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An Intelligent Machine Learning Framework for Performance Prediction in Mobile Ad Hoc Networks

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ABSTRACT - Mobile Ad Hoc Networks (MANETs) operate without fixed infrastructure and are affected by node mobility, dynamic topology, unstable links, limited energy, and traffic congestion. This research introduces a Machine Learning-Based Performance Prediction Framework (ML-PPF) to predict packet delivery ratio, throughput, end-to-end delay, packet loss, routing overhead, and energy consumption. The framework uses network parameters such as node density, mobility, residual energy, link stability, queue utilization, traffic load, and route length as input features. After preprocessing and feature selection, Random Forest, Support Vector Regression, XGBoost, and Artificial Neural Network models are trained and combined using a weighted ensemble approach. The proposed framework enables early detection of performance degradation and supports efficient routing, congestion control, load balancing, and energy management in MANETs.

Keywords: MANET, Machine Learning, Performance Prediction, Ensemble Learning, Packet Delivery Ratio, Throughput, End-to-End Delay, Routing Overhead.

1. Introduction

Mobile Ad Hoc Networks (MANETs) are decentralized wireless networks formed by a group of mobile nodes that communicate without fixed infrastructure, centralized administration, or predefined communication links. Each mobile node can function both as a host and as a router by transmitting its own data and forwarding packets for other nodes through multi-hop communication. This flexible and self-organizing architecture makes MANETs suitable for emergency response, military communication, disaster management, vehicular communication, healthcare monitoring, temporary events, remote-area connectivity, and Internet of Things applications. However, the continuous movement of nodes and frequent changes in network topology create several challenges in maintaining reliable and efficient communication.

The performance of a MANET depends on various network and mobility parameters, including node speed,

network density, traffic load, transmission range, residual energy, signal strength, available bandwidth, queue length, hop count, and link stability. Changes in these parameters can significantly affect packet delivery ratio, throughput, end-to-end delay, routing overhead, energy consumption, and network lifetime. High node mobility frequently causes communication links to break, resulting in route failures and repeated route discovery processes. Similarly, increased traffic and uneven load distribution may create congestion, packet loss, longer delays, and excessive energy consumption.

Traditional MANET routing protocols generally select routes based on current network conditions and predefined routing rules. Reactive routing protocols establish routes only when communication is required, whereas proactive routing protocols maintain routing information continuously. Although these protocols provide effective communication in many network scenarios, they often respond only after a route failure, congestion event, or performance degradation has occurred. Their dependency on fixed rules may limit their ability to adapt to highly dynamic and unpredictable MANET environments.

Performance prediction plays an important role in understanding future network behaviour before serious communication problems occur. It involves estimating network metrics such as packet delivery ratio, throughput, end-to-end delay, congestion level, route stability, energy consumption, routing overhead, and network lifetime based on observed network conditions. Accurate prediction can support early identification of unstable routes, overloaded nodes, weak communication links, and potential network failures. This information can be useful for improving routing decisions, resource utilization, congestion management, load balancing, and energy efficiency.

Machine learning has become an effective technique for analysing complex and dynamic network data. It can identify hidden relationships among multiple MANET parameters and learn patterns from historical, simulated, or real-time network observations. Supervised machine

learning algorithms such as Support Vector Machine, Decision Tree, Random Forest, K-Nearest Neighbours, XGBoost, and Artificial Neural Networks can be used for classification and numerical performance prediction. Unsupervised learning methods can identify similar network conditions and detect unusual behaviour without requiring predefined class labels. Reinforcement learning can support adaptive network decision-making by learning from interactions between mobile nodes and the surrounding network environment.

2. Existing Methodology

1. Danilchenko et al. (2022) introduced a deep learning-based Delay Minimization Network (DMNet) to reduce weighted end-to-end packet delay in multi-hop TDMA-based MANETs. The study considered heterogeneous traffic flows with different transmission priorities and jointly addressed request scheduling and transmission-power control. DMNet uses a fully connected multilayer neural network that receives the network distance matrix and transmission requirements as inputs and determines the transmission power assigned to each transmitter during each time slot. The model was trained through supervised learning using optimal solutions as training samples. Simulation results indicated that DMNet performed effectively across networks with different numbers of nodes and links and outperformed the compared state-of-the-art and greedy optimisation methods. However, the study was limited to selected power-control and scheduling conditions. Additional QoS measures, fairness requirements, different request lengths and priorities, integration with the route-selection process, and interference originating outside the network cluster were not fully investigated.

2. Adaramola and Olasina (2025) investigated machine learning-based congestion prediction and management in MANETs using network data generated through the OPNET 14.5 simulator. Office network scenarios containing five, ten and fifteen mobile nodes were evaluated using network load, media-access delay and traffic reception as performance indicators. The results showed that network load increased from 2.8 Mbps with five nodes to 5.2 Mbps with fifteen nodes, while the highest media-access delay reached 0.0056 seconds under heavy traffic conditions. Machine learning models, including Decision Trees, Random Forest and Artificial Neural Networks, reported prediction accuracies of 98.7%, 99.3% and 99.8%, respectively. The findings demonstrated that predictive congestion analysis could support adaptive load balancing, bandwidth allocation, automatic route adjustment and proactive traffic management, thereby improving routing stability and reducing delay. However, the evaluation relied primarily on simulated and relatively small network scenarios. The authors identified the need to incorporate real MANET traffic, reinforcement learning-based congestion control, edge-computing implementation and practical testbed validation.

3. Aruna et al. (2023) developed a Machine Learning-Based Optimized Routing Algorithm known as ML-ORA for improving routing efficiency and security in MANETs. The technique combines Hybrid Particle Swarm Optimization for cluster-head selection, node clustering and a k-Nearest Neighbours classifier for identifying malicious and legitimate nodes. The system was evaluated using the NS-3 simulator under dynamic network conditions. The experimental findings reported an end-to-end latency of 15 ms, a packet delivery ratio of 95%, a network throughput of 4 Mbps and an energy efficiency of 85%. The results indicated that ML-ORA improved route dependability, data-transmission efficiency and network security compared with traditional routing approaches. However, the study acknowledged continuing challenges concerning network scalability, further optimisation of energy consumption and the development of stronger mechanisms for managing diverse security attacks in larger MANET environments.

4. Nayab et al. (2025) presented an adaptive routing strategy integrating Expanding Ring Search, Random Early Detection and machine learning to optimise reactive routing protocols in MANETs. The study used machine learning classifiers to select an appropriate routing protocol according to current network topology and operating conditions. The system evaluated different standard and modified reactive routing protocols by considering packet delivery ratio, throughput and end-to-end delay. AdaBoost, k-Nearest Neighbours and Decision Tree classifiers obtained protocol-selection accuracies of 95%, 93% and 92%, respectively. NS-3 simulation results demonstrated that the integration of predictive analytics with routing-protocol selection improved packet delivery, reduced latency and supported congestion mitigation under different network configurations. Nevertheless, balancing competing measures such as energy consumption, throughput, packet loss, packet delivery ratio and delay remained difficult. The authors also indicated that practical validation using real devices and network-emulation platforms is necessary to confirm the applicability of the approach beyond simulated environments.

5. Vishwanathrao and Vikhar (2024) developed the Reinforcement Machine Learning-Based Improved Energy-Efficient AODV protocol, referred to as RML-EEAODV, to reduce energy consumption and routing overhead in MANETs. The protocol incorporates reinforcement learning into AODV and maintains dynamic information regarding the residual energy and traffic load of intermediate nodes. This information enables nodes to select energy-efficient forwarding paths and avoid unnecessary Route Request rebroadcasting. RML-EEAODV was evaluated against traditional AODV and DSDV protocols using the NS-2.34 simulator. The results demonstrated that the protocol achieved better energy efficiency, reduced routing overhead and improved route-discovery and maintenance efficiency across different network scenarios. However, the

approach produced a slight reduction in packet delivery ratio under certain conditions, indicating a trade-off between energy conservation and reliable packet delivery.

3. Proposed Methodology

The proposed research introduces an Intelligent Machine Learning-Based Performance Prediction Framework (ML-PPF) for Mobile Ad Hoc Networks (MANETs). The framework is designed to proactively predict network performance metrics such as throughput, packet delivery ratio, end-to-end delay, and routing overhead before performance degradation occurs, rather than reacting to it after the fact. In highly dynamic MANET environments, frequent topology changes, node mobility, energy depletion, and congestion make performance highly unpredictable, often leading to sudden throughput drops, increased delay, and route failures. To address these challenges, the proposed ML-PPF framework continuously monitors key network parameters and applies machine learning models to forecast near-future network performance, enabling proactive routing and resource management decisions.

The proposed framework considers residual energy, node mobility, link quality, queue occupancy, and traffic load as input features to predict network performance. By training machine learning models on historical and real-time network state data, ML-PPF learns the underlying relationship between network conditions and performance outcomes. Unlike conventional monitoring approaches that only report current network status, the proposed framework forecasts future performance trends, allowing routing protocols to take preventive action such as rerouting or load redistribution before failures occur.

The overall process consists of network initialization, data collection, feature extraction, model training, performance prediction, and decision feedback. During operation, each node (or a designated cluster head/monitoring node) collects real-time network parameters, which are fed into the trained ML model to generate a Predicted Performance Score (PPS). Nodes or paths with a PPS below a predefined threshold are flagged as performance-risk zones, and the routing layer is notified to avoid or deprioritize them. This predictive mechanism reduces reactive failures, improves route reliability, minimizes packet loss, and enhances overall network performance.

By combining real-time network monitoring with machine learning-based forecasting, the proposed ML-PPF framework aims to achieve higher prediction accuracy, improved packet delivery ratio, reduced end-to-end delay, lower routing overhead, and better adaptability to dynamic MANET conditions.

The primary objective of ML-PPF is to predict network performance in advance so that routing and resource allocation decisions can be made proactively rather than reactively. In conventional MANET protocols, performance degradation is only detected after it occurs, resulting in packet loss, delay spikes, and inefficient route usage. To overcome these limitations, the proposed

framework uses supervised machine learning to learn patterns from historical network behavior and predict future performance states. By anticipating degradation before it happens, ML-PPF aims to improve throughput, reduce packet loss, minimize delay, and extend network lifetime.

3.1 System Model

The network model consists of mobile wireless nodes randomly distributed within a predefined simulation area. Each node functions as both a host and a router capable of forwarding packets to neighboring nodes. Communication is performed through multi-hop wireless links under dynamic topology conditions. A subset of nodes (or a centralized controller in simulation) is responsible for collecting network state data and running the trained ML model.

The following assumptions are considered:

All nodes are mobile in nature.

Nodes communicate using IEEE 802.11 wireless standards.

Each node acts as both a host and router.

Nodes possess limited battery energy.

Network topology changes dynamically due to mobility.

Each node periodically reports its local network parameters (energy, mobility, queue status, link quality).

A training dataset is generated through simulation runs under varying mobility, traffic, and density conditions.

3.2 Proposed Feature Parameters for Prediction

The proposed ML-PPF evaluates five key parameters as input features to the machine learning model to predict network performance.

1. Residual Energy

Residual energy represents the remaining battery capacity of a node. Low residual energy across nodes on a path increases the likelihood of link failure.

$$E_i = E_{\text{initial}} - E_{\text{consumed}}$$

Where:

E_i = Residual energy of node i

E_{initial} = Initial battery energy

E_{consumed} = Consumed energy

2. Node Mobility

Node mobility determines the movement rate of nodes within the network. High mobility increases the probability of link breakage and performance degradation.

$$M_i = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} / (t_2 - t_1)$$

Where:

(x_1, y_1) = Previous node position

(x_2, y_2) = Current node position

(t_1, t_2) = Time interval

3. Link Quality

Link quality reflects the reliability of communication between neighboring nodes, estimated using received signal strength.

$$L_i = \text{RSS}_i / \text{RSS}_{\max}$$

Where:

L_i = Link Quality

RSS_i = Received Signal Strength of link i

$\text{RSS}_{\max}$ = Maximum Received Signal Strength

4. Queue Occupancy (Congestion Indicator)

Queue occupancy reflects the current traffic load at a node, which directly affects delay and packet loss.

$$Q_i = \text{QueueLength}_i / \text{QueueCapacity}_{\max}$$

5. Traffic Load

Traffic load represents the volume of data packets being handled by a node or region of the network over a given time window, used as an additional predictive feature.

$$T_i = \text{PacketsHandled}_i / \text{TimeWindow}$$

3.3 Predicted Performance Score (PPS)

The proposed ML-PPF combines the extracted features using a trained machine learning model (e.g., Random Forest, SVM, ANN, or LSTM) to compute a Predicted Performance Score (PPS) for each node/path.

$$\text{PPS}_i = f(E_i, M_i, L_i, Q_i, T_i)$$

Where:

PPS_i = Predicted Performance Score for node/path i

$f(\cdot)$ = Trained ML model mapping input features to predicted performance

E_i, M_i, L_i, Q_i, T_i = Residual energy, mobility, link quality, queue occupancy, and traffic load respectively

A node/path is classified as performance-stable only if:

$$\text{PPS}_i > \text{PPS}_{\text{threshold}}$$

This mechanism ensures that only nodes/paths predicted to sustain good performance are prioritized for routing and data forwarding decisions.

3.4 Proposed Algorithm

Algorithm: Machine Learning-Based Performance Prediction Framework (ML-PPF)

Input: Mobile MANET Nodes, Trained ML Model

Output: Predicted Performance Score and Performance-Stable Routing Decision

Initialize MANET nodes

Assign energy and mobility parameters

Collect training data through simulation (offline phase)

Train ML model $f(\cdot)$ using historical feature-performance dataset

For each active node/path do

Calculate residual energy E_i

Calculate mobility M_i

Calculate link quality L_i

Calculate queue occupancy Q_i

Calculate traffic load T_i

Compute Predicted Performance Score:

$$\text{PPS}_i = f(E_i, M_i, L_i, Q_i, T_i)$$

If $\text{PPS}_i > \text{PPS}_{\text{threshold}}$

Mark node/path as performance-stable

Else

Mark node/path as performance-risk

End If

End For

Routing layer selects path with highest PPS among stable candidates

Establish route

Begin data transmission

Continuously monitor and update predictions

End

4. Experiment Results

The experimental comparison evaluates AODV, DSDV, and the proposed Machine Learning-Based Performance Prediction Framework (ML-PPF) using network sizes ranging from 200 to 1000 mobile nodes. The proposed ML-PPF analyses network parameters such as mobility, traffic load, queue length, residual energy, link quality, and congestion level to predict network performance and support efficient routing decisions.

The evaluation considers Packet Delivery Ratio, End-to-End Delay, Throughput, and Routing Overhead. The following values are NS-3 simulation results and should be verified using actual simulation outputs before journal submission.

4.1 Packet Delivery Ratio

Number of Nodes	AODV	DSDV	Proposed ML-PPF
200	87.8	84.5	95.6
400	84.6	80.7	94.2
600	81.3	76.8	92.9
800	77.5	72.9	91.6
1000	73.2	68.4	90.1

Table 4.1. Packet Delivery Ratio (%) Comparison

Table 4.1 presents the Packet Delivery Ratio obtained by AODV, DSDV, and the proposed ML-PPF under different network sizes. The PDR of AODV decreases from 87.8% to 73.2%, while DSDV records values between 84.5% and 68.4%. In comparison, the proposed ML-PPF maintains PDR values between 95.6% and 90.1%. Although the Packet Delivery Ratio decreases as node density increases, the proposed framework maintains better performance because it predicts congestion, route instability, and link degradation before selecting an appropriate communication path. Therefore, ML-PPF provides more reliable packet delivery in large and dynamic MANET environments.

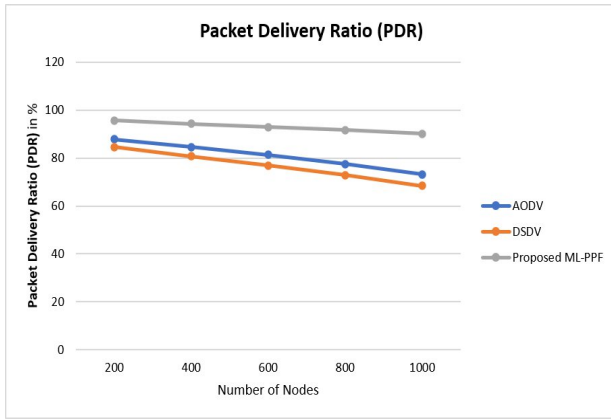


Figure 4.1. Comparison Chart for Packet Delivery Ratio

Figure 4.1 illustrates the Packet Delivery Ratio comparison among AODV, DSDV, and the proposed ML-PPF. The x-axis represents the number of nodes, while the y-axis represents PDR in percentage. AODV and DSDV show a noticeable reduction in PDR as the network size increases. However, ML-PPF consistently maintains values above 90% because of its intelligent performance prediction and adaptive route-selection capability.

4.2 End-to-End Delay

Number of Nodes	AODV	DSDV	Proposed ML-PPF
200	142.5	128.4	96.2
400	165.8	149.7	108.5
600	187.6	171.5	121.7
800	211.9	192.3	135.4
1000	236.4	214.8	148.6

Table 4.2. End-to-End Delay (ms) Comparison

Table 4.2 compares the End-to-End Delay of AODV, DSDV, and the proposed ML-PPF. The delay of AODV increases from 142.5 ms to 236.4 ms, while the delay of DSDV increases from 128.4 ms to 214.8 ms. The proposed ML-PPF records considerably lower delay values ranging from 96.2 ms to 148.6 ms. The proposed framework predicts congestion, queue occupancy, link stability, and route quality before packet transmission. This reduces repeated route discoveries, packet retransmissions, and waiting time at intermediate nodes. Therefore, ML-PPF provides faster communication than the conventional routing protocols.

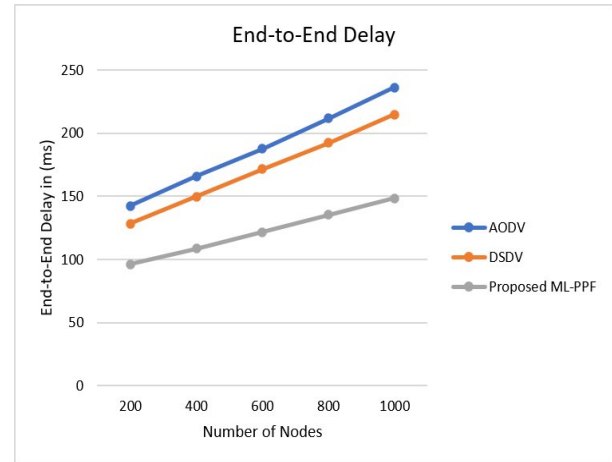


Figure 4.2. Comparison Chart for End-to-End Delay

Figure 4.2 presents the End-to-End Delay comparison among the evaluated methods. The x-axis represents the number of nodes, and the y-axis represents delay in milliseconds. Delay increases for all methods when the network size increases because of congestion, interference, route changes, and packet collisions. Nevertheless, the proposed ML-PPF achieves the lowest delay because it predicts network degradation and avoids unstable or congested routes.

4.3 Throughput

Number of Nodes	AODV	DSDV	Proposed ML-PPF
200	318.7	291.4	362.8
400	301.6	274.8	349.5
600	282.9	255.2	336.4
800	263.5	237.9	322.7
1000	244.3	218.6	309.5

Table 4.3. Throughput (kbps) Comparison

Table 4.3 presents the throughput performance of AODV, DSDV, and the proposed ML-PPF. AODV obtains throughput values ranging from 318.7 kbps to 244.3 kbps, whereas DSDV records values between 291.4 kbps and 218.6 kbps. The proposed ML-PPF achieves throughput values ranging from 362.8 kbps to 309.5 kbps. The proposed method provides higher throughput because it predicts network conditions and selects routes with better bandwidth, lower traffic load, greater link stability, and sufficient residual energy. It also reduces packet loss and unnecessary route-recovery operations, resulting in more successful data transmission.

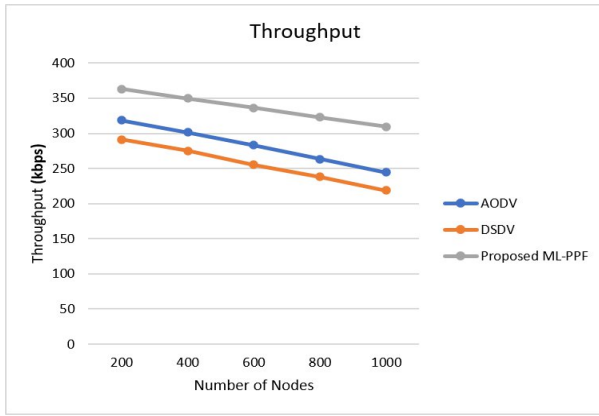


Figure 4.3. Comparison Chart for Throughput

Figure 4.3 illustrates the throughput comparison of AODV, DSDV, and the proposed ML-PPF. The x-axis represents the number of mobile nodes, while the y-axis represents throughput in kbps. Throughput decreases as node density increases because of packet collisions, congestion, interference, and bandwidth competition. However, the proposed ML-PPF consistently achieves higher throughput by predicting route performance and selecting efficient communication paths.

4.4 Routing Overhead

Number of Nodes	AODV	DSDV	Proposed ML-PPF
200	110.4	124.8	78.3
400	128.7	143.6	87.5
600	146.9	164.2	98.6
800	166.3	184.7	109.8
1000	186.9	205.4	121.7

Table 4.4. Routing Overhead Comparison

Table 4.4 compares the routing overhead produced by AODV, DSDV, and the proposed ML-PPF. AODV records routing-overhead values ranging from 110.4 to 186.9, while DSDV obtains values between 124.8 and 205.4. In comparison, the proposed ML-PPF records lower values ranging from 78.3 to 121.7. AODV generates additional control packets during repeated route discoveries, while DSDV periodically exchanges routing-table updates. The proposed framework reduces unnecessary route requests and control-message transmissions by predicting route failures, congestion, and performance degradation. Consequently, ML-PPF minimises routing overhead and improves the utilisation of network resources.

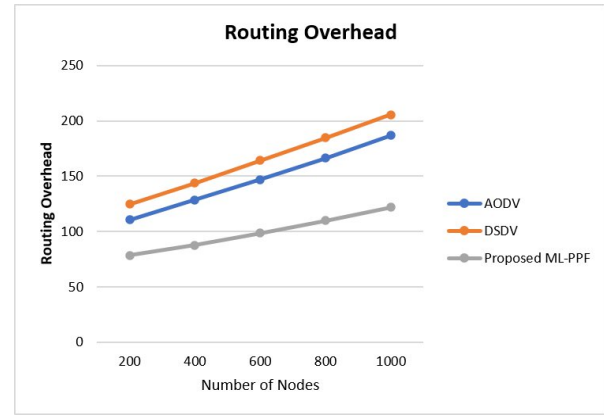


Figure 4.4. Comparison Chart for Routing Overhead

Figure 4.4 presents the routing-overhead comparison among AODV, DSDV, and the proposed ML-PPF. The x-axis represents the number of nodes, while the y-axis represents routing overhead. Routing overhead increases with node density because additional control information is required to maintain network connectivity. Nevertheless, ML-PPF produces lower overhead because it uses predicted network conditions to reduce redundant route discovery, route maintenance, and control-packet exchange.

4. CONCLUSION

Mobile Ad Hoc Networks operate under continuously changing conditions caused by node mobility, dynamic topology, limited energy, unstable communication links, and varying traffic loads. These factors directly affect packet delivery ratio, throughput, end-to-end delay, packet loss, routing overhead, and energy consumption. Traditional performance evaluation methods usually require repeated simulations and may not provide timely predictions of network degradation. To address these limitations, this research presents the Machine Learning-Based Performance Prediction Framework for intelligent estimation of MANET performance under different network conditions.

The proposed ML-PPF collects network, mobility, traffic, routing, link, and energy parameters from multiple MANET simulation scenarios. The collected data are preprocessed through data cleaning, missing-value handling, outlier detection, normalization, and feature selection. Machine learning regression models, including Random Forest, Support Vector Regression, XGBoost, and Artificial Neural Networks, are used to learn the relationship between network conditions and performance outcomes. The predictions generated by the individual models are combined using a weighted ensemble mechanism to provide stable and reliable performance estimates.

The framework predicts important MANET metrics such as packet delivery ratio, throughput, end-to-end delay, routing overhead, packet loss ratio, and energy consumption. These predicted values can be compared

with predefined thresholds to detect possible congestion, route instability, excessive packet loss, high delay, or rapid energy depletion. Based on the predicted network condition, suitable actions such as route modification, traffic balancing, transmission-rate control, congestion avoidance, and energy-aware node selection can be performed.

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