Prediction of Power to Autonomous Vehicles using Machine Learning techniques

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***Abstract*—The integration of machine learning (ML) techniques has catalyzed significant advancements in the realm of autonomous vehicle technology, particularly in the domain of Intelligent Transport Systems (ITS) and the evolution of Connected and Automated Vehicles (CAVs). This study focuses on a downlink communication network characterized by a single-antenna Base Transceiver Station (BTS) and autonomous vehicles, with the BTS transmitting information at varying power levels. The primary objective is to predict optimal transmit power for vehicles across diverse channel conditions using machine learning methodologies, aimed at mitigating interference within the system. This interdisciplinary research endeavors to optimize transmit power from the BTS to vehicles through the synergy of machine learning and optimization techniques. By addressing this imperative, we aim to enhance vehicle safety, efficiency, and reliability within modern transportation networks. Leveraging advanced ML models, including Long Short-Term Memory (LSTM) and Feedforward Neural Network (FNN), our investigation reveals promising insights into the efficacy of these algorithms in advancing autonomous driving technologies. The paper presents comparative analyses of two prominent machine learning models, with the Mean Square Error (MSE) computed at 17.2516 for LSTM and 13.8562 for the Feedforward Model. These results underscore the potential of ML-driven approaches in optimizing transmit power for autonomous vehicle communication networks, thereby contributing to the ongoing evolution of intelligent transportation systems.**

Keywords: Machine Learning (ML), Base station(BTS),Autonomous Vehicles, Intelligent Transport Systems (ITS), Connected and Automated Vehicles (CAVs), Transportation Challenges, Automotive Industry Standards, Future of Mobility, Global Transportation Systems

I. Introduction

Autonomous driving systems (ADS) [1] have evolved over a century, marked by advancements in computation, artificial intelligence (AI), and sensor technology. Despite early technological constraints, rapid progress in recent decades brings us closer to achieving truly autonomous vehicles. In recent years, automakers have integrated driver assistance systems (DAS) and onboard intelligence (OI) into their vehicles, resulting in passengers having a more acute awareness of their surroundings. Autonomous driving (AD) is regarded as indispensable for enhancing passenger convenience, reducing traffic congestion, eliminating accidents caused by human error, and enhancing vehicle safety.

On the other hand, vehicle-to-everything (V2X) communications, driven by ongoing standardization efforts, offer transportation solutions for road traffic and safety management. The integration of AI into networks beyond 5G and 6G holds great promise for optimizing user functions and supporting road safety. Moreover, vehicle networks have sparked a paradigm shift, revolutionizing autonomous vehicles and reshaping modern transportation. Six levels of vehicle automation have been established by the Society of Automotive Engineers (SAE), spanning from complete automation to no automation [2]. Increasingly, connected and automated vehicles (AV) [3] are recognized as having the potential to deliver significant benefits to society, they would significantly improve fuel efficiency and reduce emissions, thereby contributing to environmental sustainability. Despite the remarkable progress made in AD [4] technology, there are still several issues to be addressed.

One of the most pressing of these challenges is resource allocation. In the context of 5G vehicle-to-vehicle (V2V) communications, resource allocation isn't a mere distribution of bandwidth. It's a complex orchestration that involves optimizing spectrum usage, minimizing interference, ensuring timely data delivery, and critically, doing all this in an energy-efficient manner. Additionally, energy efficiency in 5G V2V communications isn't just an environmental concern; it's a critical operational one [5]. Vehicles, while having more energy resources than handheld devices, still operate under constraints. Excessive energy expenditure on communications can impact other critical vehicular functions.[5] Moreover, as we move towards electric vehicles, judicious energy use becomes even more crucial [6]. Traditional resource allocation strategies, designed primarily for static or semi-static environments, are ill-suited for the volatile world of V2V communications. The high-speed movement of vehicles means that communication links are frequently established and broken, channel qualities varies rapidly, and the network topology itself is in a constant state of flux.

The primary challenge in autonomous vehicle networks is managing interference in dynamic and densely populated environments. While exclusive spectrum assignments can reduce interference, autonomous vehicles often operate in shared spectrum environments where nearby devices can cause significant interference. Effective power management and advanced interference mitigation techniques are essential to ensure reliable communication and information transfer in such complex scenarios, also that to have spectrum for each vehicle is expensive so the whole vehicle network is considered to be in a single spectrum. We propose two machine learning models LSTM and FNN to predict the power for transmission of the signal. The dataset comprises of various features related to the transfer of information in autonomous vehicles.

The main contributions in this paper are

- Detailed literature review with research gaps of machine learning techniques in autonomous vehicles as explained in Table II.
- Objective function for optimizing power in the autonomous vehicle network with capacity and time constraints.
- A performance evaluation of 5G resource allocation network dataset by using feedforward neural network and long short-term memory (LSTM) to predict the power required by each user in the wireless communication network.

  The rest of the paper is organized as follows. Sec. II presents the literature review of significance of machine learning in autonomous vehicles. Sec. III provides system model, problem formulation and its solution with early results. Sec. IV discusses the performance analysis and finally. Sec. V presents the conclusion and outlines future work.

II. Related Work

During the past few years, extensive research has been conducted regarding the application of AI in wireless networks and V2X communications. Traffic flow prediction, local data storage, network congestion control, load balancing, vertical handover control, and wireless resource management are a few of the applications of ML that have made strides in vehicular networks. The authors in [7] additionally address the difficulties that arise when ML techniques are implemented in vehicular networks. These challenges include the high-strain dynamics of vehicle networks. On the other hand, authors in [8] analyzed possible use case of AI in analyzing the intricacies of vehicular network dynamics for traffic patterns and mobility.

Moreover, it is anticipated that AV powered by AI will revolutionize the notion of shared mobility. Fleets comprising autonomous ride-sharing vehicles have the potential to mitigate traffic congestion, enhance urban mobility, and eliminate the necessity for individual car ownership. Potential societal and commercial effects of AI-enabled shared mobility are examined in [9]. The authors in [10] examine deep learning principles that enhance the functionality of V2X communications by optimizing resource allocations of these communication systems. Gao et. al [11] present a deep learning based resource allocation approach called weighted minimum mean square error (WMMSE). Authors examine the sum rate maximization problem under individual power constraints for each vehicle to infrastructure (V2I) and V2V communication link using supervised learning. Additionally, this approach is intended to optimize the distribution of transmit power among all users to maximize the overall system throughput of the V2X connections.

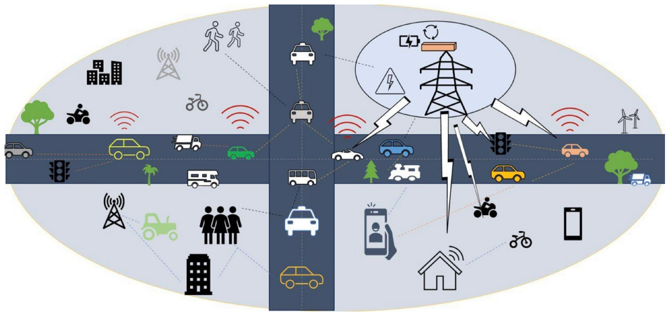

Fig. 1. An illustration of downlink communication in Dense Communication communication network

The authors in [12] focuses on cooperative perception and V2V communication for enhancing autonomous vehicle functionalities. It identifies key challenges in autonomous systems, such as occlusion handling, efficient data transmission, and scalability, which are critical for improving safety and reliability. These challenges are significant because they impact the vehicle's ability to make informed decisions in real-time, highlighting the need for advanced machine learning-based resource allocation strategies. The limitations of existing approaches, such as the reliance on extensive bandwidth and the inability to effectively manage occlusions, underscore the importance of developing innovative solutions to overcome these hurdles. In addition, a comprehensive review of autonomous vehicle advancements reveals the significant role of machine learning [13], especially deep learning techniques, in enhancing vehicle functionalities like lane detection and traffic sign interpretation. However, despite progress in machine learning algorithms such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for environmental perception, achieving complete automation remains elusive. The paper underscores the challenge in attaining full autonomy without human intervention, highlighting a critical area for future research aimed at navigating complex and unpredictable environments. In exploring the forefront of autonomous vehicle (AV) technologies, this analysis delves into the significant advancements in sensor technology and vehicular communications pivotal for intelligent transportation systems (ITS). It underscores the strides made in deploying sophisticated sensors like ultrasonic, RADAR, LiDAR, and cameras, alongside the evolution of V2X communications, encompassing V2V and V2I interactions. These gaps highlight the necessity for innovative research in sensor fusion and enhanced communication protocols, underpinning the motivation for this paper. The aim is to propose novel solutions that could bridge these technological divides, thereby unlocking the full potential of AVs within ITS [14]. Machine learning plays a crucial role in fine-tuning resource distribution in autonomous vehicle systems [15]. Data analysis techniques and flexible machine learning models that are adept at comprehending and tackling the complexities of autonomous driving are advocated in the paper. By utilizing cutting-edge machine learning methods to enhance autonomous vehicles, this thorough critique strengthens the call for heightened research in this area.

An analysis of the related work illustrated in Table I and and a comparison of the literature is presented in Table III.

III. System Model

As illustrated in Fig. 1, we consider a dense downlink communication network in which a single antenna base station (BS) transmits data x_n to all single antenna randomly distributed autonomous vehicles in the network where $x_N = \{ x_1, x_2, \ldots, x_N \}$ whereas N is the total number of autonomous vehicles in the network. Due to the high density in the network nakagami-m fading is considered between the BS and all the users. The received signal at each user are given as

$$y_{bn} = \sqrt{P_n}(\mathbf{G}_n \Theta_n) x_n + n_{b_n} (1)$$

where P_n is the transmit power of the BS and y_b is the received signal at user. The channel vector from BS to user is denoted by $\mathbf{G} \in C^{N \times 1}$ where n_b is the additive gaussian noise (AWGN) at user. Similarly $\Theta_n \in [0, 2\pi)$ denotes the phase shift at the user [19].

A. Objective Function and constraints

The objective function minimizes the power consumed to route the traffic of Self-Driving cars through available access points.

$$Minimize \sum_{i=1}^{N} P_i \tag{2}$$

1. All data traffic is routed

$$\sum_{j=1}^{T} \sum_{x=1}^{A} \sum_{y=1}^{Ch_x} \lambda_{ij}^{xy} = \lambda_i \tag{3}$$

2. Capacity constraints for channels are maintained

$$\sum_{i=1}^{N} \sum_{j=1}^{T} \lambda_{ij}^{xy} \leq C_{xy} \quad \forall y \in Ch_x \tag{4}$$

3. Power consumption of data transmission of each car

$$P_i = \sum_{j=1}^{T} \sum_{y=1}^{Ch_x} \lambda_{ij}^{xy} \cdot PAP_x \quad \forall i \in N, \forall x \in A \tag{5}$$

4. Delay of traffic type *j* car *i* does not exceed the maximum allowed by the traffic type

$$\max \left(\sum_{x=1}^{A} \sum_{y=1}^{Ch} \frac{\lambda_{ij}^{xy}}{D_{xy}} \right) \leq DMax_j \quad \forall i \in N, \forall j \in T \tag{6}$$

The explanation of variables is found in Table II.

B. Problem Formulation

In the rapidly evolving landscape of wireless communication networks, the challenge of optimizing power allocation for multiple users becomes increasingly complex. This complexity is further amplified in the context of autonomous vehicles, where efficient resource allocation is paramount for seamless operation. Specifically, our research addresses the optimization of power allocation for 400 users within such networks, taking into account the diverse requirements dictated by their applications (e.g., video streaming), the power of the signal received (measured in dBm), required bandwidth, and the bandwidth that has been allocated to them. The quintessence of this problem lies in the development of a predictive model capable of accurately estimating the power needs for each user based on these parameters. Addressing this issue is not only pivotal for enhancing the efficiency of resource allocation but also for the overarching network management and the operational efficacy of autonomous vehicles within wireless communication systems.

TABLE I
SUMMARY OF RESEARCH IN VEHICULAR NETWORKS

Author(s) and Year	Research Aims/Objectives	Key Findings	Research Gaps/Opportunities
Ye, H., et al (2018) [7]	Review advances in ML applications in vehicular networks.	ML enhances vehicular networks for safety and efficiency.	• Nascent Machine Learning in Vehicular Networks • Addressing learning dynamics • Addressing method complexity • Addressing distributed representation.
Liang, L., et al (2019) [8]	Apply ML to optimize vehicular network performance.	ML significantly enhances network decision-making and resource management.	Need for more dynamic algorithms and integration with 5G/IoT.
Guanghua Chai et al., (2022) [9]	Develop a resource allocation framework for V2X networks using large-scale channel information.	Improved resource allocation efficiency with a learning-based approach	Adapt to various network conditions and integrate with new V2X technologies.
Yuan, Y., et al., (2021) [10]	Develop DRL-based algorithms for dynamic resource allocation in V2X communications.	Introduced algorithms improve V2I and V2V communications adaptability and performance.	More efficient solutions could be explored in the future.
Gao, J., et al., R.T., (2019) [11]	Develop an efficient resource allocation method for V2X communications using deep learning	DNN approach approximates WMMSE algorithm with less computational overhead.	Explore unsupervised learning for power allocation to enhance V2X systems.
Khan, ., et al., U.A. (2019)[12]	Optimize resource allocation in D2D-based vehicular networks.	Developed a 3D matching and hypergraph colouring approach for resource allocation.	Study varied network structures and the impact of multiple antennas on D2D in V2P communication.
AlQerm ., et al ., (2019) [13]	Develop an energy-efficient traffic offloading strategy for 5G networks.	Significant improvements in energy efficiency and QoS through offloading.	Explore dynamic, scalable offloading strategies adaptable to real-time conditions.
Gao, L., et al, M., (2019) [14]	Optimize resource allocation in V2V networks to maximize transmissions.	The algorithm outperforms existing schemes in throughput and capacity especially in high vehicle density.	Explore RSAC algorithm in diverse vehicular network scenarios..
Niu, Z.,et al ., (2020) [15]	Propose a SAGiven architecture for enhanced communication and autonomous driving support.	Identified challenges in network integration and suggested solutions including reconfiguration, reliable communication, etc	Research on dynamic resource integration and real-time communication for autonomous vehicles.
Jamal, M., et al , (2023) [16]	Improve V2X communication using DRL for resource allocation.	Successful application of Deep Reinforcement Learning (DRL) enhanced V2V and V2I communications.	Further exploration in autonomous vehicle communication and advanced AI integration.

TABLE II
PARAMETERS AND VARIABLES

N	Number of Self-Driving cars
T	Number of traffic types
A	Number of access points
D_{xy}	Data rate of channel y of access point x
C_{xy}	Maximum capacity of channel y of access point x
Ch_i	Number of channels owned by access point i
λ_i	Traffic demand of car i
$MaxT_i$	Maximum traffic at access point i maintaining acceptable QoS
PAP_i	Power consumption of occupying a channel in APi
P_i	Power consumption of Self-Driving car i
$DMax_j$	Maximum delay allowed by traffic type j

To navigate the complexities of predicting power requirements in wireless communication networks, we propose the development of two distinct yet complementary regression models: Long Short-Term Memory (LSTM) and Feedforward Neural Network (FNN)[18] . These models are selected for their proficiency in capturing and leveraging historical data patterns and dependencies, which are crucial for making accurate power allocation predictions.

The LSTM model, known for its ability to remember information for long periods, is particularly suited for understanding and predicting the dynamic power needs based on temporal variations in user behavior, application requirements, and network conditions. On the other hand, the FNN model offers a robust framework for capturing the static relationships between the input features and the power requirements, providing a comprehensive understanding of the underlying system dynamics.

The input features for these models are meticulously chosen to encompass a wide range of relevant

TABLE III
RESEARCH METHOD SOLUTION

Research Method	Why this method was used	Benefits	Significance of the Research
Long Short-Term Memory (LSTM) Model	LSTM models excel in analyzing sequential data, making them ideal for time-series data in autonomous vehicles .	Predicts future resource needs by learning from past and present data, enhancing decision-making in resource allocation.	Enhances predictive capabilities in autonomous vehicles, enabling proactive resource management for safer and more efficient operations.
Feedforward Neural Network (FNN) Model	FNNs efficiently map static inputs to outputs, ideal for scenarios with direct relationships between vehicle sensors/data and resource needs without time dependencies.	Enables rapid processing of sensor data for instant resource allocation decisions.	Facilitates real-time resource allocation for adaptive autonomous vehicles, enhancing scalability and computational efficiency in specific allocation challenges.

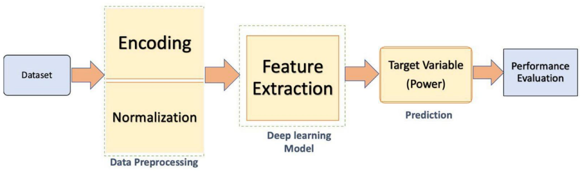

Fig. 2. Flow chart for implementation of models.

information, including user ID (to capture individual usage patterns), required application (to understand the demand placed on the network by different services), required bandwidth (to gauge the volume of data transmission), allocated bandwidth (to assess the network's response to demand), and the power of the signal (to factor in the quality of the connection).

C. Dataset

The dataset [17] comprises various features related to the quality of service (QoS) in a communication network. Each entry in the dataset is associated with a unique User ID and includes the following features:

User ID: A unique identifier for each vehicle in the network.

Application Type: Type of application being used by the user, indicating the nature of data transmission, such as video streaming, file transfer, or voice communication.

Signal Strength: Represents the power level of the signal received by the user's device, typically measured in decibels (dBm). Signal strength is a crucial factor in determining the reliability and performance of the communication link.

Latency: Refers to the delay between sending and receiving data, indicating the responsiveness of the network. Lower latency values are generally desired for real-time applications.

Required Bandwidth: Specifies the amount of bandwidth that the user's application ideally requires for optimal performance. Bandwidth is a key factor in determining the capacity of the network to handle data traffic.

Allocated Bandwidth: Represents the actual bandwidth allocated to the user by the network. Discrepancies between required and allocated bandwidth may impact the user's experience.

Resource Allocation: Provides information on how resources, such as bandwidth, are allocated to the user. Efficient resource allocation is critical for maintaining a high level of service quality.

This dataset [17] is valuable for exploring the relationships and dependencies between these QoS-related features and can be used to develop predictive models.

IV. PERFORMANCE ANALYSIS

A. Research method solution

We used to regressor model LSTM and FNN to predict the power required by each user in the wireless communication network. The evaluation metrics for each model are training, validation loss, mean absolute error(MAE) and mean square error(MSE). This paper shows early results of machine learning.

B. Training and Validation loss

The training and validation loss are essential metrics used to assess the performance and generalization capability of the enhanced LSTM and FNN models. The training loss represents the mean squared error between the predicted and actual target values which is power(dB) in our case during the model training phase, while the validation loss measures the model's performance on a separate dataset not used for training.

Fig 3 and fig 4 depicts the training and validation loss of LSTM and FNN models respectively. The downward trend of each graph illustrates that with an increase in the number of epochs both losses decrease. The decrease in the training loss indicates that the model is effectively learning patterns in the data while the validation loss graph illustrates the model's ability

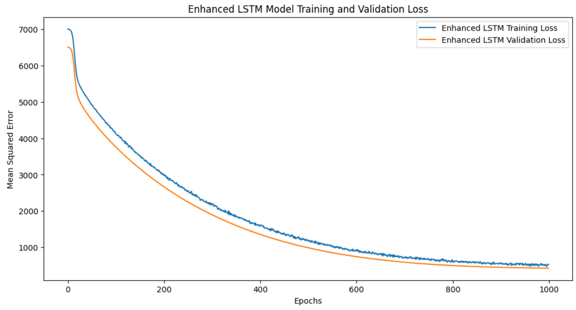

Fig. 3. Training and validation loss of LSTM model.

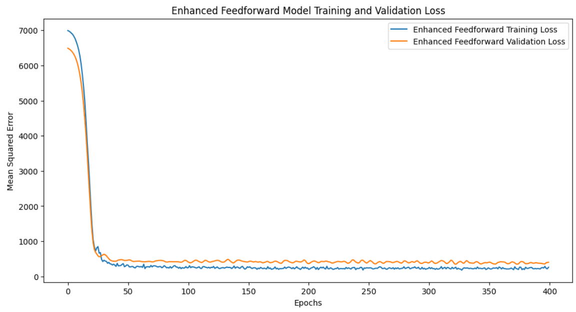

Fig. 4. Training and validation loss of feedforward neural network model.

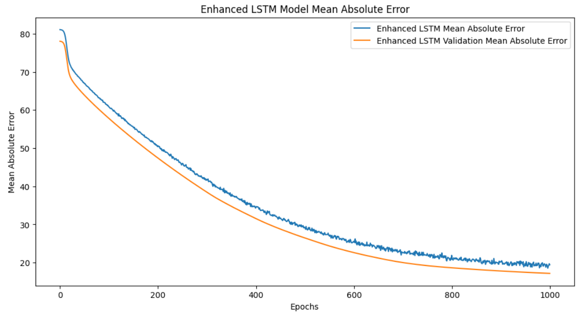

Fig. 5. Mean average error of LSTM model.

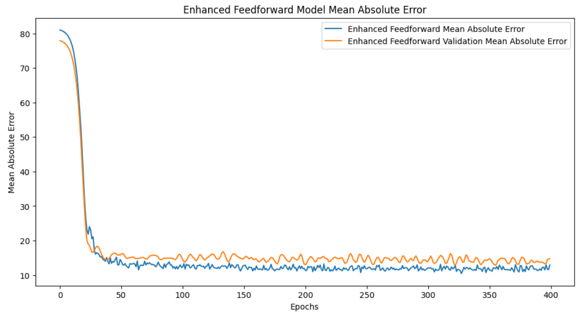

Fig. 6. Mean average error of LSTM model.

to generalize to unseen data. A decreasing validation loss suggests that the model is not overfitting to the training set and can make accurate predictions on new data.

C. Mean absolute error

MAE is a measure of the average absolute differences between predicted and actual values. Monitoring both training and validation MAE is crucial for assessing the model's predictive accuracy and ensuring that it generalizes well to unseen data.

Fig 5 and fig 6 illustrate the MAE for training and validation of LSTM and FNN models respectively. The training MAE graph illustrates the MAE between the predicted and actual target values during the training phase for the LSTM and FNN models. A decreasing training MAE indicates that the model is becoming more accurate in its predictions on the training dataset while the validation MAE graph reflects the mean absolute error on a separate validation dataset, offering information on the model's ability to make accurate predictions on new data MAE Value of LSTM Model is 427.7760 dB and for Feedforward Model is 379.1476 dB, respectively. in addition the MAE values MSE is 17.2516 dBfor LSTM and for The Feedforward Model is 13.8562 dB.

V. Conclusion and Future Work

In this study, we have addressed a critical challenge encountered in autonomous vehicle networks the optimization of signal transmission within constrained power parameters to mitigate interference. By employing advanced machine learning models, specifically Long Short-Term Memory (LSTM) and Feedforward Neural Network (FNN), we have made significant strides in predictive accuracy, as evidenced by reductions in Mean Absolute Error (MAE) during both training and validation phases.The LSTM model, incorporating bidirectional layers and dropout regularization, demonstrated consistent error reductions over 1000 epochs, while the FNN model, with multiple dense layers and dropout, exhibited substantial improvements over 400 epochs. These results underscore the efficacy of our approach in enhancing the efficiency and reliability of autonomous vehicle communication networks.Looking ahead, our future endeavors will focus on the seamless integration of these models into the operational framework of autonomous vehicles. Our objective extends beyond mere power allocation optimization, we aim to empower autonomous vehicles with the capability to dynamically manage their resource allocation.

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