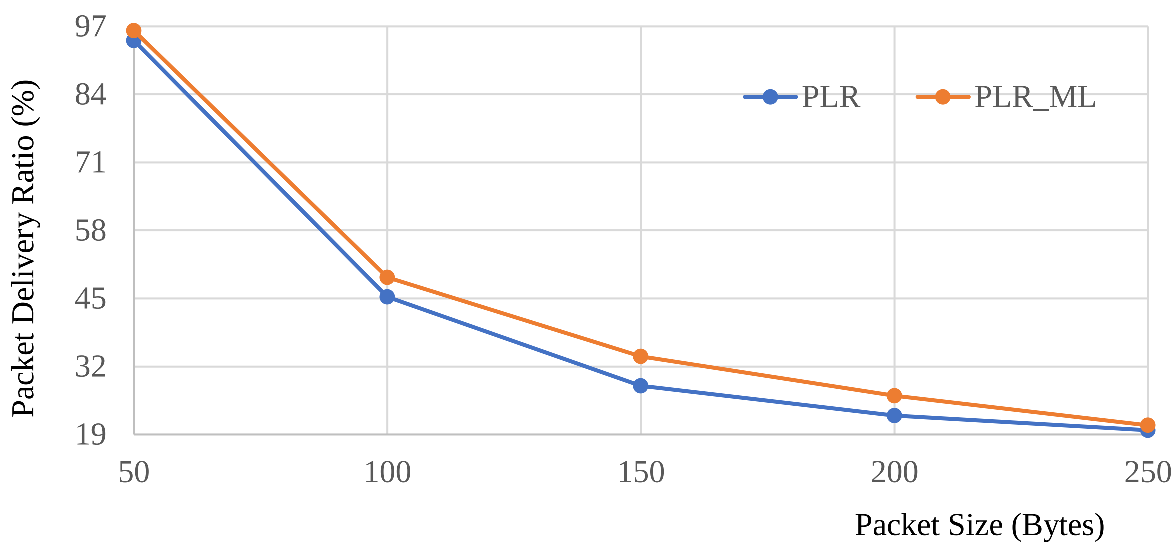

Fig. 5 Packet Delivery Ratio vs Packet Size

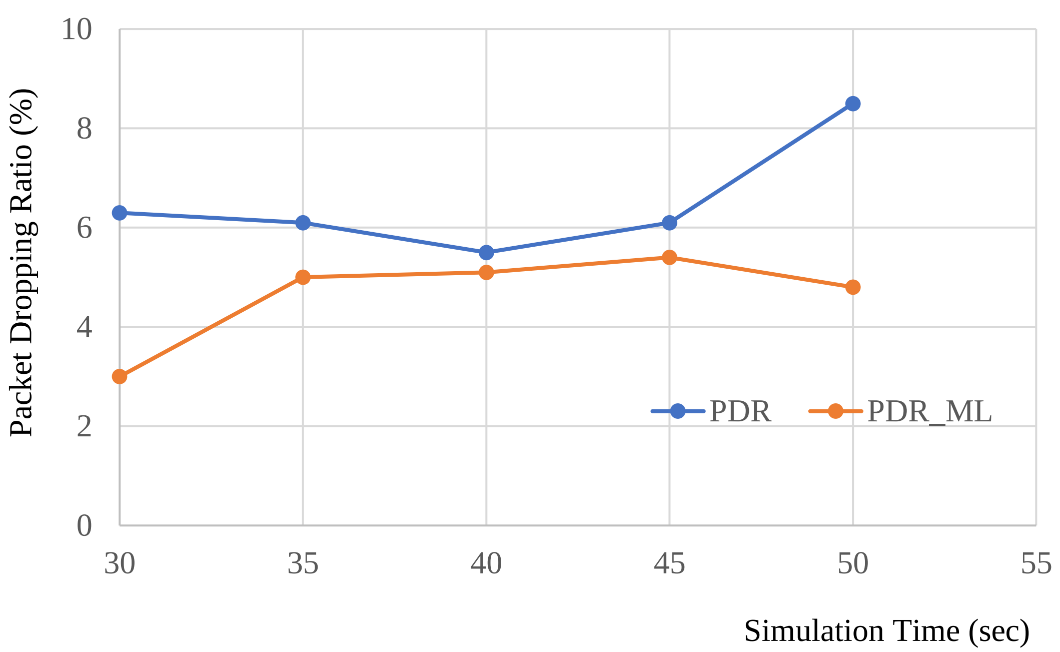

Fig. 6 Packet Dropping Ratio vs Simulation Time

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Fig.6 shows packet dropping ratios with and without training the network against time. The packet dropping ratio starts with a modest 4 % with a machine learning algorithm. The dropping ratio shoots up and decreases thereafter. Fig.7 displays throughput with and without training the system. The throughput achieved increases steadily. A proposed data set used for training can recommend a good channel. It achieves a maximum throughput gain of 22.22 %.

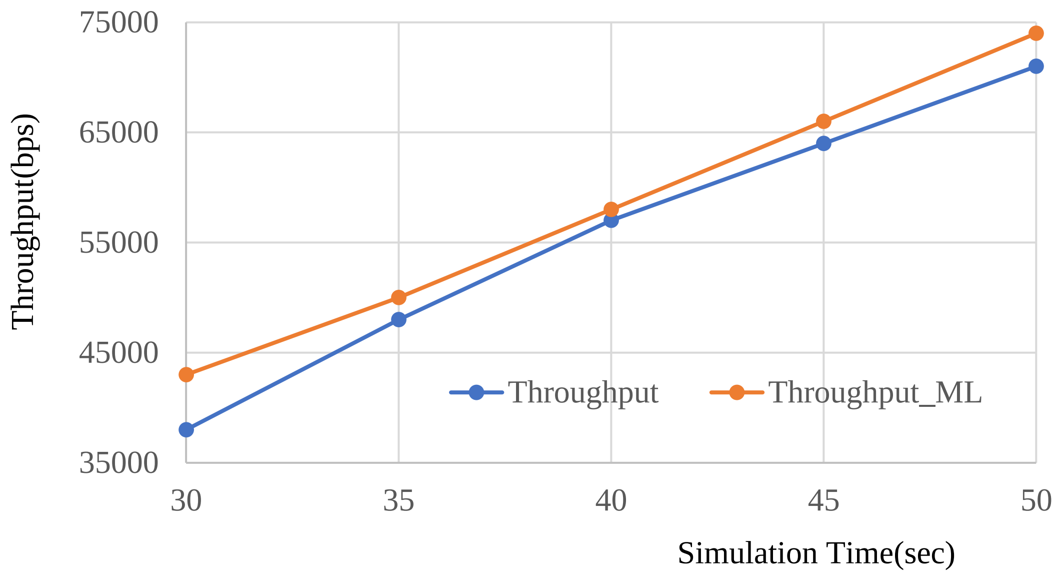

Fig. 7 Throughput vs Simulation Time

Fig. 8 Packet Dropping Ratio vs Nodes

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Fig. 8 and Fig. 9 portray the consequence of node density to evaluate performance metrics. Here, nodes are increased again in a distinct range to measure packet drop ratio as well as throughput. In this simulation, 85,000 frames are transmitted. In general, node mobility increases the collision probability. A packet drop ratio perfectly maps to an equal reduction in throughput. This correlation occurs at the node density count equal to 200. The proposed algorithm can achieve a maximum packet drop ratio enhancement of 12.5 % at a node density of 250. Further, a throughput gain of 7.24 % is also achieved as compared to an algorithm without machine learning.

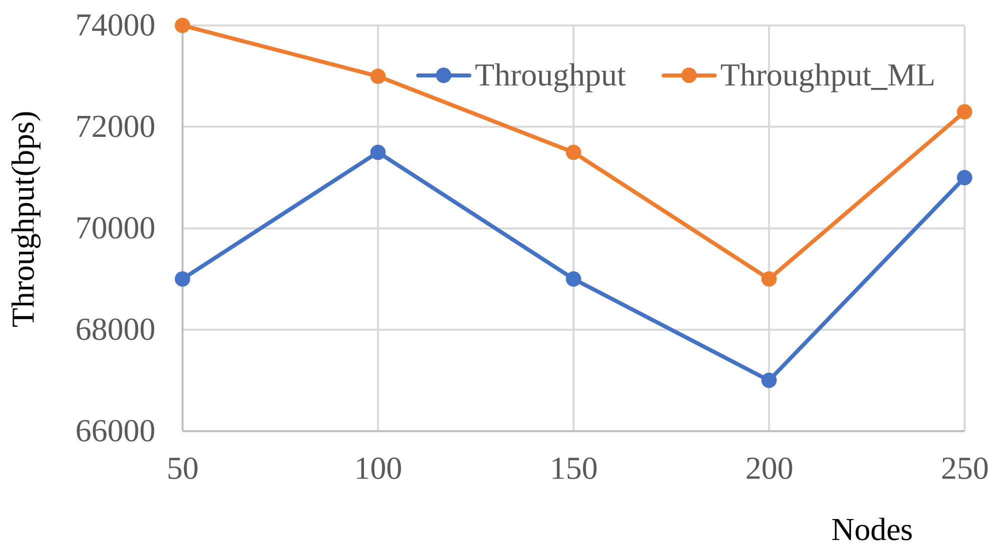

Fig. 9 Throughput vs Nodes

5. Conclusion

The key focus of the work is designing an algorithm to enhance the QoS performance of the network. The algorithm is implemented in a network simulator. The performance metric evaluated are packets drop ratio, packet loss ratio, and throughput. The investigated algorithm focuses on maximizing throughput. In this paper, a machine learning technique is proposed to train the network. For mobile nodes, though it keeps the highest throughput, its performance is at par as nodes density increases. It provides acceptable throughput as well as packet delivery for varying packet size, simulation time, and node density. The simulation result obtained for the presented scenario can attain improvement in Quality of Service by training the network for given traffic scenarios.

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