Optimizing Downlink Resource Allocation for High-Speed LTE-V Networks Through Intelligent Scheduling

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***Abstract*—The rapid expansion of vehicular communication systems emphasizes the integration of LTE-V networks, crucial for applications like road safety, traffic management, and infotainment. High-speed scenarios demand efficient downlink scheduling due to constantly changing channel conditions influenced by factors like throughput and Bit Error Rate (BER). Mobility-induced channel variations lead to signal quality fluctuations, interference, and congestion. LTE-V networks require robust Quality of Service (QoS) for safety applications, necessitating algorithms that detect and mitigate interference by dynamically adjusting scheduling. Existing algorithms struggle with Doppler shift effects, interference, and predicting network patterns, prompting the exploration of an Intelligent Downlink Scheduling (IDS) scheme based on Support Vector Machines (SVM) for high-speed LTE-V networks. This work focuses on the optimization of the resource allocation, improving spectral efficiency, and predicting network congestion. Leveraging machine learning and optimization, it addresses challenges posed by varying vehicle densities, mobility patterns, and QoS needs. Extensive simulations show the IDS's superiority, significantly enhancing throughput and reducing BER. The improved throughput signifies reduced data loss in scheduling queues, while lower BER indicates enhanced received data post-scheduling. The IDS facilitates real-time decision-making and data-driven insights, ideal for managing and optimizing downlink scheduling in dynamic Long-Term Evolution-Vehicle (LTE-V) networks. Simulation results demonstrate a substantial 13 dB improvement over the best CQI scheduler at a 10^{-4} BER and a 24 Mbps increase at a 20 dB SNR for a vehicle density of 40, showcasing the IDS's performance enhancements.**

***Keywords*—Long-Term Evolution-Vehicle (LTE-V), intelligent downlink scheduling, vehicular communication, machine learning, spectral efficiency, quality of service**

I. Introduction

The increase of Internet of Things (IoT) devices and intelligent vehicles has led to an exponential increase in data traffic within vehicular environments. Long-Term Evolution-Vehicle (LTE-V) networks have emerged as a promising solution to cater to the communication needs of vehicles, enabling applications ranging from safety-critical vehicle-to-vehicle (V2V) communication to infotainment services for passengers [1]. However, the inherent challenges of high mobility, varying traffic densities, and a need to maintain stringent quality of service requirements demand innovative approaches to optimize the utilization of network resources and ensure seamless connectivity demands [2].

Vehicular communication systems introduce a unique set of challenges that traditional cellular networks often do not encounter. The highly dynamic nature of vehicular environments gives rise to rapid changes in network topology as vehicles move in and out of cellular range. Rapid changes like these present challenges for downlink scheduling, which involves allocating transmission resources to vehicles. Traditional static scheduling schemes often struggle to effectively adapt to this ever-changing connectivity landscape [3]. Moreover, the Quality of Service (QoS) requirements vary widely in vehicular networks, with safety-critical applications necessitating ultra-low latency and high reliability. In contrast, entertainment and infotainment applications can tolerate slightly higher latency [4].

The effect of high-speed mobility exacerbates these challenges. As vehicles move at over 80 miles per hour, their relative positions concerning base stations change rapidly. The rapid movement leads to fluctuations in channel conditions, resulting in variations in signal strengths, fading conditions, and Doppler shifts. Consequently, traditional downlink scheduling algorithms that do not consider the impact of high-speed mobility may lead to suboptimal resource allocation, decreased spectral

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efficiency, and increased packet loss [5]. These challenges call for intelligent downlink scheduling solutions that dynamically adapt to changing network conditions and make real-time decisions to ensure efficient resource allocation and reliable communication.

Machine learning has emerged as a pivotal tool in addressing the intricate downlink scheduling challenges encountered in LTE-V networks. The ability of machine learning models to gain insights from vast and diverse datasets in dynamic network conditions enables the creation of adaptable scheduling strategies that can dynamically respond to real-time variations in network conditions [6]. Machine learning models can learn complex patterns of vehicle mobility, traffic density, and channel conditions, enabling them to allocate resources to vehicles predictively, thereby enhancing spectral efficiency and ensuring high-quality communication links. Furthermore, as LTE-V networks grapple with the demands of high-speed mobility, machine learning's capability to process and analyze data quickly allows for rapid decision-making to accommodate fast-changing scenarios [7]. Ultimately, machine learning-driven downlink scheduling optimizes resource utilization and latency and contributes to LTE-V networks' overall throughput and effectiveness in delivering seamless, high-performance vehicular communication experiences with lower Bit Error Rate (BER) [8]. Table I summarizes downlink scheduling algorithms and LTE-V networks' challenges and the importance of proposing machine learning algorithms to overcome them.

In light of the proposed challenges, this paper aims to assess the utilization of a machine learning algorithm as a scheduler within an LTE-V network, particularly for high-speed travel scenarios. The proposed algorithm, known as Intelligent Downlink Scheduling (IDS), is engineered to address interference issues, leverage network insights, and predict optimal throughput while minimizing Bit Error Rate (BER). It leverages Support Vector Machines (SVM) as the underlying machine learning algorithm to enhance overall system throughput and reduce system BER. By examining simulation results and comparing them to existing literature, the contributions of this paper can be summarized as follows:

TABLE I. SUMMARY OF THE DOWNLINK SCHEDULING LTE-V NETWORK CHALLENGES

Challenge	Machine Learning as a Solution	Description
Changeable network conditions	Dynamic Adaptation to Network Conditions	High-speed LTE-V networks experience varying and dynamic network conditions due to the mobility of vehicles [9]. Machine learning algorithms can analyze real-time data from the network, such as traffic patterns, signal quality, and congestion levels, to adapt downlink scheduling strategies accordingly. This dynamic adaptation can improve network throughput.
Future prediction of the network conditions	Predictive Scheduling	Machine learning can predict future network conditions and optimize downlink scheduling in anticipation of congestion or high-demand periods [10]. By considering historical data and real-time information, machine learning models can make informed decisions to allocate resources more effectively.
	Traffic Pattern Analysis	Machine learning can analyze and detect vehicular traffic patterns, helping optimize downlink scheduling by allocating resources more efficiently to areas with higher vehicle density and demand [11]. This can improve overall network performance.
	Real-Time Decision-Making	Machine learning models can make near-instantaneous downlink scheduling decisions, allowing faster response to changing network conditions and improving user experiences.
	Self-Healing Networks	Machine learning can enable self-healing capabilities by continuously monitoring the network and automatically adjusting downlink scheduling in response to faults or interference [12]. This can reduce downtime and enhance network reliability.
Limitation in QoS due to constraints of schedulers	QoS Improvement	Machine learning algorithms can prioritize data transmission based on QoS requirements, ensuring critical applications, such as emergency services or vehicle-to-vehicle communication, receive higher priority in downlink scheduling [13]. This can lead to safer and more reliable communication in high-speed vehicular environments.
	Resource Allocation Optimization	Machine learning can optimize resource allocation by considering channel conditions, interference, and device characteristics. This ensures that available resources are used effectively, resulting in higher throughput and reduced BER [14].
	Scalability	As the number of connected vehicles and devices in LTE-V networks continues to grow, machine learning algorithms can provide scalable solutions for managing downlink scheduling efficiently, adapting to changes in network size and complexity [15].

- Introducing the Intelligent Downlink Scheduling (IDS) algorithm for LTE-V, tailored to high-speed vehicular networks and applicable across a range of network densities.
- Conducting a comprehensive evaluation of the newly introduced algorithm in comparison to established scheduling algorithms within the field. The comparative analysis will help analyze the superior throughput performance exhibited by the proposed algorithm.
- Enhancing LTE-V network throughput and minimizing Bit Error Rate (BER) by taking insights from network

scenarios and characteristics. This approach provides a holistic view of the system's evolution, enabling the selection of optimal throughput and reduced BER for individual users and the entire network.

The rest of the paper has been structured as follows. Section II provides a literature review of the related articles to analyze their methodologies and findings. Section III describes the proposed work's methodology. Section IV delineates the simulation results and analysis based on throughput results and BER. Section V concludes the study and provides along with providing some future recommendations.

II. Literature Review

The study of scheduling methods is contingent upon the QoS of the network, making throughput performance the primary measure in this study. Table II summarises the literature review for this paper. Mahdi *et al.* [16] introduced an enhanced variant of the Best-CQI scheduling algorithm to bolster network throughput. A comparative analysis is conducted between the proposed algorithm and three user scheduling algorithms: Round Robin (RR), Proportional Fair (PF), and the original Best-CQI algorithm. The evaluation is conducted in a Line-of-Sight (LoS) scenario using a carrier frequency of 2.6 GHz to cater to LTE-V in a high-speed context. The Best-CQI algorithm is good to use but has a limitation when the dynamic environment comes into consideration because it depends on the actual environment under the simulation and does not consider the previous or future conditions.

Various scheduling methods are employed to enhance network throughput for V2I links. The fundamental approach is an exhaustive search, which involves documenting all possible user subsets [17]. However, in dense networks, this becomes computationally intricate. Consequently, there's an increase in the load on the Base Station (BS) due to numerous scheduling requests. To mitigate this, imperfect scheduling techniques have been proposed to simplify computations while maintaining throughput close to exhaustive search [18]. The QoS-aware scheduling begins with establishing a connection to the LTE's eNodeB. Subsequently, the LTE node evaluates incoming signals and their attributes to conduct scheduling based on QoS performance.

The widely employed Best-CQI algorithm in LTE-V networks hinges on Transmission Time Interval (TTI) to allocate BS to users. This channel-aware algorithm prioritizes channel conditions, ensuring superior throughput compared to other LTE-V schedulers. Nevertheless, it falters when users experience poor channel quality, potentially inhibiting scheduling [19].

Taha *et al.* [20] presented an innovative downlink scheduling algorithm named Advanced Fair Throughput Optimized Scheduler (AFTOS) tailored for ultra-dense networks, focusing on channel quality and Quality of Service (QoS) awareness. AFTOS serves as a multi-QoS scheduler to enhance system-wide spectrum efficiency and user throughput and ensure improved fairness, reduced delays, and minimized Packet Loss Ratio (PLR). It accommodates both Real-Time (RT) and Non-Real-Time (nRT) traffic. The algorithm introduces two novel strategies: Adjusted Largest Weighted Delay First (ALWDF) and Fair Throughput Optimized Scheduler (FTOS), designed for RT and nRT traffic. These strategies are then combined to create the AFTOS scheduler. To assess the effectiveness of the proposed approach, a series of experiments were conducted to determine optimal parameter values and to benchmark it against existing best practices. The results substantiate the AFTOS algorithm's capability to surpass alternative techniques and successfully achieve its intended objectives. However, an innovative communication scheduling method based on deep learning is suggested in [21] for addressing the service scheduling challenge. This approach introduces a three-phase scheduling algorithm comprising RSU clustering, deep learning-powered traffic prediction, and a vehicle access scheduling algorithm. The primary objective is to optimize vehicle service capacity while minimizing energy expenditure. Thorough simulations were conducted, and the outcomes demonstrate that the algorithm outperforms other scheduling methods across various scenarios by efficiently accommodating more vehicles while conserving energy.

The optimization problem, framed as minimizing overall system cost, is tackled through the application of Deep Reinforcement Learning (DRL) techniques in [22], explicitly employing the Deep Deterministic Policy Gradient (DDPG) algorithm. Simulation outcomes validate the scheme's effectiveness in achieving convergence, reducing system delay, curbing average task energy consumption, and minimizing system cost. This efficacy is particularly notable in dynamic IoV scenarios, as demonstrated through comparative analysis with alternative algorithms.

DRL is also used in [23]. They Introduce an innovative algorithm called Multiagent Graph Convolutional Deep Reinforcement Learning (M-AGCDRL), which unites individual agent observations with a lower-resolution global map as input. This amalgamation facilitates policy learning for each agent. Through graph attention networks, agents exchange information, leading to a powerful collective policy. Simulation outcomes affirm that the M-AGCDRL technique enhances the Quality of Experience (QoE) for Internet of Things (IoT) applications and attains commendable overall performance.

Zhang *et al.* [24] delved into the joint optimization challenge of resource allocation and transmission mode selection in cellular V2X communications. The central issue is framed as a Markov decision process, and a decentralized algorithm based on Deep Reinforcement Learning (DRL) is introduced. The aim is to maximize the cumulative capacity of vehicle-to-infrastructure users while simultaneously meeting the latency and reliability prerequisites of V2V connections. A two-timescale federated DRL method is developed to address the constraints of training local DRL models. This involves executing a graph theory-based vehicle clustering algorithm on a larger timescale and applying the federated learning algorithm on a smaller timescale. The simulation findings demonstrate the superior performance of the proposed DRL-based approach compared to other decentralized benchmarks and underscore the effectiveness of the two-timescale federated DRL approach in catering to newly activated V2V pairs.

TABLE II. LITERATURE REVIEW SUMMARY

Ref.	Scheduler	Importance	Challenge
Mahdi *et al*. [16]	Best-CQI	To Take into account the quality of the channel between the vehicle and the base station. This enhances the scheduling results, especially for throughput and error rate.	The limitation when dynamic environment becomes considered because it depends on the actual environment under the simulation and does not consider the previous or future conditions.
Raeisi and Sesay[17]	exhaustive search	To have the optimal algorithm depends on considering all the environmental conditions.	Complexity increases because of the need for exhaustive search.
Agyare *et al*. [18]	Imperfect QoS-aware scheduling	To have a QoS performance-based algorithm to perform scheduling.	Limitation of scheduler because it depends on the network QoS. In a dense network, this becomes challenging.
Mai and Li [19]	Best-CQI based on TTL	To have a channel-aware algorithm prioritizes channel conditions, ensuring superior throughput compared to other LTE-V schedulers.	The challenge of poor channel quality.
Taha *et al*. [20]	AFTOS scheduler.	To have a multi-QoS scheduler to enhance system-wide spectrum efficiency and user throughput and ensure improved fairness, reduced delays, and minimized packet loss ratio (PLR).	It needs to determine optimal parameter values, which means an increase in the computational process required.
Li *et al*. [21]	Three-phase scheduling algorithm comprising RSU clustering, DL-powered traffic prediction, and a vehicle access scheduling algorithm.	To optimize vehicle service capacity while minimizing energy expenditure.	It used a deep learning algorithm to minimize the overall system cost. This means that DL is used to help the scheduler, not as a scheduler itself. This leads to computational complexity increase.
Zhao *et al*. [22]	DDPG algorithm	To have optimal service quality based on future environmental conditions prediction.	Increase in the computational process.
Dai *et al*. [23]	M-AGCDRL algorithm	To facilitate policy learning for each environment by exchanging information between available networks, which leads to an assertive collective policy of data.	A large data set is required to facilitate the learning process.
Zhang *et al*. [24]	Markov decision process and a decentralized algorithm based on DRL.	To maximize the cumulative capacity of V2I vehicles while simultaneously meeting the latency and reliability prerequisites of V2V connections.	It needs a large data set based on executing a graph theory-based vehicle clustering algorithm on a larger timescale and applying the federated learning algorithm on a smaller timescale. This means an increase in computational requirements.

This proposed model makes use of SVM as a machine learning tool. The developed design ensures that less reliance is on the use of large-scale datasets which gives it an edge over the use of deep learning models. Yet, the model ensures the effectiveness of the system design and is suited well for scenarios where the availability of the data is limited. Thus the choice of the model ensures that the network dynamics are met while relying on low data demands and lower computational requirements. This makes it an optimal method in the given scenario.

This strategic choice of algorithm not only reduces computational demands but also enhances adaptability to the network's dynamics, making it an optimal fit for the proposed approach in this paper.

III. Methodology

Fig. 1 illustrates the simulation setup for the proposed research, which involves a single eNodeB serving a group of high-speed traveling vehicles. This configuration is designed to simplify computations while adhering to the Multi-User, Single-Input Single-Output (MU-SISO) network model. The Vienna LTE System Level Simulator is employed for the simulation, starting with network initialization queries. These pertain to parameters such as the number of users at each Base Station (BS), bandwidth allocation, and channel estimation techniques. Additionally, the simulation gathers information about user velocity (set at 100 km/h for high-speed movement), as well as Signal-to-Noise Ratio (SNR) values for calculating network throughput and Bit Error Rate (BER) under three distinct scheduling algorithms: Round Robin (RR), Best-CQI, and the Enhanced Best-CQI from a previous study [9]. Quadrature Phase-Shift Keying (QPSK) modulation is used due to its favorable properties in wireless communication and lower error rates.

The SNR values are varied from –5 dB to 55 dB to assess algorithm performance across different SNR levels. The simulation considers the 100 km/h velocity and employs a channel model suitable for high-speed scenarios to minimize errors. Throughput and BER metrics are computed for varying SNR values. Multiple iterations are conducted for each scheduling algorithm to construct the dataset needed for the proposed Intelligent Downlink Scheduling (IDS). The dataset contains vehicle speed, concurrent vehicle count, carrier frequency, network bandwidth, and channel type. These parameters facilitate network simulation to calculate network-wide and individual user throughput and BER. The simulation is repeated under various conditions, encompassing diverse densities, speeds, and network scenarios. SVM is employed to train the IDS on the collected dataset. Predicted throughput and BER values are computed for the entire network and individual users, with a 70% split for training and 30% for testing purposes.

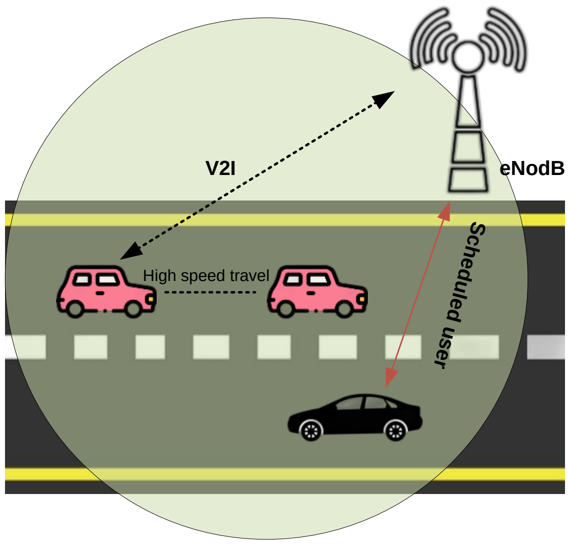

Fig. 1. Simulation scenario.

There are three stages of this work as mentioned in Fig. 2. Each one of these stages has several operations that are performed to attain the desired outcomes of the study.

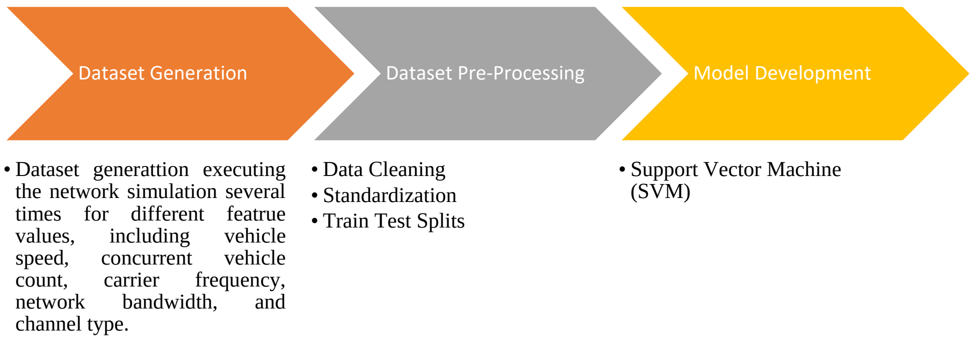

Fig. 2. Methodology stages.

A. *Dataset Generation*

This work utilizes four distinct datasets, each serving a specific predictive purpose. The first dataset is dedicated to forecasting network throughput, while the second focuses on predicting the Bit Error Rate (BER) of the network. The third and fourth datasets are tailored to predict the throughput and BER for individual vehicles. Each dataset encompasses 13 columns, capturing throughput and BER results for various scenarios across Signal-to-Noise Ratio (SNR) values ranging from –5 to 55 dB. Additionally, these datasets include columns reflecting vehicle speed (set at 100 km/h), the channel characteristics governing vehicle-to-infrastructure communication, and the carrier frequency employed (2.6 GHz). The selection of these features for predicting throughput and BER with the proposed Intelligent Downlink Scheduling (IDS) stems from their crucial role in high-speed mobility environments, a key focus of this study. Vehicle speed influences changes in the network's topology and channel characteristics due to the Doppler effect, making it a pivotal factor in this predictive analysis.

The Vehicle-to-Infrastructure Expressway (V2I-E) channel model is a communication model used in this paper. The V2I-E channel model focuses on communication between vehicles and infrastructure elements, such as roadside units, traffic management systems, and other fixed infrastructure on expressways or highways. This communication enables vehicles to exchange information with infrastructure components to improve safety, traffic management, and various applications.

The V2I-E channel model takes into account various factors that affect wireless communication in an expressway environment, including:

- Propagation Characteristics: It considers how radio signals propagate in an expressway environment with specific attention to reflections, shadowing, and signal attenuation due to vehicles and surrounding structures.
- Doppler Shift: Due to the high speeds of vehicles on expressways, there can be significant Doppler shifts that affect the frequency of the received signals. The channel model may account for these shifts.
- Multipath Effects: Expressway environments can introduce multipath propagation, where signals take multiple paths before reaching the receiver. The channel model may consider how these various paths impact signal reception.
- Interference and Noise: It considers interference from other vehicles, infrastructure, or sources, as well as ambient noise, which can affect signal quality.
- Latency: The channel model may also consider the communication latency between vehicles and infrastructure, which is critical for time-sensitive applications like scheduling at high speed.

All datasets gathered contain 5000 rows to satisfy most of the network conditions. These 5000 rows represent the throughput and BER results when running the code 5000 times for different scenarios.

B. Dataset Generation

Since the dataset contains different numbers in different ranges, Standardization and Normalization are the two processing techniques obtained for a homogeneous dataset. A homogeneous dataset is essential to prevent sub-optimal performance of the machine learning model.

1) Standardization

The throughput and BER values exhibit varying ranges based on the network condition, which leads to differences in the dataset's characteristics. These disparities in dataset values are undesirable for machine learning predictions as they introduce bias in the results. To mitigate this issue, standardizing the dataset is proposed as a solution. In simpler terms, this process involves transforming each element in the dataset to new values so that the entire dataset has a mean of 0 and a standard deviation of 1. This standardization can be achieved by implementing [25]:

$$e_{new} = \frac{e-\mu}{\sigma} \tag{1}$$

where e is the original data, μ is the mean of the feature, and σ is the standard deviation.

2) Normalization

Diverse network conditions indicate that the dataset being employed possesses an unknown distribution. Consequently, it becomes crucial to normalize the dataset to establish a Gaussian distribution. This normalization process entails adjusting all dataset values to fall within the range of 0 to 1, ensuring that [26]:

$$X_{norm} = \frac{X-X_{min}}{X_{max}-X_{min}} \tag{2}$$

where X_{norm} is the normalized data, X is the original value in the dataset, and X_{min} and X_{max} are the minimum and maximum values in the dataset respectively.

C. Model Development

This stage in the proposed model involves training and predicting network throughput and BER for each vehicle. To prepare the dataset for prediction, two key steps have been followed:

- Dataset Splitting: The dataset was divided into two sets: the training set, which contains data used to train the machine learning algorithm, and the test set, which includes data used to evaluate the algorithm. The train-test ratio has been kept at 70:30.
- Utilizing Machine Learning Algorithms: This study's chosen machine learning algorithm is SVM. SVM was selected because of its effectiveness in modeling non-linear data relationships. In LTE-V, where vehicle movements influence intricate and dynamic channel conditions, SVMs can capture and adapt to these non-linear patterns, leading to improved scheduling decisions.

Figs. 3–4 outline the workflow for this study. It commences by executing the network simulation 5000 times to collect the necessary dataset. The throughput and BER results at various SNR values are recorded and stored in the dataset during each run. Once all the required data has been gathered, preprocessing steps like standardization and normalization are applied. Data preparation is carried out for the SVM algorithm, with 70% of the data allocated for training and 30% for testing. The SVM model is trained over 100 epochs. Following the SVM model training, the network is evaluated by making predictions for the throughput and BER values using the same LTE-V network configuration, covering SNR values from –5 to 55 dB.

IV. Result and Discussion

To evaluate the proposed IDS, the dataset that the IDS learned from was gathered from a simulated vehicular scenario with the simulation parameters provided in Table III. Among these parameters, the paper considers the response of two vehicles out of 10 and 40 to replicate scenarios with highly dense eNodeB. The selected carrier frequency is 2.6 GHz, aligning with LTE standards. To minimize sub-carrier interference, a subcarrier spacing of 15 kHz is adopted. Orthogonal Frequency Division Multiplexing (OFDM) is used with a Fast Fourier Transform (FFT) of size 1024. This is the standard physical layer requirement in LTE-V networks. The bandwidth is changeable to gather the dataset. The machine learning algorithm is SVM. Vehicle speed is constant, equal to 100 km/h. this is logical to simulate the speed of a vehicle in high-speed environments such as highways. The modulation used is Quadrature Phase Shift Keying (QPSK), and the simulation is performed several times with SNR range from –5 to 55 dB. This range is for satisfying a range from very low SNR to high SNR to evaluate the proposed algorithm on a large scale of received signal quality.

The proposed workflow description:

Initialization:
for I=1:5000
  for SNR=-5:5:55
    Calculate throughput (SNR,I).
    Calculate the BER(SNR,I)
    Calculate user throughput (SNR,I)
    Calculate user BER (SNR,I)
  End
End
save the dataset as dataset.xlsx
apply e_{new} for all values.
Apply X_{norm} for all data.
Apply the IDS algorithm.
Obtain IDS accuracy.
Test the algorithm.
Find the predicted throughput and BER.
Compare results.
END

Fig. 3. The proposed workflow description

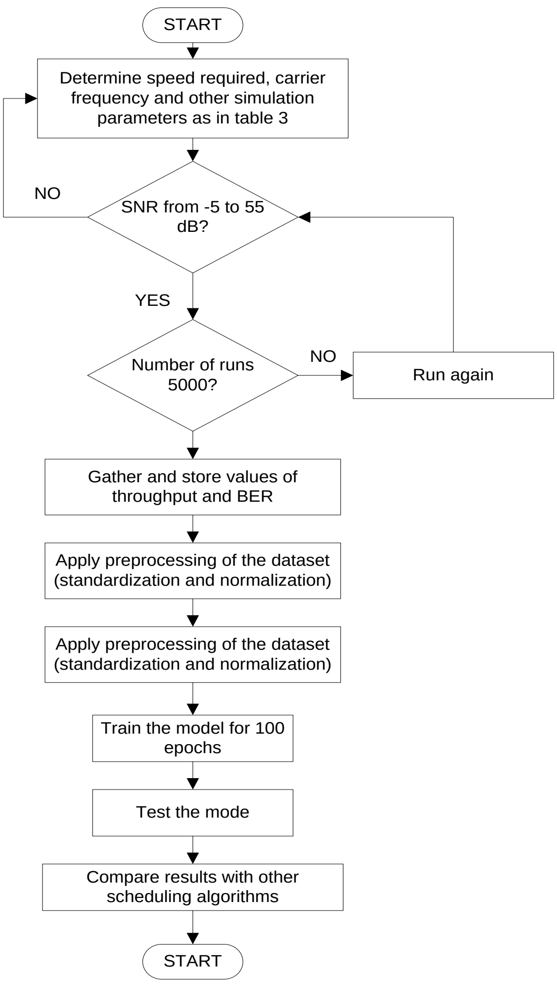

Fig. 4. Methodology flowchart.

TABLE III. SIMULATION PARAMETERS

Simulation parameter	Values
Network bandwidth	5 MHz. 10 MHz, 20 MHz
Carrier frequency	2.6 GHz
ML algorithm	SVM
Modulation	QPSK
Vehicle speed	100 km/h
Scheduling algorithms	RR, Best CQI, IBCQI, IDS
#of vehicles	10, 40
#of eNodeB	1
SNR	[–5 : 55] dB
Channel characteristics	V2I-E
#of epochs	100
#of code running (I)	5000

Fig. 5 depicts the throughput assessment for the proposed IDS, contrasting its results with throughput outcomes derived from the RR, Best-CQI, and IBCQI algorithms presented in prior work [9]. As illustrated in Fig. 5, the RR algorithm maintains a consistent throughput of 26 Mbps regardless of channel conditions. The performance of the Best-CQI algorithm exhibits fluctuations, dipping below 22 Mbps at low SNR values but escalating linearly as SNR values increase, reaching a peak of 88 Mbps at 55 dB SNR, representing the maximum throughput attainable.

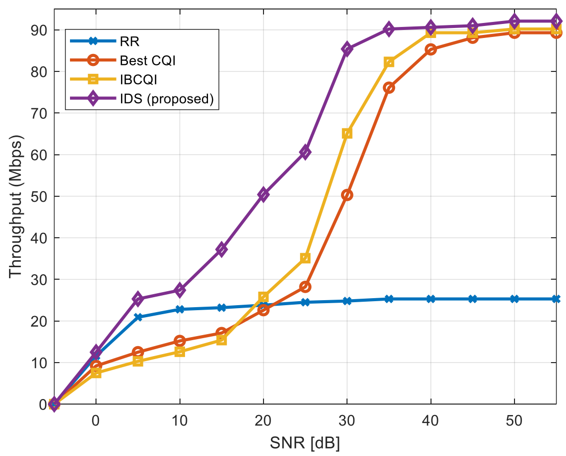

Fig. 5. Throughput vs. SNR when density equals 10.

Throughput results from IBCQI align closely with Best-CQI's, as the two algorithms are almost identical, except that IBCQI addresses interference. In comparison, the proposed IDS outperforms all other algorithms in two aspects: first, it achieves high throughput even at low SNR values, and second, it maintains steadier performance across varying SNR values, indicating greater resilience to changing channel conditions. Notably, the IDS yields a 22 Mbps throughput enhancement compared to IBCQI at an SNR of 20 dB. These results are logical because the IDS predicts the throughput values after training on a large dataset. This means the IDS knows the network's performance rather than only the channel characteristics and signal quality.

Assessing the proposed algorithm's performance under escalating network density is crucial. Fig. 6 illustrates how throughput performance changes as network density rises from 10 users to 40 users. Notably, the performance of all algorithms declines as density increases. This outcome is reasonable, as maintaining good channel quality amid high-speed vehicle movement becomes more daunting with an expanding user count within the same eNodeB. This is aggravated by amplified interference, transmission errors arising from signal collisions, and heightened overhead on the single available BS.

Fig. 6 underscores several vital observations. Firstly, the performance of the RR scheduler remains largely unaffected by the number of users, consistently yielding around 20 Mbps, indicating its resilience to channel conditions. Secondly, while maintaining high throughput, the Best-CQI scheduler displays reduced fluctuations at low SNR values. This suggests its viability even in high-density networks. Remarkably, the IDS's performance remains constant despite user count increases. This robustness in the face of dynamic channel conditions and network density growth highlights the IDS's effectiveness. This robustness comes from the fact that the IDS is pre-trained by a large dataset that allows it to predict throughput and BER for similar networks at any condition. The difference between IDS and IBCQI is that the IBCQI depends on the channel and signal quality, while the IDS depends on the amount of dataset used to train the model. In the case of BICQI, there is an effect when increasing the number of vehicles because of the reduction of signal quality due to congestion, while in the case of IDS, this is not a problem because of the pre-trained model.

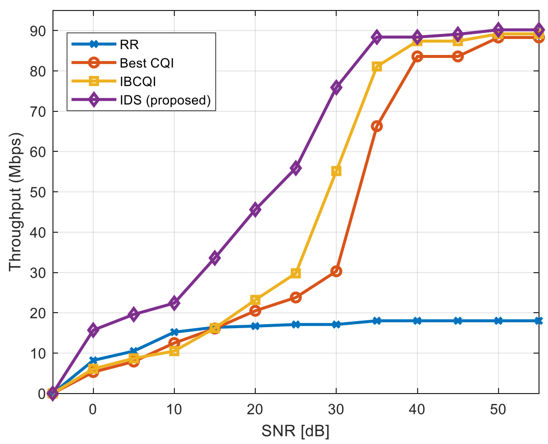

Fig. 6. Throughput vs. SNR when density equals 40.

Assessing BER provides insight into the efficiency of downlink scheduling algorithms in preserving communication quality across varying scenarios. As demonstrated in Fig. 7, a clear inference can be drawn: higher throughput corresponds to lower transmission errors. In dynamic mobile communication, BER is a performance indicator, revealing how well the scheduler responds to errors stemming from channel characteristics, Doppler effects, and interference. Fig. 7 further illustrates the superior performance of the proposed IDS compared to other schedulers, yielding lower BER results. The proposed IDS showcases a 13 dB improvement over the best CQI scheduler for the same BER level at 10^–4. This is because the IDS knows the overall configuration of the network after training it with a large dataset. This allows us to predict the best suitable value of BER for each SNR without knowing the channel characteristics or signal quality.

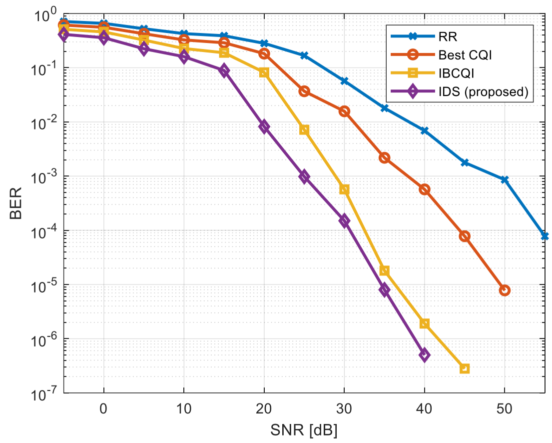

Fig. 7. BER vs. SNR when density equals 10.

The same conclusion in Fig. 7, comes from Fig. 8, when the density increases. The proposed IDS still gives lower BER values compared to other schedulers. The proposed algorithm depends on learning all the network conditions before predicting the BER value. This will enhance the predicted values compared to the other schedulers.

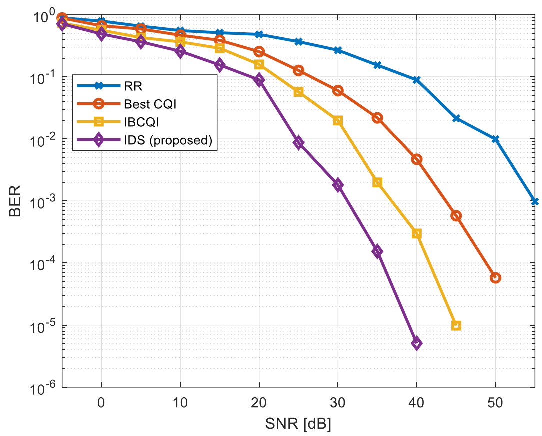

Fig. 8. BER vs. SNR when density equals 40

All the above results are for the eNodeB performance. This means they are for the overall throughput and BER values. Fig. 9 and Fig. 10 show the throughput and BER values, respectively, for each vehicle. For simplicity, the Figures show only the performance of two vehicles only.

Fig. 9 shows the throughput comparison between the IDS and the IBCQI algorithm. The proposed IDS gives a higher throughput for each vehicle. The note here is that the total throughput of the network is distributed at the same level between all vehicles (around 1.8 Mbps). This means that no vehicle has high throughput, and the one has low throughput. This distribution allows a communication link to each vehicle without causing dropping for other vehicles.

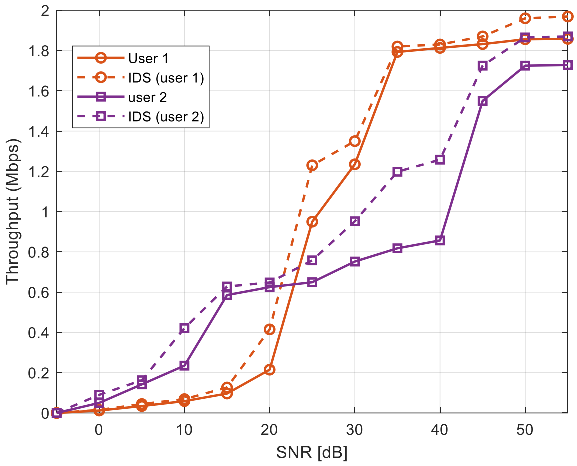

Fig. 9. Throughput vs. SNR for users.

Fig. 10 shows the BER performance for two users. The proposed IDS still gives the lowest BER values compared to the IBCQI algorithm.

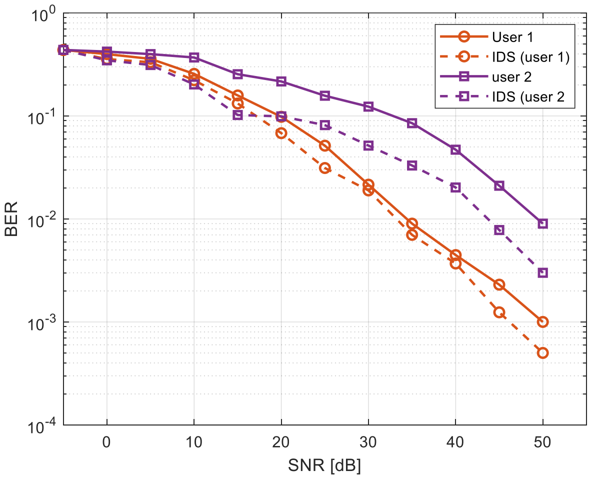

Fig. 10. BER vs. SNR for users.

V. Conclusion

In conclusion, the integration of machine learning techniques to enhance LTE-V downlink scheduling in scenarios characterized by high-speed mobility has been introduced in this paper. The evaluation encompassed three widely used user scheduling algorithms in LTE-V networks: RR, Best CQI, and IBCQI. Throughput and BER are the two-performance metrics used in this paper that play a pivotal role in strengthening LTE-V network capacity during periods of high demand and minimizing interference. Results show that throughput is increased when using the proposed IDS compared to other schedulers. This means that for scheduling purposes in high-speed environments, there are fewer losses in the data that might come from the scheduling queue because of the ability to predict the environment conditions. The same conclusion comes from BER results: fewer errors come because the prediction ability means less BER. Moreover, it should be underscored that the lowest BER is achieved by our IDS, as compared to other algorithms. This achievement can be attributed to the IDS's ability to adapt to various network conditions, enabling it to predict the best values for throughput and BER. Expanding the dataset size and incorporating additional features can further enhance throughput and BER predictions, potentially leveraging deep learning algorithms. Furthermore, future research endeavors could explore the application of the proposed IDS in contexts involving multiple Radio Access Technologies (Multi-RAT) rather than limiting the focus to a single eNodeB. This expansion in scope could broaden the relevance and utility of the IDS in a broader range of scenarios.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

S.H.A. Conducted the literature review, M.A.A. analyzed the methodology, gathered the results and form the dataset, S.K.A. analyzed the dataset and discussed the results, and finally S.H.A. wrote the paper; all authors had approved the final version.

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