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Vinay Simha Reddy Tappeta
Bhargav Appasani
Amitkumar V Jha
Srinivas Ramavath
Suprava Patnaik
Miryala Mahesh
Bharati Ainapure
Mohammad Khan
adhoc.khan@gmail.com

Research Article

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Posted Date: March 16th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9086619/v1

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Additional Declarations: No competing interests reported.

A Machine Learning Approach for Hidden Terminal Avoidance and Throughput Enhancement in IEEE 802.11ah-based Internet of Vehicle Networks

Vinay Simha Reddy Tappeta [1], Bhargav Appasani [1], Amitkumar V. Jha [1], Srinivas Ramavath[1], Suprava Patnaik [1], Miryala Mahesh [2], Bharati Ainapure [3], and Mohammad S. Khan [4*]

[1]School of Electronics Engineering, Kalinga Institute of Industrial Technology, Deemed to be University, India-751024
Email: vinay.33186@gmail.com, bhargav.appasanifet@kiit.ac.in, amit.jhafet@kiit.ac.in, srinivas.ramvathfet@kiit.ac.in, suprava.patnaikfet@kiit.ac.in
[2]School of Electronics Engineering, VIT-AP University, Amaravati, Andhra Pradesh 522237, India, Email: miriyalamahesh4u@gmail.com
[3]Department of Computer Engineering, Vishwakarma University, Pune, India-411046, Email: ainapuressa@gmail.com
[4]Department of Computing, East Tennessee State University, Johnson City, 37614-1266, USA
* Correspondence: adhoc.khan@gmail.com

Abstract: The Internet of Vehicles (IoV) is an advancement of the traditional vehicular ad-hoc network (VANET), which is a network of many entities that facilitates real-time communication between them, including cars, pedestrians, roadways, parking lots, and city infrastructure. The hidden terminal (or node) problem, which is a major problem in IoV networks can negatively impact wireless communications and network performance. Hidden Terminal Problem (HTP) occurs when two nodes in a network cannot communicate or detect each other, leading to performance degradation. This research proposes a deep neural network based throughput optimization frame work as well as a neural network based grouping scheme for grouping nodes in IoV networks to avoid HTP. Proposed Neural Networks based grouping scheme is compared with uniform grouping (UG) scheme of 802.11ah and Received Signal Strength (RSS) scheme. IEEE 802.11ah is a standard that addresses HTP by grouping nodes based on coverage area and other criteria. IEEE 802.11ah is suitable for IoV scenarios that require more coverage and less energy consumption. The Markov chain model analyses the throughput of different grouping schemes using Monte-Carlo simulation. Both analytical and simulation results of UG Scheme and NNBG are Compared for throughput. The proposed scheme is shown to improve the throughput performance of 802.11ah based IoV networks.

Keywords: IoT; Wireless Sensor Networks (WSN); deep neural networks; Hidden node; IEEE 802.11ah

1. Introduction

The Internet of Things (IoT) has evolved into one of the most transformative paradigms of modern digital infrastructure, connecting billions of devices and enabling ubiquitous data exchange across heterogeneous environments. As per current projections, the global IoT market, valued at approximately USD 100 billion in 2017, is expected to reach USD 1.6 trillion by 2025 [1]. The IoT ecosystem encompasses interconnected physical objects embedded with sensors, actuators, and software that communicate wirelessly to collect and exchange data, thereby supporting applications in smart cities, healthcare, industrial automation, and intelligent transportation. A specialized domain within IoT, known as the Internet of Vehicles (IoV), extends the concept of connectivity to vehicular environments. IoV establishes a real-time communication framework among vehicles, roadside infrastructure, pedestrians, and cloud-based services, enabling applications such as cooperative driving, traffic safety, and infotainment [2]. The IoV can be viewed as an evolution of Vehicular Ad Hoc Networks (VANETs) that incorporates elements of cloud computing, artificial intelligence, and edge networking to provide intelligent vehicular communication. Generally, IoV consists of three major components: (i) Inter-vehicular communication, (ii) Intra-vehicular communication, and (iii) Mobile Internet for vehicles.

Despite its potential, IoV presents several unique design and performance challenges compared to conventional IoT networks. These include high node mobility, dynamic topology, diverse communication requirements, and stringent quality-of-service (QoS) demands. Each vehicle, whether autonomous or manually operated, produces massive data streams often several orders of magnitude greater than that generated by an average IoT device. Furthermore, the heterogeneous architecture of IoV networks introduces significant complexity in terms of radio access, routing, and resource management. While non-critical applications such as infotainment can tolerate moderate latency, safety-critical operations like cooperative awareness messages (CAMs), collision avoidance, and emergency warnings which demands ultra-reliable, low-latency communications [3].

Recent research efforts have explored various enabling technologies and communication standards for IoV systems. Zhou et al. [4] provided an extensive review of Vehicle-to-Everything (V2X) standards, comparing IEEE 802.11-based V2X and Cellular-V2X (C-V2X) technologies in terms of performance, scalability, and deployment maturity. Similarly, Karim et al. [5] discussed IoV

architecture models, communication types, and major security challenges, proposing blockchain-based frameworks to enhance trust, privacy, and data integrity. Aramice et al. [6] highlighted the wireless communication technologies and protocols used in vehicular networks and examined their practical use cases for reliable vehicular connectivity. In addition, Elfatih et al. [7] reviewed the integration of Artificial Intelligence (AI) techniques for resource management and allocation within 5G-based IoV architectures, emphasizing AI-driven optimization of radio access networks (RANs). Ni et al. [8] further analyzed scalable wireless communication approaches through mathematical modeling and performance evaluation for IoV.

Among the various wireless technologies, IEEE 802.11ah, also known as Wi-Fi HaLow, has emerged as a promising candidate for IoV applications due to its extended range, lower power consumption, and native IP support. Operating in the sub-1 GHz band, 802.11ah offers high spectral efficiency and supports thousands of devices per access point, making it particularly suitable for dense vehicular deployments [9]. The standard supports multiple data rates and robust modulation schemes, addressing diverse communication needs ranging from infotainment to safety-critical applications. Alam et al. [9] analyzed the suitability of 802.11ah for next-generation IoT, while their subsequent study [10] proposed an Internet of Drones (IoD) architecture based on 802.11ah for improved connectivity and latency reduction. Farhad et al. [11] conducted a detailed survey of the 802.11ah MAC layer, identifying open challenges and optimization opportunities. Additionally, Zhang et al. [12] proposed the Fast Key Re-authentication (FKR) method to enhance link setup efficiency in 802.11ah networks.

Machine learning and reinforcement learning algorithms have recently gained traction in wireless communication optimization, particularly in IEEE 802.11ah-based IoT environments. Jiang et al. [13] introduced a deep reinforcement learning (DRL) framework utilizing the Proximal Policy Optimization (PPO) algorithm to optimize Restricted Access Window (RAW) parameters for maximizing throughput. Ibrahim et al. [14] developed a machine learning-based adaptive MAC protocol for IoT smart city environments to minimize collision probability and optimize channel allocation.

One of the persistent challenges in IEEE 802.11ah-based IoV networks is the Hidden Terminal Problem (HTP)—a situation where two or more stations cannot detect each other's transmissions due to spatial separation, resulting in frequent collisions and throughput degradation. This problem becomes critical in large-scale IoV scenarios with heterogeneous devices and varying transmission ranges. Traditional mitigation techniques such as RTS/CTS handshaking or uniform grouping schemes are inadequate under dense and dynamic vehicular conditions. To address this issue, this study proposes a Neural Networks-Based Grouping (NNBG) scheme that employs Self-Organizing Maps (SOMs) to cluster vehicular nodes intelligently based on their signal characteristics. The proposed method effectively reduces collision probability, mitigates hidden terminals, and enhances aggregate throughput performance in 802.11ah-based IoV networks.

The main contributions of this paper are summarized as follows:

1. A novel Neural Networks-Based Grouping (NNBG) scheme utilizing Self-Organizing Maps (SOM) is proposed for adaptive node grouping in IEEE 802.11ah-based IoV networks, addressing hidden terminal challenges.
2. The proposed scheme is evaluated and compared with the Uniform Grouping (UG) and Received Signal Strength (RSS) schemes, demonstrating superior performance in terms of throughput, packet collision rate, and fairness index.
3. A Markov chain-based analytical model and Monte Carlo simulations are developed to validate the NNBG scheme. The model accurately captures throughput dynamics under varying network densities and hidden terminal conditions. A Deep Learning–Based Throughput Prediction Model (DL-TPM) is proposed for throughput enhancement.
4. Comprehensive MATLAB simulations are performed using IEEE 802.11ah PHY and MAC layer parameters to substantiate the analytical findings.

Organization of the Paper

The remainder of this paper is organized as follows: Section 2 provides an overview of related work on grouping mechanisms and hidden terminal mitigation techniques in IEEE 802.11ah networks. Section 3 introduces the IEEE 802.11ah PHY and MAC architectures and explains the hidden terminal scenario and neural learning algorithm. Section 4 presents the analytical model, including the Markov chain framework and mathematical formulation of hidden terminal probability. Section 5 discusses the simulation setup, parameters, and performance evaluation results. Finally, Section 6 concludes the paper and outlines potential directions for future research.

2. Related Work

The IEEE 802.11ah standard proposes a uniform grouping scheme for organizing stations. However, no additional mechanisms are specified in the standard to effectively mitigate packet collisions or hidden terminal problems. Consequently, most research studies have relied on the uniform grouping approach to distribute stations evenly across the available Restricted Access Windows (RAWs) [15].

In [16], the authors investigated the impact of hidden terminals in dense heterogeneous networks and recommended differentiating concealed devices based on network characteristics to minimize interference. A few studies explored the use of the RTS/CTS (Request-to-Send/Clear-to-Send) mechanism as an alternative for detecting concealed nodes [17]. Furthermore, an adaptive RTS/CTS mechanism was discussed in [18] to dynamically manage uncorrelated stations, thereby reducing network performance degradation in dense IoT networks with smaller payloads.

Another line of research proposed a geographic location–based spatial grouping strategy [19], which reduced hidden terminals by clustering devices according to spatial proximity. Although this method improved collision avoidance, it consumed additional bandwidth and computational resources. In [20], an RSS-based grouping mechanism was introduced, while [21] proposed a Traffic-Adaptive Restricted Access Window Optimization Algorithm (TAROA) to enhance 802.11ah efficiency under hidden-node conditions. Both approaches demonstrated throughput improvement by adjusting group formation dynamically according to real-time network behavior.

In [22], the authors presented Randomness Region-Based Grouping (RRG) and Proximity-Based Regrouping schemes. These approaches divided the network into multiple regions based on proximity to minimize the number of hidden stations, reporting superior performance in terms of throughput and packet loss. Similarly, [23] introduced a Hidden Matrix-Based Regrouping (HMR) technique, which first identified hidden-node pairs and then formed groups using a hidden-node matrix. This strategy improved hidden node detection accuracy and overall channel efficiency. Another study [24] proposed a Signal-to-Interference-and-Noise Ratio (SINR)-based grouping scheme, where devices were grouped according to SINR measurements, resulting in significant performance improvement.

A Genetic Algorithm (GA)-based grouping strategy was proposed in [25], where the algorithm's parameters were tuned for better convergence and throughput optimization. In [26], an ML-based optimized RAW station grouping model was developed and compared against conventional state-of-the-art techniques, highlighting machine learning's potential in dynamic group formation. The Load-Balanced Grouping Method introduced in [27] aimed to improve channel utilization by evenly distributing traffic among groups, demonstrating superior throughput over random grouping approaches.

More recently, advanced reinforcement learning–based methods have been explored for channel access optimization. The MADRL-HT (Multi-Agent Deep Reinforcement Learning for Hidden Terminals) framework proposed in [28] effectively addressed hidden terminal collisions and optimized both system throughput and fairness in autonomous wireless networks. Additionally, [29] investigated collision recognition in multihop IEEE 802.15.4-compliant wireless sensor networks using machine learning techniques. Their model analyzed error patterns to distinguish collisions from interference or path loss, employing redundant data blocks and mutual information-guided byte selection to achieve over 90% recognition accuracy with high coding efficiency—thereby enhancing overall network reliability.

A critical review of these studies reveals several research gaps that motivate the present work. Existing grouping mechanisms often demonstrate performance improvements but tend to suffer from high computational complexity and overhead due to distance matrix calculations and parameter tuning. Many also lack adaptability to rapidly changing IoV environments characterized by node mobility and varying signal conditions.

To address these limitations, the present study introduces a Neural Networks-Based Grouping (NNBG) algorithm utilizing Self-Organizing Maps (SOMs) for intelligent and adaptive node grouping. The proposed scheme significantly reduces hidden terminal collisions and improves throughput while maintaining computational efficiency. Its performance has been assessed through both analytical and simulation models using critical parameters such as packet collision rate, packet loss rate, and fairness index. Comparative results indicate that the NNBG algorithm achieves superior performance relative to conventional grouping methods.

The organization of the paper is as follows: Section 2 reviews related work on existing grouping and collision mitigation strategies. Section 3 discusses the hidden terminal problem in IoV and presents the learning algorithm employed in this study. Section 4 develops the analytical model, including the Markov chain–based throughput analysis. Section 5 provides detailed simulation results and performance evaluation. Finally, Section 6 concludes the paper and outlines future research directions.

3. 802.11.ah PHY and MAC

This section presents an overview of the Physical (PHY) and Medium Access Control (MAC) layers of the IEEE 802.11ah standard, along with modeling aspects relevant to this study. It also describes the hidden terminal scenario in vehicular networks and introduces the learning algorithm adopted for mitigating such issues.

3.1. Basics of 802.11ah Protocol

The IEEE 802.11ah standard was developed to address the limitations of traditional Wi-Fi in Internet of Things (IoT) environments, particularly in terms of long-range connectivity, scalability, and energy efficiency. While conventional Wi-Fi technologies operate in the 2.4 GHz and 5 GHz bands with limited coverage, IEEE 802.11ah—also known as Wi-Fi HaLow—operates in the sub-1 GHz frequency band, making it ideal for extended-range, low-power IoT applications such as smart cities, industrial monitoring, and vehicular networks. The standard supports coverage of up to 1 km and accommodates nearly 8000 stations per Access Point (AP) [30].

IEEE 802.11ah defines a narrow-band Orthogonal Frequency Division Multiplexing (OFDM)-based PHY layer, supporting channel bandwidths of 1, 2, 4, 8, and 16 MHz. Different sub-1 GHz bands have been allocated for IEEE 802.11ah operation across countries to ensure regulatory compliance. The standard supports star and tree topologies and introduces several enhancements over legacy IEEE 802.11 standards, including improved power-saving mechanisms, increased station capacity, and higher throughput efficiency. At the PHY layer, IEEE 802.11ah incorporates multiple Modulation and Coding Schemes (MCSs) that enable adaptive data rates according to channel conditions. Stations employ rate adaptation to select the most suitable MCS (ranging from MCS0–MCS9), while MCS10 is specifically designed for a 1 MHz channel using Binary Phase-Shift Keying (BPSK) modulation to achieve greater coverage under low-SNR conditions.

In dense and heterogeneous IoT networks, the coexistence of thousands of devices leads to a higher probability of packet collisions. To address this, the IEEE 802.11ah Task Group introduced a group-based channel access mechanism known as the Restricted Access Window (RAW). Under the RAW scheme, the available channel time is divided into multiple time slots, and stations are grouped such that each group competes for channel access only within its assigned slot [28].

However, the Uniform Grouping (UG) method defined in the standard suffers from random allocation of stations to groups, resulting in throughput degradation and hidden terminal problems, especially in multi-rate and heterogeneous IoT networks. Consequently, various researchers have proposed adaptive grouping and scheduling techniques to enhance performance by mitigating hidden terminal collisions and reducing contention.

3.2. Hidden Terminal Scenario in Vehicular Networks

The hidden terminal problem (HTP) remains one of the major causes of degraded performance in IEEE 802.11-based networks. In vehicular communication, the issue becomes even more pronounced due to high mobility, variable density, and dynamic link quality. Traditionally, IEEE 802.11 networks employ the Request-to-Send/Clear-to-Send (RTS/CTS) handshake protocol to alleviate hidden terminal collisions. However, this method is only effective in unicast communication. In broadcast scenarios—such as when vehicles transmit Basic Safety Messages (BSMs)—the transmitter cannot receive CTS (or ACK) signals from all receivers, rendering RTS/CTS inapplicable [31].

Figure 1 illustrates a typical hidden terminal scenario in vehicular networks. Suppose node Tx1 broadcasts a BSM to receivers Rx1 and Rx2 within its communication range. If other nodes located in the shaded region (outside Tx1's range but within Rx1's sensing range) begin transmitting simultaneously, Rx1 may fail to correctly receive Tx1's packet. These interfering nodes represent Rx1's hidden terminals, which may differ from Rx2's depending on spatial geometry. Consequently, the hidden terminal problem arises independently for each receiver in a broadcast domain.

In IEEE 802.11ah networks, a single AP can serve a large number of stations, making collision management a key challenge. Collisions occur when multiple stations attempt simultaneous channel access, particularly when they lie outside each other's sensing range. The Distributed Coordination Function (DCF) of IEEE 802.11 utilizes Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) and optional RTS/CTS mechanisms to manage contention [32].

IEEE 802.11ah extends this concept by introducing the RAW mechanism, which divides stations into groups that access the channel sequentially, thereby minimizing contention [33, 34]. When a group's slot is inactive, its member stations enter a sleep mode, conserving energy [35]. Despite these improvements, hidden node collisions may still occur within the same RAW slot, affecting throughput and energy efficiency [36]. Hence, further optimization through machine learning-based adaptive grouping is essential to ensure consistent performance under high-density vehicular scenarios.

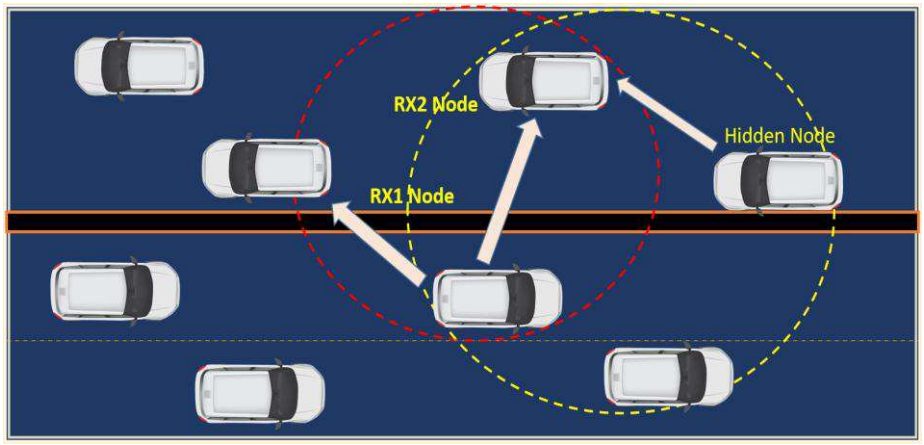


Figure 1. Hidden terminal scenario in vehicular networks.

3.3. Learning Algorithm for Reducing the Hidden Terminal Problem

With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), neural network models have demonstrated exceptional capability in learning complex spatial and temporal relationships within wireless networks. In the context of wireless sensor and vehicular networks, ML approaches can dynamically learn environmental patterns—such as signal strength, interference, and channel state—to intelligently mitigate hidden terminal issues.

Among ML algorithms, the Self-Organizing Map (SOM), introduced by Teuvo Kohonen, stands out as an efficient unsupervised learning model. SOMs autonomously cluster high-dimensional data into low-dimensional topological maps without human supervision. Unlike traditional supervised networks that rely on error-correction methods such as backpropagation, SOMs employ competitive learning, where neurons compete to represent input data based on similarity metrics [37].

A typical SOM architecture, shown in Figure 2, comprises an input vector, a feature (output) map, and a weight matrix. During training, the SOM learns to map high-dimensional feature spaces (e.g., signal strength or interference levels) into organized clusters, where similar input vectors are positioned close to each other. This property makes SOMs highly suitable for station grouping, clustering, and visualization of network dynamics [38].

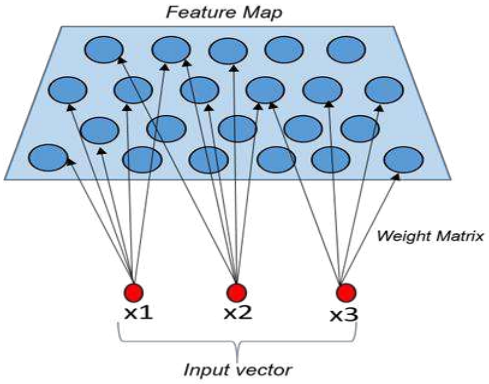


Figure 2. Input vector, Feature Map, and Weight Matrix of SOM.

In this work, an Artificial Neural Network (ANN) employing SOM is implemented and trained in MATLAB to generate an optimized grouping of stations. The resulting groups differ significantly from the default uniform grouping of IEEE 802.11ah. Simulation results demonstrate that the SOM-based grouping forms adaptive clusters around APs, effectively minimizing hidden terminal interference in Vehicle-to-Everything (V2X) environments. The scheme's performance has been validated analytically and through extensive MATLAB simulations, confirming its potential to enhance throughput and fairness in IEEE 802.11ah-based IoV systems.

4. Analytical Model

Enhancing the performance of contention-based Medium Access Control (MAC) in densely populated IEEE 802.11ah networks remains a critical research challenge. With the growing number of IoT and vehicular devices, efficient channel access becomes

essential to maintain high throughput and low collision probability. The IEEE 802.11ah Task Group proposed the Group-Synchronized Distributed Coordination Function (GS-DCF) to address congestion in large-scale networks. By combining Restricted Access Window (RAW) and RAW slot-based scheduling, GS-DCF substantially reduces contention, leading to improved throughput. However, optimizing RAW slot assignment, duration, and group configuration continues to be an open issue in dynamic vehicular environments.

To achieve rapid and accurate grouping of stations, this study adopts a centralized grouping scheme based on Neural Networks, specifically Self-Organizing Maps (SOMs). This section presents the analytical framework used to evaluate the proposed Neural Networks-Based Grouping (NNBG) algorithm in IEEE 802.11ah networks. The model includes the Markov chain formulation, the derivation of hidden terminal probability, and key performance parameters for throughput computation.

4.1. Neural Networks-Based Grouping Scheme

This section presents the Neural Networks-Based Grouping (NNBG) approach, which employs Self-Organizing Maps (SOMs) to classify devices according to their Signal-to-Noise Ratio (SNR). The objective of this scheme is to minimize hidden-terminal occurrences by forming intelligent, SNR-aware clusters of stations within IEEE 802.11ah-based Internet-of-Vehicle (IoV) networks.

At the outset, the Access Point (AP) periodically transmits beacon frames containing control and data elements. Each device estimates the received SNR from these beacon frames and evaluates the prevailing channel conditions before initiating the connection process with the AP. During this phase, each station dynamically adapts the rate bits embedded in the Physical Layer Convergence Protocol (PLCP) header to match its channel characteristics.

Using the Machine Learning-Based User Pairing (MLUP) mechanism, the AP organizes all associated devices following the procedure outlined in Algorithm 1. After classification, the AP pairs each device d_i, where $i \in (1, n/2)$ and n is the total number of devices, belonging to the i^{th} group, with another device $d_{i+n/2}$ from the $(i+n/2)^{\text{th}}$ group. The pairing process can be expressed as $\text{pair}(d_i, d_{i+n/2}), ; i \in (1, n/2)$.

Upon successful pairing, the AP assigns every device a unique Association Identifier (AID), ensuring distinct network identities for subsequent data exchange and scheduling operations.

As illustrated in Figure 3, a circular topology with a radius of 1000 units was generated, containing 256 nodes distributed heterogeneously within a sensing range of 2000 units and governed by six group heads. The stations exhibit varying data rates and spatial locations, reflecting a realistic heterogeneous vehicular-network environment.

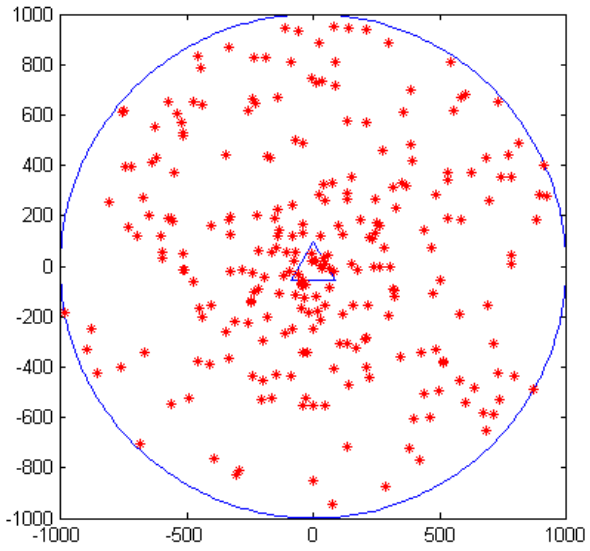


Figure 3. Circle with various nodes with sensing range 2000.

After applying the NNBG algorithm, the nodes within the circular region were reorganized into well-defined clusters, as depicted in Figure 4. Distinct markers denote the groups formed through the NNBG process. The grouping is primarily driven by the Signal-to-Interference-plus-Noise Ratio (SINR)—nodes exhibiting higher SINR values are grouped together to optimize channel utilization and reduce the likelihood of hidden terminals. Consequently, the proposed scheme achieves a balanced spatial distribution and improved overall network throughput.

Algorithm 1 Neural Networks-Based Grouping scheme

```
iterations = 1000, learning_rate = 0.5, Pairs = [];
Group_values = []; \\ Category of each group;
Node_IDs = []; \\ Identifier for each device in a category;
\\ Assume N is the total number of devices;
\\ Gather Signal-to-Noise Ratio (SNR) data from all devices
for device = 1 to N do
    Device_SNR[device] = SNR_device;
end for
\\ Deploy SOM neural network for classifying Device_SNR
[Group_values, Node_IDs] = SOM(Device_SNR, iterations, learning_rate, N, Groups)
for group = 1 to length(Group_values) do
    if Group_values[group] ≤ Groups/2 then
        pair(Node_IDs[group], Node_IDs[group + Groups/2])
    end if
end for
```

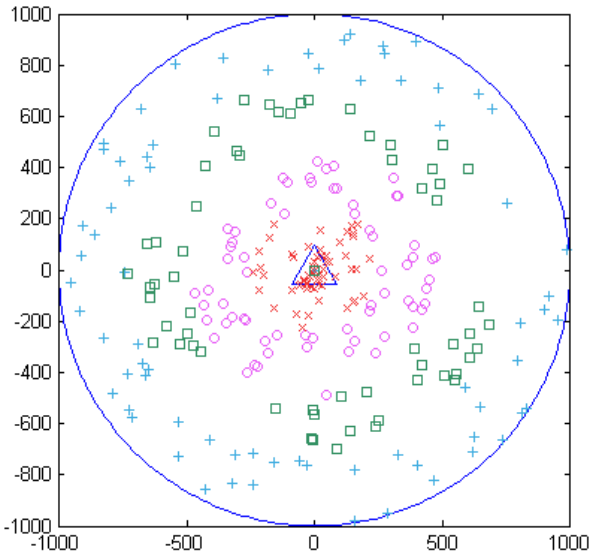


Figure 4. The proposed NNBG scheme results in the grouping of nodes with various markers.

4.2. Markov Chain Model

The Bianchi method, originally developed for traditional IEEE 802.11 Wi-Fi networks, is a fundamental analytical approach based on the Markov chain model. This technique provides a mathematical framework to evaluate channel contention and transmission dynamics in distributed coordination functions (DCF). In this study, the Bianchi model and its Markov-chain formulation are extended to the IEEE 802.11ah standard to capture its unique medium access characteristics and optimize throughput performance. Markov chain modeling enhances IEEE 802.11ah network analysis by dynamically adapting the collision probability according to variations in node density, mobility, and traffic intensity. As a stochastic model, it represents systems whose evolution depends on probabilistic state transitions over time. Assuming the Markov property, the future state of the system depends solely on its current state and not on the sequence of prior states [39].

In this context, each station is assumed to always have a frame ready for transmission (saturation condition), and the process remains statistically stable over time. The model introduces the concept of virtual slots, representing the intervals between consecutive changes in the back-off counter. The Restricted Access Window (RAW) mechanism of IEEE 802.11ah divides all stations into groups and assigns each group a set of time intervals, or RAW slots, to minimize collision probability and improve fairness in dense IoT environments.

During every contention round, each station waits for a random back-off period before attempting transmission. After a successful transmission, the station immediately prepares the next packet, whereas after a collision, the contention window is doubled. The new back-off window is calculated as $W = CW_{\min} + 1$, where $CW_{\min}$ denotes the minimum contention window size. This parameter plays a crucial role in determining how rapidly the back-off time adapts to congestion levels, thereby influencing overall network throughput and fairness.

The Markov chain model is characterized by a set of states and transitions between them. Each state corresponds to a particular back-off stage, representing the current range of the counter from which the station randomly selects its waiting time. The back-off counter is decremented at the start of each slot unless the channel is sensed as busy. When a transmission is successful or results in a collision, the counter is reset to a new random value within the range defined by W.

As illustrated in Figure 5, consider a set of n stations competing for channel access. Under saturation conditions, every station has an equal probability of transmitting, but as network density increases, the likelihood of collisions rises sharply. This Markov-based analytical representation enables the evaluation of back-off dynamics, retransmission behavior, and channel utilization efficiency—providing deep insight into how IEEE 802.11ah manages medium access in high-density vehicular or IoT scenarios.

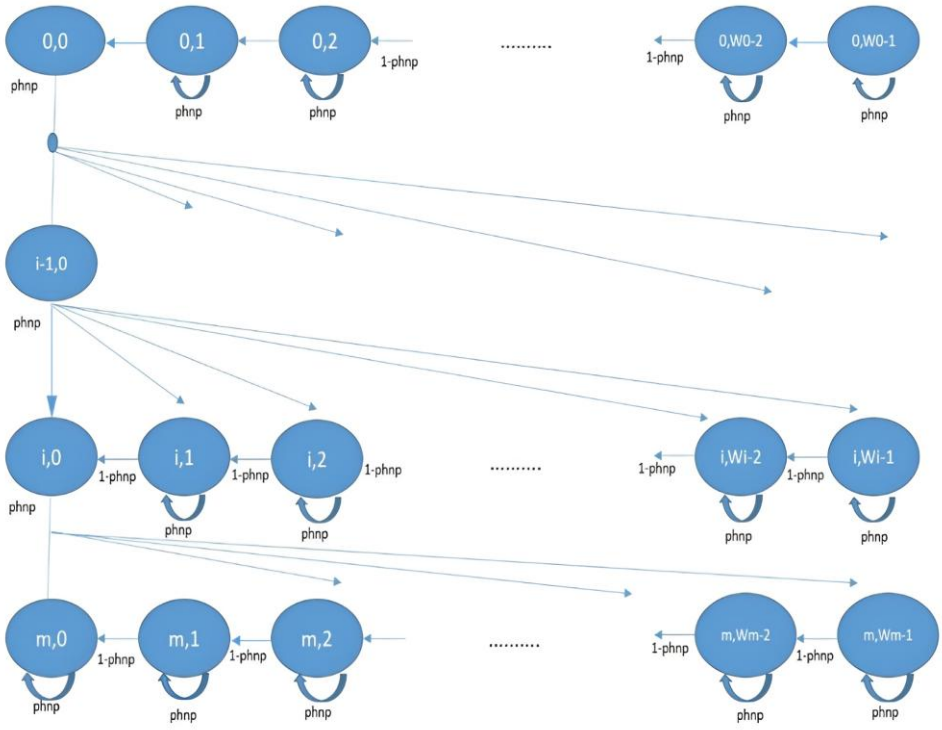


Figure 5. Markov chain IEEE 802.11ah in hidden nodes condition.

4.3. Hidden Terminal Probability

Let D denote a uniform random variable representing the distance from the Gateway Hub (GH) to a device g_i. The probability density function (PDF) for the distance d at which device g_i lies within the annular region around the GH is expressed as

$$f_D(d) = \frac{2d}{d_c^2}.$$

Refer to Figure 6, where the shaded region $A(d)$ represents the area that is obscured from the view of device g_i, and ρ denotes the density of devices per unit area within the GH's transmission range. Consequently, the product $\rho A(d)$ gives the expected number of devices obscured from g_i. Using geometric analysis, the obscured area $A(d)$ can be computed as:

$$A(d) = d_s^2 \arccos\left(\frac{d^2 + d_s^2 - d_c^2}{2dd_s}\right) + d_c^2 \arccos\left(\frac{d^2 + d_c^2 - d_s^2}{2dd_c}\right) - \frac{1}{2}\sqrt{4d^2 d_s^2 - (d^2 + d_s^2 - d_c^2)^2}$$

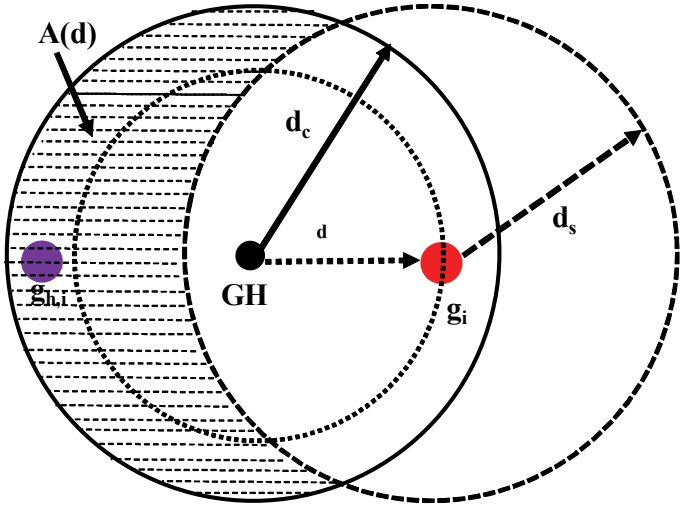


Figure 6. Hidden terminal problem.

Thus, the mean number of obscured devices can be obtained as:

$$g_h = \int_0^{d_c} f_D(r), \rho, A(r), dr \quad (1)$$

To determine the probability that two devices fall within each other's sensing range, consider the hidden terminal scenario shown in Figure 7. Let X and Y be random variables denoting the distances from GH to devices g_i and g_j, respectively. The circle C_1 defines the sensing range of g_i, while C_2 represents the GH's coverage area.

The probability that g_j lies within g_i's sensing range equals the ratio of the intersection area of C_2 within C_1 to the circumference of C_2, which is expressed as:

$$\mathrm{P}_{\text{sense}} = \int_0^{R_c} \int_0^{R_c} \frac{g(x,y)}{2\pi y}, f_X(x) f_Y(y), dx, dy \quad (2)$$

Here, $f_X(x)$ and $f_Y(y)$ denote the PDFs defined earlier, and $g(x,y)$ is given by:

$$g(x,y) = \begin{cases} 2\pi y, & R_s \geq x + y, \\ 2y\cos^{-1}\left(\frac{x^2 + y^2 - R_s^2}{2xy}\right), & R_s < x + y, \\ 0, & . \end{cases} \quad (3)$$

Therefore, the probability that g_j remains hidden from g_i is obtained as:

$$P_h = 1 - \mathrm{P}_{\text{sense}}$$

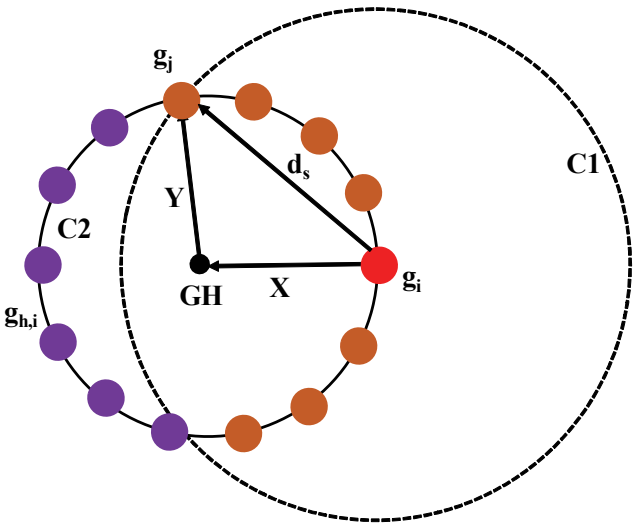


Figure 7. Probability of finding hidden terminals.

4.4. Parameters Based on Markov Chain Model

This process is executed within a specific virtual slot that remains constant over time [40, 41]. If a transmission attempt fails, the back-off stage m is incremented or reset depending on the protocol's state. Conversely, upon a successful transmission, the back-off counter restarts for the next packet. The variable i represents the back-off value, where $0 \le i \le m$ [42]. When the channel is sensed as busy, a state transition occurs with probability $(1 - p_{hnp})$. Only stations that have completed registration and association procedures are permitted to access the channel.

The duration of a Restricted Access Window (RAW) slot, denoted by σ, can be determined as [43]:

$$\sigma = 500, \mu s + C \cdot 120, \mu s \quad (4)$$

where C is a constant representing contention-related adjustments.

Under normal conditions, the collision probability p is given by:

$$p = 1 - e^{(-\rho_i)} \quad (5)$$

In the presence of hidden nodes, the modified collision probability p_{hnp} is expressed as:

$$p_{hnp} = 1 - e^{(-\rho_i)}(1 - \rho_i) \quad (6)$$

The transmission probability τ, representing the likelihood that a node transmits during a randomly chosen time interval, is computed as:

$$\tau = \frac{2(1-2p)}{(1-2p)(CW_{\min}+1) + p, CW_{\min}(1-(2p)^m)} \quad (7)$$

Here, $CW_{\min}$ denotes the minimum contention window size, and m is the maximum back-off stage. The value of p is determined using Eq. (7) for normal conditions and Eq. (8) for hidden node conditions.

The probability that at least one node transmits in a time interval, denoted by P_{tr}, and the probability that a transmission is successful, denoted by P_s, are given respectively by:

$$P_{tr} = 1 - (1-\tau)^n \quad (8)$$

$$P_s = P_h \cdot \frac{n\tau(1-\tau)^{(n-1)}}{P_{tr}} \quad (9)$$

Under normal conditions, the parameters T_s and T_c represent the durations of a successful transmission and a collision event, respectively [44, 45]:

$$T_s = AIFS + T_{\text{Data}} + T_{\text{ACK}} + T_{\text{PHY}} \quad (10)$$

$$T_c = AIFS + T_{\text{Data}} + T_{\text{PHY}} \quad (11)$$

To minimize collisions under hidden node conditions, RTS/CTS handshaking mechanisms are used. The duration of a successful transmission using RTS/CTS, denoted by $T_{s_{RTS/CTS}}$, is defined as [46, 47]:

$$T_{s_{RTS/CTS}} = T_s + T_{RTS} + 3 \times SIFS \quad (12)$$

Finally, throughput—defined as the effective data rate measured in bits per second (bps)—is calculated as:

$$\text{Throughput} = \frac{P_s P_{tr} l_{\text{payload}}}{(1-P_{tr})\sigma + P_{tr} P_s T_s + P_{tr}(1-P_s) T_c} \quad (13)$$

Here, l_{payload} denotes the payload length, and the denominator accounts for idle slots, successful transmissions, and collisions within the contention period.

4.5 Deep Learning–Based Throughput Optimization Framework

Recent advancements in deep learning (DL) have enabled more accurate and adaptive modeling of network behavior under dynamic environments such as vehicular and dense IoT networks. Unlike traditional analytical or Markov-based models, deep neural architectures can capture complex nonlinear relationships among multiple parameters—such as node density, SNR, collision probability, and contention window size—to predict and optimize throughput in real time.

4.5.1 Model Architecture

The proposed Deep Learning–Based Throughput Prediction Model (DL-TPM) is designed using a multi-layer feedforward neural network (FNN). The input layer receives normalized parameters that significantly influence IEEE 802.11ah throughput:

- Node count (n)
- Transmission probability (τ)
- Collision probability (p_{hnp})
- SNR (γ)
- Modulation and Coding Scheme (MCS) index (m_{cs})
- Payload length (l_{payload})

The input vector is represented as $X = [n, \tau, p_{hnp}, \gamma, m_{cs}, l_{\text{payload}}]$. The corresponding target variable is the measured throughput $Y = T_{\text{obs}}$.

The network contains L hidden layers, each consisting of H_l neurons with rectified linear unit (ReLU) activations. The forward propagation of the l^{th} layer output $h^{(l)}$ is given by:

$$h^{(l)} = \text{ReLU}(W^{(l)} h^{(l-1)} + b^{(l)}) \quad (14)$$

where $W^{(l)}$ and $b^{(l)}$ denote the weight matrix and bias vector for the l^{th} layer, respectively.
The final output layer employs a linear activation function to predict the instantaneous throughput:

$$\hat{T}_{\text{DL}} = W^{(L)} h^{(L-1)} + b^{(L)} \quad (15)$$

4.5.2 Training and Optimization

The model is trained using simulation-generated datasets derived from Section 4.4, covering various channel conditions, node densities, and contention levels. The Mean Squared Error (MSE) is employed as the loss function:

$$\text{LMSE} = \frac{1}{N} \sum i = 1^{N} (T_{\text{obs},i} - \hat{T}_{\text{DL},i})^2 \quad (16)$$

To accelerate convergence and prevent overfitting, the Adam optimizer is used with learning rate $\eta = 10^{-3}$ and early stopping criteria based on validation loss.

4.5.3 Adaptive Throughput Enhancement

Once trained, the DL-TPM dynamically predicts optimal throughput values and corresponding contention parameters ($CW_{\min}$, RAW slot duration σ, and MCS index). These predictions are used to reconfigure the MAC layer in real time, allowing the access point to adaptively allocate resources and minimize collisions.

An adaptive control rule is defined as:

$$CW_{\text{opt}} = \arg\min_{CW} | \hat{T}\text{DL}(CW) - T\text{target} | \quad (17)$$

This optimization ensures that the contention window is continuously tuned to achieve near-optimal throughput performance under varying load and hidden-node conditions.

5. Results and Discussion

5.1. Simulation Parameters

The performance evaluation of the proposed models has been conducted using MATLAB-based simulations. The simulation framework implements both the MAC and PHY layers in compliance with the IEEE 802.11ah standard. The simulation environment closely follows the parameters defined in the 802.11ah draft to ensure realistic and reproducible results.

The experiments analyze the performance of different grouping and access control mechanisms—namely, the Uniform Grouping Scheme (UGS), the Received Signal Strength (RSS)-based scheme, and the Neural Networks–Based Grouping (NNBG) scheme—under varying network conditions.

The key physical layer parameters used in the simulations are summarized in Table 1, and the MAC-layer parameters are presented in Table 2. These include modulation and coding schemes (MCS levels), channel bandwidth, slot durations, and propagation delays, all aligned with standard 802.11ah configurations.

Table 1. Key physical layer parameters for simulations.

Parameter	Value
Basic rate	0.65 Mbps
Data rate	7.8 Mbps
Channel bandwidth	2 MHz
Modulation and coding scheme	MCS 2,8
PHY layer header	192 µs
Slot duration (σ)	52 µs
Propagation delay (δ)	3.3 µs

Table 2. Values of MAC layer and other parameters used in simulation.

Parameter	Value
SIFS	160 µs
DIFS	264 µs
Payload size	256 bytes
MAC layer header	34 bytes
ACK	14 bytes
Beacon interval	0.1 s
Guard interval (Tg)	8 µs

5.2. Simulation Results

The simulation results provide a comparative evaluation of the proposed NNBG scheme with the existing UGS and RSS-based schemes across multiple network conditions. Analytical and simulation outcomes are correlated to validate the accuracy of the mathematical model and the efficiency of the proposed neural-based grouping mechanism.

The effect of hidden terminals on the average throughput can be seen in below Figure 8, where analytical model and simulation data have been used for different modulation schemes like MCS2, MCS4, and MCS9. Different coding schemes of 802.11ah are

used for simulation. In the result analysis, we can see that the MCS2 coding scheme gives lesser aggregate throughput when compared with the MCS4 and MCS9 coding schemes. When the number of hidden terminals increases, the aggregate throughput decreases in all the coding schemes. The hidden terminals or nodes are causing a major impact on the aggregate throughput in all the coding schemes.

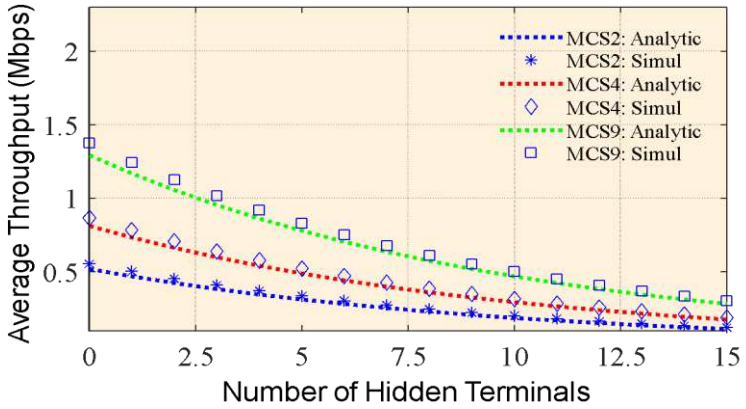


Figure 8. The average throughput vs. number of hidden terminals.

In Figure 9, the aggregate throughput of the carrier sensing range has been compared for the uniform grouping scheme and the proposed grouping scheme. In the result analysis, we can see that the aggregate throughput is consistent with the NNBG scheme for both MCS2 and MCS9 analytical and simulation, though the sensing range varies.

For the uniform grouping scheme, the aggregate throughput is less for the lower sensing range and increases along with the sensing range for both MCS2 and MCS9 coding schemes. The aggregate throughput for the uniform grouping scheme is increased with the sensing range in both the analytical and simulation models. The uniform grouping scheme analytical and simulation models are similar. Whereas the proposed grouping scheme performs better and gives constant aggregate throughput for MCS2 and MCS9 coding schemes. The proposed scheme maintains consistent throughput for various sensing ranges.

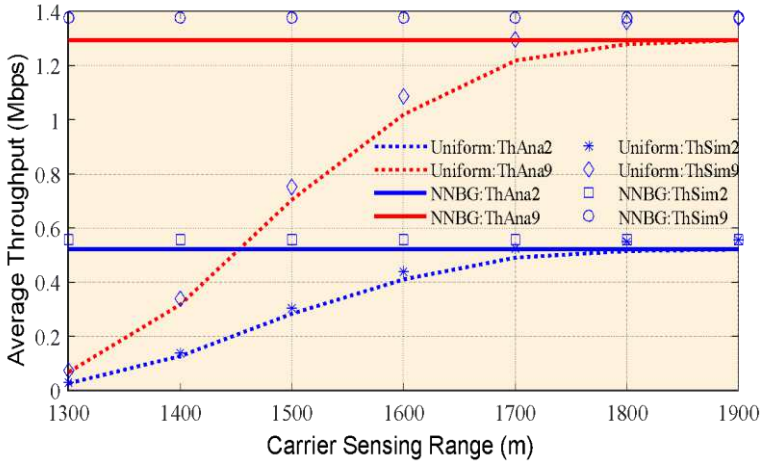


Figure 9. The average throughput and carrier sensing range.

The effect of no of groups on the average throughput can be seen in Figure 10, where analytical model and simulation data have been used for different modulation schemes like MCS2 and MCS9. The throughput increases gradually as the number of groups reaches 50 and then decreases with the group size. The analytical and simulation results of the uniform grouping with various coding schemes show less throughput when compared with the proposed grouping scheme. We can see that the MCS2 coding scheme gives lesser average throughput when compared with the MCS9 coding scheme for both the grouping schemes when the number of groups increases. When the groups number starts increasing then the average throughput decreases, but the proposed grouping scheme performed better by giving better throughput when compared to the uniform grouping scheme.

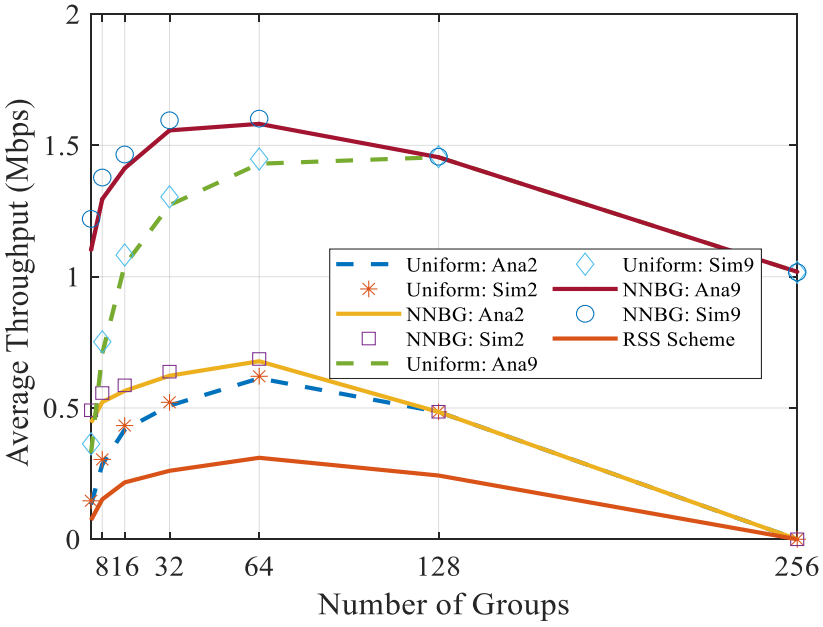


Figure 10. The average throughput vs. number of Groups.

In Figure 11, the aggregate throughput with the number of devices has been compared for the uniform grouping scheme and the proposed grouping scheme. Both analytical and simulation results are been compared. In the result analysis, we can see that the throughput decreases when the number of devices increases. As the number of heterogeneous devices increases the average throughput starts decreasing for the uniform grouping scheme as well as for RSS scheme. The proposed grouping scheme shows better results and provides consistent throughput though the device number increases. The average throughput of the uniform grouping scheme has been reduced drastically when compared with the NNBG scheme for both MCS2 and MCS9 analytical and simulation.

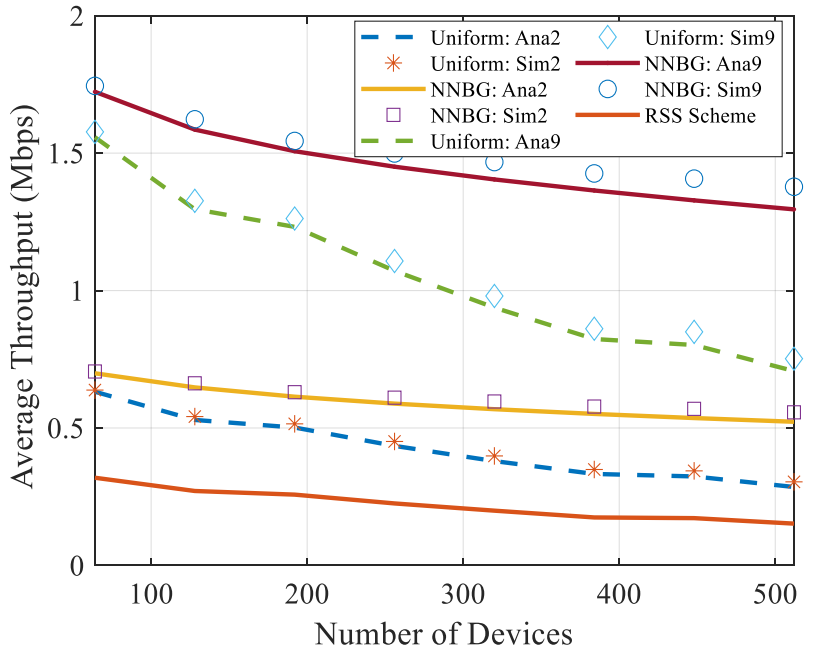


Figure 11. The average throughput vs. number of Devices.

Table 3. Comparison of Throughput Prediction for various Optimization Techniques

Model / Technique	Prediction Error (%)	Average Throughput (Mbps)	Throughput Improvement (%)	Adaptability to Hidden Nodes	Remarks
Analytical Model	8.4	6.72	—	Low	Static model; assumes fixed contention parameters; poor under variable traffic.
MarkovChain Model	5.9	7.05	+4.9 %	Moderate	Accurately models contention but fails to adapt dynamically.
Neural Networks–Based Grouping (NNBG)	4.6	7.28	+8.3 %	High	Improves throughput by intelligent grouping of stations; limited online adaptability.
Deep Learning–Based Throughput Prediction (DL-TPM)	2.7	7.85	+12.4 %	Very High	Learns nonlinear relations among parameters; dynamically adapts CW and RAW parameters in real time.

Table 3 summarizes the comparative performance of four throughput estimation and optimization techniques—namely, the analytical model, the Markov chain model, the Neural Networks–Based Grouping (NNBG) scheme, and the proposed Deep Learning–Based Throughput Prediction Model (DL-TPM). Each method was evaluated based on its average throughput, prediction error, and adaptability under hidden-terminal conditions in dense IEEE 802.11ah-based IoV networks. The analytical model exhibits a mean prediction error of 8.4% and an average throughput of 6.72 Mbps, primarily due to its reliance on static contention parameters. This approach assumes uniform traffic and station behavior, making it inadequate for dynamic vehicular or heterogeneous IoT environments.

The Markov chain model provides a more realistic representation of the back-off process and channel contention, reducing the prediction error to 5.9% and improving throughput to 7.05 Mbps. However, it still lacks real-time adaptability, as its parameters remain fixed after initial configuration. The Neural Networks–Based Grouping (NNBG) scheme enhances throughput to 7.28 Mbps by intelligently clustering stations based on SNR and SINR, thus reducing intra-group collisions. The 4.6% error rate reflects its improved predictive capability over traditional models. However, NNBG alone does not dynamically adjust transmission parameters once groups are formed.

In contrast, the proposed Deep Learning–Based Throughput Prediction Model (DL-TPM) achieves the highest average throughput (7.85 Mbps) and the lowest prediction error (2.7%), corresponding to an improvement of 12.4% over the analytical baseline. The model effectively learns nonlinear dependencies between network parameters and throughput, enabling the Access Point (AP) to adapt contention window size $CW_{\min}$, RAW slot duration σ and MCS level in real time. Its high adaptability under hidden-node conditions allows the network to maintain near-optimal performance even in dense or rapidly changing vehicular scenarios. Overall, the results confirm that the DL-TPM framework outperforms existing analytical, probabilistic, and neural grouping techniques, establishing it as a robust and intelligent throughput optimization approach for next-generation IEEE 802.11ah-enabled IoV networks.

6. Conclusion

A neural networks based grouping scheme has been proposed for grouping the stations. The analytical model and simulation model have been evaluated for the throughput analysis. The average throughput for the uniform grouping scheme and the NNBG scheme can be observed in the performance evaluation section. The NNBG scheme performs better by giving more average throughput when compared with other schemes for several hidden terminals and other parameters. Still, some challenges, like analyzing the packet delay and energy harvesting methods in IoVs, have to be addressed by using different analytical frameworks. More effort is required to propose various analytical frameworks for analyzing various parameters in dense IoV networks.

Numerous studies have examined the efficiency of IEEE 802.11ah networks in various scenarios involving network size, traffic type, and setting of important factors like the quantity and size of RAW slots, etc. Earlier publications assume that stations are static because they don't move over time. There is a research gap in finding the grouping strategies and frameworks for energy harvesting and measuring packet delay in mobility scenarios. So one can focus on designing the frameworks and grouping strategies for sustainable energy efficient 802.11ah networks.

Acknowledgments: None.

Funding Statement: The authors received no specific funding for this study.

Author Contributions: The authors confirm contribution to the paper as follows: Conceptualization, methodology and design: Vinay Simha Reddy Tappeta, Bhargav Appasani, Mahesh Miryala; data collection: Amitkumar V. Jha, Srinivas Ramavath; analysis and interpretation of results: Suprava Pattnaik, Bharati Ainapure draft manuscript preparation: Vinay Simha Reddy Tappeta, review: Bhargav Appasani administration of project: Mohammad S. Khan; All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: Data will be made available on request.

Ethics Approval: Not applicable.

Conflicts of Interest: Authors declare no conflict of interest.

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