Service-Oriented LSTM Multi-Criteria RAT Selection Scheme for Vehicle-to-Infrastructure Communication

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ABSTRACT The evolution towards future Intelligent Transportation Systems (ITS) is significantly influenced by enabling telematics and safety services for vehicular use-cases, especially for autonomous driving. These vehicular use-cases have their own network requirements, with a variety of instantaneous requirements and dynamic characterizations that make delivering data via a single Radio Access Technology (RAT) severely challenging. By utilizing current and future network context and vehicular use-case requirements, the RAT selection scheme must select the optimum network that guarantees the continuity and high throughput data transfer. Moreover, the consideration of on-time stochastic queue backlog of all use-cases in each RATs, while maximizing throughput is important for a reliable vehicular use-case deployment. In this paper, we developed a Service-Oriented Joint LSTM Multi-Criteria (SOLMC) RAT selection scheme for Vehicle-to-Infrastructure (V2I) networks. The objective of this scheme is to maximize the overall network throughput while reducing the current stochastic queue backlog in deployed RATs. LSTM prediction technique is used as a network filter process that rejects the worst channel quality before the initialization RAT selection scheme. Transmission capacity, connectivity time, data delivery cost, and queue backlog are the decision criteria in our proposed SOLMC RAT scheme. In particular, to characterize the importance of these criteria factors, we construct Analytical Hierarchy Process (AHP) for each use-case. Extensive simulations are carried out under different network context conditions. The results demonstrate that the SOLMC scheme can significantly achieve up to 47.5% network throughput maximization and 20.42% packet delivery ratio improvement, using lower queue length compared to nearest-RAT-based selection. In addition, implementing LSTM in SOLMC improves the total average throughput by up to 3.1% and 6% packet delivery ratio.

INDEX TERMS LSTM, multi-criteria decision-making, RAT selection, reliability enhancement, V2I.

I. INTRODUCTION

Wireless technologies exist in a variety of systems to enable a wide range of applications and use-cases in Vehicular Networks (VNs). These applications are classified according to their main functions, namely, road safety, traffic efficiency, and infotainment. Each application has its own set of functional and performance requirements. VNs have dynamic and rapid topology, which leads to performance degradation and low reliability in high speed and dense mobility [1].

The 5G Automotive Association (5GAA) [2], which consists of automotive and telecommunications institutions, such
as Audi, BMW, Daimler, Ericsson, Huawei, Intel, Nokia, and Qualcomm, has introduced the Key Performance Indicators (KPIs) for Vehicle-to-everything (V2X) use cases, as shown in Table 1. For example, the Cooperative Collision Avoidance (CCA) technology, which shares information with neighboring vehicles via Vehicle-to-Vehicle (V2V) communication, requires an ultra-high reliability of $10^{-5}$ and a low End-to-End (E2E) latency below 10 ms [3].

Although many Radio Access Technologies (RATs) are introduced to support V2X use-cases and their requirements, neither one of them could be substantially adapted to fulfill all V2X requirements nor dealt alone with the huge data generated from autonomous vehicles related sensors and technologies [4]. Moreover, selecting the most optimum RAT to deliver the targeted V2X information throughout the vehicle journey is important and has been carefully studied in several works.

Currently, the two main RATs adopted for V2X communications are the IEEE 802.11p/Dedicated Short-Range Communication (DSRC) and LTE Cellular-V2X (C-V2X). In the next section, each RAT is explored and a comprehensive comparison between RATs for specific V2X applications is discussed. The comparison highlights the pros, cons, and applicability of each RAT.

Recently, the study of Multiple RAT (Multi-RAT) in V2X networks has been conducted [6], [7], and [8] as a way to enhance reliability, increase throughput, and reduce end-to-end delay. Figure 1 presents the different RATs that can be utilized to exchange transport information via V2I. In a heterogeneous network, managing and coordinating between heterogeneous RATs are vital to adapt to the V2X requirements throughout the vehicle journey [9], [10].

Mainly, the final selection decision is classified according to the most suitable approach. In general, the utility-based, machine learning-based, or hybrid-based methods can be utilized in the Multi-RAT V2X network to select the most optimum RAT for different scenarios. This selection can be performed either on the network infrastructure side, called Network-Centric (NC), or on the user side, called User-Centric (UC). The NC technique requires more overhead signalling and vehicles may suffer from sudden link interruption due to the high vehicle mobility. In this case, a vehicle must select its RAT under uncertain network conditions. A promising solution to mitigate link interruption is the preparation of a communication profile that is sent to a target vehicle when it is connected to any RAT [8], where each vehicle knows the condition of each RAT before leaving the RAT communication coverage, and the final decision is locally performed. Meanwhile, in the UC approach, a vehicle gathers information on RAT condition and computes the optimum RAT selection. However, one drawback of UC is the unforeseen lack of RAT information that can cause an undesirable effect on RAT selection [11].

The RAT selection algorithm can be improved if it is accompanied by the ability to foresee and grant users with the recommended Quality of Service (QoS) per application according to the network link-state and user’s prerequisites [8]. To meet these requirements, mobile terminals have to select the suitable RAT that satisfies their QoS requirements of applications while minimizing the end-to-end delay, as well as avoiding a network with a high traffic load or congested. The RAT selection algorithm should be dynamic and well-timed, where the vehicle can select an appropriate RAT that meets current application requirements using measurements, such as network load, available bandwidth, backlogged queue, and cost of purchasing. Predicting the near-future state of the deployed networks and their channel conditions are utilized in selecting the optimum RAT can guarantee the continuity of service and a high success rate of information delivery.

However, RAT selection in multi-RAT V2X networks involves a few major problems:

1. Connectivity issue: High-speed vehicles leave the communication coverage of deployed RAT can cause a communication interruption and shorten the window for data delivery. Thus, selecting a targeted RAT that has a minimum Time-to-Leave (TTL) with the client vehicle will maximize the data delivering period and enhance the reliability of the RAT selection approach by minimizing the packet loss.
2) Limited transmission capacity: Selected RAT must satisfy the minimum transmission capacity of the target vehicle among its connected vehicles during the connectivity time slot. An instantaneous transmission capacity calculation based on bandwidth requirement, using metrics such as SNR and data rate at the physical layer (PHY) is required for RAT selection.

3) Stochastic queue problem: Vehicles may stochastically select a RAT without any prior information about its current queue buffer size and queue length, which leads to severe packet drops in the case of the overloaded buffer. Thus, stochastic queuing delay bound modelling is needed and must be carefully computed when a RAT is selected, particularly with V2X use-cases that required ultra-reliable low latency communication (URLLC).

4) High network cost: Vehicles generate different data volumes while moving along the road. Sharing data that are generated by the variety of V2X use-cases is crucial during driving trips, especially for autonomous vehicles. Low-cost communication technologies, such as Wi-Fi and VLC, are attractive compared to high-cost communication technologies like cellular networks. Automotive makers and related occupational health and safety organizations encourage free or low-cost road safety data sharing in emergency cases [12].

5) Signaling overhead: Vehicles require knowing the channel strength measurements of the selected RAT before completing the association. Broadcasting the PHY measurements of each RATs is impractical and causes severe network overloading. Thus, each vehicle is responsible to indicate the channel quality from its side and can connect to an appropriate RAT, where the final decision is performed either at the network, user, or both (hybrid). It is important for signaling overhead reduction and lowering the computational complexity.

6) Inconsistent data delivery: It is very challenging for vehicles to share data in a highly reliable manner and without any future interruption. Thus, deep learning and prediction techniques, such as Long Short-Term Memory (LSTM), are valuable to predict the future received signal strength from each of the available RATs and encourage the vehicle to connect with the most optimal RAT. Moreover, consideration of a context-aware multi-criteria optimum RAT selection, combined with predicted preference, will promote improved network performance.

Therefore, in our work, we propose on the prediction of the deployed RATs channel condition using the LSTM approach. Our proposal also integrates a Multi-Criteria Decision-Making (MCDM) method that can anticipate future network conditions, thus enhancing the reliability of RAT selection. Specifically, this paper develops a joint LSTM multi-criteria utility-based RAT selection algorithm that considers all the RAT selection concerns mentioned above. Moreover, V2X services orientation is promoted and quantified to weigh the relative preferences among four selection criteria for each V2X use-case. The Analytic Hierarchy Process (AHP) weights the four selection criteria for the three diverse selected use-cases with differing requirements as published in 3GPP TS 22.186, Release 15. Furthermore, the current measurements of deployed networks are quantified using different utility functions to rank them according to their current performance. An auto-encoder LSTM is applied to predict the channel quality of each deployed RAT, except C-V2X because it has a wide coverage to all participating vehicles used in the road scenario in our simulation model in Section IV [13]. The optimization problem focusses on the maximization of the utility preference of each vehicle at each RAT and V2X use-case. Additionally, the throughput maximization with conditional maximum channel quality is computed to achieve a reliable RAT selection. The main contributions of this paper are summarized below:

1) In contrast to previous network selection methods, this work proposes a hybrid intelligent scheme that combines the LSTM with the MCDM technique to select the most optimum RAT.

2) An encoder-decoder based sequence-to-sequence deep learning LSTM model is designed, which captures channel quality variations in different historical mobility information to predict the future channel quality, then passed as a decision factor for optimum RAT selection.

3) The MCDM is based on quantifying the requirements of the V2X use-case by utilizing the AHP to find the weight of importance for several network criteria, namely bandwidth, queue length, network cost and TTL.

4) A RAT Selection Orchestrator (RSO) is proposed to provide an intelligent control and management of various RATs in V2X networks.

5) Several utility functions are proposed for the network selection technique considering the vehicle’s use-case preferences and the current network conditions.

The rest of this paper is organized as follows. The related works are summarized in Section II. We describe the proposed network selection algorithm in Section III and evaluate its performance in Section IV. Finally, Section V concludes the paper.

II. RELATED WORKS
A. WAVE IEEE 1609/802.11p
Short-range V2X technologies are tailor-made for road safety applications and services [14]. The ITS-G5, in Europe, and IEEE 802.11p/IEEE 1609 Wireless Access in Vehicular Environments (WAVE), in the United States, are the standards that define the network architecture and security protocols for vehicular communications. Short-range communication gives a cost-efficient and low-latency performance. IEEE 802.11p defines both the physical and Medium Access Control (MAC) layer protocols for short-range vehicular
communications. It has a radio spectrum band in the operation region of 5.850-5.925 GHz, 5.795-5.815 GHz, and 5.770-5.850 GHz, in North America, Europe, and Japan, respectively. The IEEE 802.11p has the desirable feature of DSRC between the source and the endpoint in a distributed manner without the need for infrastructure suitable for V2X applications [15]. However, it suffers from several drawbacks such as low scalability, high latency in dense traffic, and intermittent connectivity [16]. Poor scalability comes from throughput and latency performance degradation in high-dense road scenarios because its MAC is based on the Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) approach to sense the channel availability [17]. This means that exchanging road information in a high-dense scenario is subject to either a drop due to a channel collision or an unbounded delay due to the exponential back-off procedures [18]. In addition, the limited radio range and insufficient Roadside Units (RSUs) especially in a rural area, may cause intermittent and short-lived connectivity into the IEEE 802.11p [19]. Bandwidth is another constraint of IEEE 802.11p because it is limited to 10 MHz per channel, which is insufficient for 5G applications such as the augmented reality (AR), with a minimum required data rate of 40 Mbps [20]. These drawbacks are currently being addressed by the draft IEEE 802.11px standard, which will add the Multiple-Input Multiple-Output (MIMO) antenna competencies into the existing standard. This is expected to enhance the overall throughput of the vehicular network by up to 60 Mbps [21]. Besides, the perceived Signal-to-Noise-plus-Interference (SINR), the Low-Density Parity Check (LDPC) codes for channel coding, and the Space-Time Block Coding (STBC) will also be supported to enhance the network performance in noisy and fading channels [21]. IEEE 802.11px is still in the early development stage and it has not yet been tested [22].

B. CELLULAR VEHICLE-TO-EVERYTHING (C-V2X)

The above-mentioned drawbacks of IEEE 802.11p have inspired increasing interest in Long Term Evolution (LTE) as a promising technology for V2X applications [23]. In September 2016, the 3rd Generation Partnership Project (3GPP) Release 14 standard [24] supports cellular short-range V2X communication, also known as LTE-V, LTE-V2X, or C-V2X [25]. The release introduced two additional communication modes on top of the Mode 1 and Mode 2 of D2D communication or Proximity Services (ProSe) that were initially introduced in Release 12. The LTE-ProSe allows the User Equipment (UE) to discover and communicate directly to others, whether they are in or out of coverage of E-UTRAN Node B (eNB) [26]. Modes 3 and 4 were exclusively developed for V2X communication enhancements. This enhancement focuses on improving the network scalability and mitigating performance degradation in a high-density vehicular scenario. The collision avoidance, improved channel access, sub-channelization schemes, and Hybrid Automatic Repeat Request (HARQ) are examples of such enhancement [27].

In Mode 3 (LTE-V-Cell), the cellular network behaves as the infrastructure that allocates and manages the radio resources used by the vehicles to enable them to exchange road information using V2I/I2V communication. Meanwhile, in Mode 4 (LTE-V-Direct), the radio resources management and allocation are performed autonomously from the vehicles themselves, enabling more efficient V2V capability particularly when the BS coverage is overburdened or out of coverage [28]. Mode 4 represents the alternative approach to IEEE 802.11p [24] and is considered as the baseline technology for safety applications in C-V2X networks. The C-V2X standard provides two radio interfaces, namely the cellular Uu and PC5 interfaces that support V2I, V2V, V2N (Vehicle-to-Network) and V2P (Vehicle-to-Pedestrian) communication, as shown in Figure 2. The 3GPP has also identified different use-cases and potential service requirements to enhance the support of V2X services, which require a reliable and efficient communication link.

C. WI-FI FOR V2X COMMUNICATION

Recently, Wi-Fi networks are deployed in V2X networks to increase the diversity of applied RAT to increase the network capacity, especially as bandwidth requirements increase with the deployment of new driver-assistance and autonomous driving systems [29]. Wi-Fi networks have relative advantages such as being less expensive compared to licensed networks, C-V2X, easy deployment, and high throughput for the newer IEEE 802.11ac/ad/ay standards.

Nevertheless, they have some drawbacks in the time of association, security requirements, and interference with other RATs. In studies such as [4], [30], [31], [32], [33], and [34], the coexistence techniques between C-V2X and Wi-Fi in different spectrum variation cases and network
densities have been investigated. The spectrum interference issue is raised when Wi-Fi is implemented, and crucial consideration must incur to avoid network performance degradation. However, note that the interference issue is out of the scope of this study. The authors in [35] study the effectiveness of Wi-Fi historical data for forecasting network performance in a realistic vehicular environment. In an optimistic outcome, they concluded that its offloading technique based on data rate forecasting was able to deliver 80% of vehicular data. The study applied high throughput Wi-Fi standards such as IEEE 802.11n/ac/ad.

D. MULTI-RATs SELECTION

According to ETSI TS 122 186, the 3GPP system shall be able to support the operators to select which 3GPP RAT to use for a V2X application. The selection should precisely depend on the importance of the exchanged data and the capability of achieving the target QoS, which make variations in the network requirements and architecture [35]. Multi-RAT is defined as a mobile device that can connect to more than one type of wireless network. The term vertical handover is also used in literature to represent the network selection in multi-RAT. Reliability and latency are the main QoS requirements of V2X or URLLC. Reliability is defined as the capability of the vehicle to deliver all its packets within the specified period and without incredible packet loss. While a vehicle is moving through the coverage zone of a selected RAT, ensuring all sent packets reach the destination without exceeding the maximum latency and with fewer drops is important. Latency and reliability are considered QoS requirements for the RAT selection technique that should be aware [36]. RAT selection in VN is classified based on either the technique that is utilized in RAT selection or the user awareness that is entitled in the selection process. The MCDM-based, machine learning-based, or hybrid-based RAT selection techniques have been presented in several works in the literature.

In the MCDM-based technique, several parameters about the RAT’s current characteristics or about vehicle contexts such as mobility information, shared data size, or the number of surrounding vehicles that share the same RAT, are participated in the RAT selection process. In addition, MCDM-based technique, selection criteria are weighted according to their importance in delivering the V2X service. Then, the current network conditions are passed to different utility functions that are used to measure the satisfaction level of deployed RATs. The final score of the competition is determined by maximizing the RAT selection objective. One drawback of MCDM methods is the lack of priority consideration in the selection process, where all criteria have the same level of priority; designing a multi-objective optimization algorithm is a solution that solves this drawback. The first objective considers the maximization of throughput or QoS of the network and the second objective deal with the priority issue such as the work of [37].

Besides that, a machine learning (ML) method can be used by utilizing reinforcement learning techniques such as game theory, where reward and penalty on game player determine the most competitive optimum RAT [38], or deep learning approaches such as LSTM [39], [40], where particular decision parameters are predicted in the future and participated in the selection process. Moreover, the prediction of the mobility or the direction will determine the next position of the vehicle. Then, this information can be used to prepare the RAT selection profile before the vehicle arriving its next position [39]. Some works like [40] predict future communication status, such as signal strength or channel quality, to estimate the QoS required and determine the qualification of RAT selection before occurred.

Context-aware, QoS-aware, throughput-aware, or signal-aware are objective awareness that are considered in selecting the optimum RAT. Context-aware considers context information such as the geographical position of Wi-Fi access points (APs), eNB stations or RSUs, the vehicle’s route or direction, the time needs to leave the communication coverage, and traffic density that communicated to the same RAT. QoS-aware ensuring all data stream are delivered according to target QoS. While throughput-aware solution assimilates the needs of different vehicle’s application size and content. Then it tries to fairly allocate resources that maximize the throughput of all participated vehicles. Finally, the signal-aware solution ensures the qualification of signal strength between the source and destination to perform data exchanging.

The next section presents the related works conducted by MCDM to select the optimum RAT according to specific awareness objectives. In [41], a joint multi-criteria with utility function RAT selection approach is proposed for V2I communication. The proposed solution considers QoS, energy efficiency, and vehicle application preferences for RAT selection. Signal strength, bandwidth, cost, and maximum delay are parameters that are measured using the utility function in each RAT. The final RAT selection, which is locally executed, is performed according to energy efficiency, cost, and QoS parameters. The supposed algorithm outcomes show better performance in terms of application satisfaction when compared to the random RAT selection technique up to 10%.

In [6], a RAT selection method depending on the relative direction index, proximity index, residence time index, and network load index to select the best candidate network is proposed. A moving vehicle would be able to select the most appropriate RAT, in this case either LTE-A or IEEE 802.11n, by selecting one or more of the above parameters. The proposed technique also offers up to 50% higher throughput and 43% lower end-to-end delay than the random RAT selection approach.

The authors in [42] proposed a utility function-based RAT selection in multi-RAT. The proposed utility function considers both user’s satisfaction and provider’s satisfaction. According to the user context-aware approach, the QoS requirements for video streaming and voice communication can be supported by each user sending the bandwidth requirements to the available RATs. Then, the selected RAT must provide a data rate to the user above the specified threshold.
Moreover, the provider’s satisfaction in terms of load balancing is achieved. In [43], a three-layered QoS-aware RAT selection approach is proposed for V2I communication. Authors consider WAVE, long-range Wi-Fi, and 4G/LTE cellular networks. RAT selection is made by the vehicles to the RAT that has the best suitability of application requirements, namely throughput, delay, or other user preferences such as cost. The results show network metrics improvement compared to the greedy RAT selection approach. Switch from V2I to V2V is implemented in emergency situations and is a part of RAT selection studies. A RAT selection based on data priority is performed in [44], where a V2V data transfer is used when a RSU is not available for urgent situations, such as an accident. It provides a QoS-based traffic classification that categorizes the data into high, medium, and low priorities. The RAT selection also consists of an overload control that defines the threshold values of the maximum allowed load at RSUs for medium and low-priority data.

Edge computing is one of the advancements that is used to enhance the throughput of the network and reduce the latency of communication. In [45], an offloading mechanism based on an edge computing network using the concept of pre-allocation for vehicle tasks is proposed. This technique improves the RAT selection service interruption caused by vehicle movement and limited edge coverage. The simulation results show an improvement in the overall task execution performance and reduce the time overhead of task offloading. Authors in [46], proposed an SDN controller for the RAT selection using a utility function that measures the network available bit rate and the vehicle the required bit rate, this measurement is called the fitness factor (FF) metric. This configuration allows a centralized approach to the control process that enables knowing all the network conditions that help in the realization of the selection strategy. This model enhances the throughput and QoS of users, but increases the latency required to determine the RAT selection.

Related works applying reinforcement techniques to optimally select the RAT are presented in the next paragraph.

In [47], a base station (BS) selection strategy based on a Markov Decision Policy (MDP) for a vehicle in heterogeneous networks is proposed. The proposed work predicts the received signal strength (RSS) from macro and femtocell base stations based on the current position of the vehicle. Next, the Markov decision policy is used to predict all base station selection possibility sequences, so that the most appropriate BS sequence can be chosen. The simulation results guarantee that the usage rate of the femtocell base station does not reach the upper limit. When a resource conflict occurs in the femtocell base station area, resources are reasonably allocated to improve the system’s QoS. A part of ML-based solutions for RAT selection, a fuzzy logic inference approach that is aimed to select the optimum base station for V2I communication in high-speed heterogeneous networks is proposed in [48]. The context-aware approach evaluates the offered QoS of the deployed use-cases and its capability to deliver the packets within the constrained QoS requirements. Context parameters that are used as input to the fuzzy logic inference approach are the distance between the target vehicle to the AP and the vehicle mobility information. A sufficient reduction of vertical handover is achieved by performing RAT switching in advance. Federated Q-Learning (FQL) method is implemented in [49] to select the optimum RAT when the vehicle offloaded its data. C-VDX and DSRC is the communication technology in this study. The results prove that optimum RAT selection can reduce the offloading failure probability and communication cost.

Moreover, applying recent prediction techniques, deep learning techniques, such as LSTM, GRU, and CNN, will enhance the autonomy and self-management of network selection, as well as increase the reliability when predicting the behaviour of the network before selecting it.

In [50], the QoS of the C-VDX network is predicted before selecting RAT and transferring data. Different traditional linear regression machine learning techniques such as Rain Forest (RF) and Multi-layer perception (MLP) are applied besides the autoregressive integrated moving average (ARIMA) filter. The proposed ML method classified the received packet after checking the reception time, either it was received on time or not. This trained feedback is used to predict the quality of the network under different conditions to decide whether it can achieve the targeted QoS or not. The objective is to optimize the main utility function that is responsible to select the proper RAT that can minimize delay for safety user-cases. Furthermore, the study [51] proposed an online LSTM-based channel prediction approach and compared it with traditional Feedforward Neural Networks (FNN). The authors propose, this approach could be used in the future for RAT selection purposes and traffic scheduling. LTE and 5G new radio (NR) communications technologies are utilized in the study. The outcomes show that LSTM achieves high accuracy of channel quality indicator (CQI) prediction than FNN. Study of [52] predicts the channel quality as well but for different communication technologies like 4G LTE, Wi-Fi, Zigbee, and WiMAX. Again, LSTM and Gated Recurrent Unit (GRU) are used and compared with the traditional linear regression method. Both deep learning approaches outperform linear regression in terms of accurate channel quality prediction.

From the above, deep learning methods are implemented to accurately predict the channel statuses. Up to our knowledge, there is a lack of studies that integrate the deep learning approaches in RAT selection techniques. In this study, we generate predicted values of Received Signal Strength Indicator (RSSI) from the deployed network and then pass them to the proposed multi-criteria algorithm. RSSIs are time series as the vehicle moves, and the RSSI value changes, thus LSTM is the suitable deep learning method that is built for forecasting in time series. Moreover, the stochastic behaviour of any vehicular network is considered, thus queue length caused a significant delay when large packets are transferred and stored inside the RSU buffers. Reminded bandwidth, queueing delay, cost, and TTL the network are parameters
that are conducted in our study. Besides, LSTM output values are checked before the final decision occurs. Table 2 summarizes the recent works on multi-RATs selection.

III. PROPOSED SOLMC SCHEME
This section presents the proposed generic system model for the Service-Oriented Joint LSTM Multi-Criteria (SOLMC) RAT selection to enable ubiquitous services using V2I communication. Table 3 summarizes the main symbols and their definition.

Assume that along the road, \( k_i \) numbers of RSU are deterministically deployed on both sides at position \((x_k, y_k, z_k)\) and having a communication coverage of \( D_k \). A single C-V2X base station (eNB) is in this road scenario and can communicate to any vehicle on the road at any position. It assumes that each RSU and the eNB are connected to an RSO by a high-quality backhaul channel, where the monitoring of the overall network is performed. Besides the LTE C-V2X RSU, wireless connectivity to vehicles can also be provided by IEEE 802.11p/DSRC, Wi-Fi IEEE 802.11n at 2.4 GHz and IEEE 802.11n 5 GHz operating bands, where \( k_i \in [\text{DSRC, } 802.11n \text{ 2.4 GHz, } 802.11n \text{ 5 GHz, C-V2X}] \).

There are \( N \) vehicles \((\Phi_{Vj} \Phi_N)\) that move from the starting point using discrete Poisson distribution at each segment of the road in both directions. At time \( t \), each \( v \) has a list \( L_j = [s_j, d_j, \psi_j] \), that contains speed, direction and 3D position information, where \( \psi = (x_v, y_v, z_v) \). Moreover, each vehicle can communicate to a maximum of \( K(\forall k_i \epsilon \Phi) \) different RATs.

A. VEHICLE REQUEST MESSAGE
When a moving vehicle senses a RSSI performance degradation on its received data requests, a new RAT switching is triggered. Suppose that each vehicle can share with RSO its request message \( RM \), which contains context information (speed, direction, and current position) and type of use-case, i.e., \( RM_j = [V_{ID}, s, d, \Psi, S] \) at any \( t \) during the simulation using currently available communication path. The RSO is responsible for generating the communication profile (CP) for the current communication context. Finally, the RSO sends the \( RM \) that has been updated with the CP for the final ranking score \( f \) for each \( RATs \) and use-cases. Figure 3 shows the request message structure that it is triggered at random time slots over the simulation time.

![Figure 3. Request message structure.](image)

B. V2X SERVICE REQUIREMENTS
V2X use-cases have diverse reliability, latency, and security requirements. In [53], the authors introduce a summary of different existing V2X applications and their main requirements of each. In this paper, three types of V2X applications are conducted, namely safety (\( S_1 \)), traffic efficiency (\( S_2 \)), and infotainment (\( S_3 \)). At time \( t \), \( v_j \) can download \( X \) number of V2X use-cases having the message property \( S_j = S_1, S_2, S_3 \) from any \( k_i \). A multi-service technique needs to be designed to cater to the different demands of the V2X drivers and use-cases.

In our system model, the reliability term is quantified by three context and network criteria:

1) Maximum allowable queueing delay bound \( Q_S \) at each \( k_i \) for \( (\forall k_i \epsilon \Phi) \) for each \( S_j \). Queueing delay must not exceed the maximum pre-allocated buffer delay to prevent packets drop.
2) Connectivity time is defined by (\( TTL \)) parameter that determines the number of packets that can be transferred by the vehicle within the coverage area of the targeted \( RAT \).
3) Predicted values from LSTM are involved for reliability evaluation. The high accuracy of predicted channel quality ensures communication connectivity in the near future, which enhances the reliability as well.

In other words, each \( S_j \) has its own requirements and properties and can be described as \( S_j \triangleq (S_b, S_c, S_t) \), where \( S_b \) is the required bandwidth, \( S_c \) is payload, and \( S_t \) is the mandatory reliability to accomplish the use-case \( QoS \) requirements.

For example, in a platooning safety application, real-time road safety messages are disseminated between convoyed vehicles. Another type of safety use-case is the cooperative collision avoidance and cooperative lane change. Compared to non-safety V2X application, it has a stringent minimum delay and high reliability requirements.

Traffic efficiency and infotainment are categorized under non-safety use-cases. Traffic efficiency use-cases are related to online delivery of road information to the transportation management control centre. It usually does not have a strict latency requirement because there is no urgent reaction required from any vehicles, and it comes with a high reliability requirement. Traffic efficiency application is applied in many V2X use-cases, such as traffic light optimal speed advisory, optimal route selection, and electronic toll collection. Infotainment applications have similar latency requirements as traffic efficiency applications, but with lower reliability requirements. Media download, map update, and local commerce point-of-interests are examples of its use-cases.

C. CRITERIA WEIGHT COMPUTATION
In the network selection, AHP is used to fetch the preference weights of various V2X services on network attributes by using past experience and allocate these weights as objective weights for each deployed RATs. Each \( S_j \) has a criteria weights list \( W_S^X \triangleq [W_b^X, Q_S^X, C_S^X, TTL_S^X] \) that are related to the selection attributes in this study, namely bandwidth, queueing delay, cost, and connectivity.

At any \( t \), each \( k_i \) can share its current selection attributes list \( Z \) to the corresponding \( v_j \) at \( S_j \), where \( Z = [b_k(t), Q_k^S(t), C_k, TTL_k^S] \). From each \( Z \) and \( W_S^X \), the weights of all decision attributes are computed using AHP.
| Study | Contribution                                                                 | ML technique | Metrics                                      | Limitation                                                                 | Multi-RATs                  | Multi-Use Cases | Dec. locs. |
|-------|------------------------------------------------------------------------------|--------------|----------------------------------------------|---------------------------------------------------------------------------|-----------------------------|-----------------|------------|
| [41]  | QoS-aware RAT selection approach using multi-criteria utility theory         | Not used     | Y Energy efficiency                          | Low data rate applications                                               | LTE, WLAN 802.11a/g WiMAX   | Y               | NC         |
| [6]   | Vertical handover mechanism in a multi-tier heterogeneous network           | Not used     | Y HO failure ratio                            | Increased handover failure rate due to high-speed vehicles.               | LTE-A Wi-Fi 802.11n         | N               | UC         |
| [42]  | Guarantee QoS of the system using utility functions                           | Not used     | Y Bit rate per user                          | Complex operation                                                        | HSPA/ HSPA+/LTE WiMAX       | Y               | NC         |
| [43]  | Three-layer RAT selection architecture in V2I communication                  | Not used     | Y RAT load Throughput Latency                | The central operation which increases the server load                     | WAVE Wi-Fi 4G/LTE           | Y               | NC         |
| [44]  | RAT switching from V2I to V2V in urgent situations                           | Not used     | Y Latency                                    | Limited Application                                                      | IEEE 802.11p 4G/LTE         | N               | UC         |
| [45]  | QoS-aware RAT selection, traffic classification, and overload control        | Not used     | Y Latency                                    | Simple scenario and Limited selection criteria                           | C-V2X                       | N               | NC         |
| [46]  | A QoS-aware utility-based RAT selection considering SINR of each vehicle     | Not used     | Y Data rate                                  | Complex for real-time use                                                | LTE Wi-Fi                   | Y               | NC         |
| [47]  | Base station selection based on predicted RSS                                | Markov       | Y Speed                                      | Limited selection criteria                                               | C-V2X                       | N               | UC         |
| [48]  | Vertical handover scheme for high-speed vehicles using fuzzy logic inference | Fuzzy Logic  | Y Distance Velocity                          | Limited metrics                                                          | LTE Wi-Fi                   | N               | NC         |
| [49]  | Intelligent RAT selection apath that considering the stochastic upper bound delay in the queue | FQL           | N Offloading failure                          | Limited selection criteria                                               | C-V2X DCRC mm-Wave          | N               | UC         |
| [50]  | Comparative study between different linear regression techniques for QoS prediction | Linear regression | Y Accuracy Packets received | Limited RATs Overlapped Cells in C-V2X                                 |                            | N               | UC         |
| [51]  | An online CQI prediction using LSTM                                          | LSTM-FNN     | Y Throughput Accuracy                        | No RAT selection technique                                               | LTE 5G-NR                   | N               | -          |
| [52]  | A deep learning model for future channel conditions for different networks   | LSTM-GRU     | Y Accuracy                                   | No RAT selection technique                                               | 4G LTE Wi-Fi Zigbee WiMAX   | N               | -          |
|       | Our proposed work                                                            | LSTM-MCDM    | Y Throughput PDR Queue Length Network satisfaction |                            | C-V2X Wi-Fi DSRC            | Y               | Hybrid     |
TABLE 3. Main symbols used and descriptions.

| Symbol  | Definition |
|---------|------------|
| $\Phi_N$ | Set of $N$ vehicles in the network |
| $v_j$ | $j^{th}$ vehicle in the set $\Phi$ |
| $N$ | Total number of vehicles in the set $\Phi$ |
| $L_j$ | List of $v_j$ information |
| $t$ | Current simulation time |
| $s_j$ | The speed of $j^{th}$ vehicle (m/s) |
| $d_j$ | The direction of $j^{th}$ vehicle |
| $\Psi_{v_j}$ | The position list of $j^{th}$ vehicle |
| $\mathcal{R}$ | Set of available RATs |
| $k_i$ | $i^{th}$ RAT in the set $\mathcal{R}$ |
| $K$ | Total number of RATs in the set $\mathcal{R}$ |
| $S_x$ | $x^{th}$ V2X use-cases $v_j$ can share |
| $X$ | Total number of V2X use-cases |
| $S_b$ | Bandwidth of $S_x$ (Mbps) |
| $S_p$ | Payload of $S_x$ (bytes) |
| $S_t$ | Reliability of $S_x$ (%) |
| $S_{Q}$ | Maximum queuing delay of $S_x$ |
| $S_c$ | Required cost of each $S$ |
| $S_{TTL}$ | Required TTL of $S$ (seconds) |
| $W_S$ | List of $S_x$ weights |
| $Z_i$ | Selection attributes list of $k_i$ |
| $RSO$ | RAT Selection Orchestrator |
| $RM$ | Request message |
| $Q_{S(t)}^k$ | Queuing delay of $k_i$ for $S_x$ |
| $TTL_{k_i}^k$ | TTL of $k_i$ |
| $b_{k_i}$ | Available bandwidth of $k_i$ |
| $c_{k_i}$ | Maximum cost of each $k_i$ |
| $UL(k_i)^x$ | Utility function list at $k_i$ for $S_x$ |
| $CP$ | Communication profile |
| $D$ | Communication coverage |
| $\zeta(t)$ | List of LSTM output sequence |
| $E_{i}$ | Current RSSI at $k_i$ |
| $\gamma$ | Forecasted RSSI at $k_i$ |
| $f$ | Final selection decision |
| $r$ | PHY rate of $k_i$ |
| $A(t)$ | Deterministic arrival envelope at $k_i$ |
| $S(t)$ | Deterministic service envelope at $k_i$ |
| $B(t)$ | Queue backlog at $k_i$ |
| $\rho_A$ | Packet arrival rate |
| $\rho_S$ | Packet service rate |
| $U$ | Burst parameter |
| $QW$ | Current queuing delay at $k_i$ |
| $H$ | AHP hierarchical model |
| $M$ | Pairwise comparison matrix |

which indicates the satisfaction degree of $S_x$ for $k_i$. In other words, the AHP evaluates the matching probability between the V2X use-case requirements and the RAT capability for each selection factors. The output of AHP implementation creates the RAT decision factor weight list $W_i^Z \triangleq w_i^S, w_i^{TTL}, w_i^Q, w_i^c$ for each $S$ at each $k_i$. $W_i^Z$ is the first input of the algorithm (3) which is for generating final CP. After that, each RAT selection attribute is quantitized using different utility functions to evaluate the current RAT conditions and their suitability for each $S_x$. The final utility-based score list UL is computed using algorithm (2), and it is the second input of algorithm (3) which is for generating final CP.

The winner RAT is the RAT that is capable to provide the $S_x$ requirements with a high QoS performance, particularly, throughput and packet delivery ratio (PDR). The UL are sorted according to their suitability rank and sent as a communication profile (CP) by the RSO to targeted vehicle. The final selection decision, $f$ is executed locally at the vehicle when it receives the CP from the dedicated RSO, and after checking the RSSI at $k_i$, termed as $E_i$.

The AHP hierarchical model $H$ is constructed based on four criteria as shown in Figure 4. The $H$ is computed three times, based on the number of V2X use-cases applied in this paper. The AHP has three layers: goal, criteria, and alternatives layers. Each RAT in alternative must have weight at the end of AHP calculating weight process.

![FIGURE 4. AHP hierarchical layers and structure.](image)

Figure 6 shows the flow chart of the AHP process in the simulation for each proposed V2X applications. The AHP is used to determine the relative degree of priority among the targeted V2X use-case requirements using the following procedures:

1) Populating a pairwise comparison matrix $M$ for each use-case with a comparison score in range of $[1/9, 9]$. These values are assessed according to the relative importance between the row attribute to the column attribute. The comparison matrix is called reciprocal matrix because all attributes relative values are reciprocally computed for $z$ number of attributes: $M(a, b) = 1/M(a, b)\forall a, b \in \{1, 2, \ldots, z\}$ [63].

2) Compute the normalized relative weight by sum each column of the reciprocal matrix and divide each element of the matrix with the sum of its column. The sum of each column must be 1.
3) Steps 1 and 2 are repeated for each targeted V2X applications. Figure 7 depicts the weight preferences for different network attributes.

4) Calculate the eigenvalues by multiplying each value of the column in pairwise matrix by the normalized criteria weights. Then, sum all values in each row to get the weighted sum values. Next, divide each weighted sum values by the criteria weight to get the eigenvector. Maximum eigenvalue $\lambda_{\text{max}}$ is calculated using sum of all values in eigenvector and divided by the number of criteria $z$.

5) Calculate the Consistency Index (CI) using the following equation:

$$ CI = \frac{\lambda_{\text{max}} - z}{z - 1}. \quad (1) $$

6) Calculate the Consistency Ratio (CR), which is given by dividing the CI over the Random Index (RI). According to [54], the CR must be below 0.1 to continue the AHP analysis without revising the judgments to locate and correct the cause of the inconsistency. In our example, for safety application, the $CR = 0.008 < 0.1$ is obtained. Therefore, the minimum CR requirement is satisfied.

7) The previous procedures are repeated for the selected V2X use-cases. The weights for the selected criteria are computed for V2X use-cases for the AHP hierarchical analysis computation.

Figure 5 presents the computation of pairwise comparison, normalized relative, and weights calculation for the three V2X use-cases. The assigned relative importance between the selection criteria is specified according to the prioritization of use-cases. There are nine levels of relative importance, with level 9 as the highest priority and level 1 as the lowest priority. For safety use-cases that need superior reliability [53], short queueing delay and long TTL of each RSU have the highest importance in the network selection matrix rather than the required bandwidth and cost. Thus, the weights of queue delay and TTL are the highest. In the pairwise comparison matrix shown in 5(a), the queueing delay has 9 times higher importance than the required bandwidth and...
7 times higher importance than the cost. In addition, TTL has 7 times higher importance than the required bandwidth and 5 times higher importance than the cost. On the other hand, infotainment use-cases requiring higher bandwidth [53] is assigned a higher importance in the network selection matrix rather than the queueing delay and cost. We have adjusted the TTL for such use-cases to ensure a continuous connection during data transfer. Thus, the weights of required bandwidth and TTL are the highest. In the pairwise comparison matrix shown in 5(b), we can say that the required bandwidth has 5 times higher importance than the queue delay and the cost.

D. LONG SHORT-TERM MEMORY (LSTM)

Various deep learning methods are proposed in the literature to address the prediction of channel quality estimation in real-time. The works in [51], [52], and [55] have demonstrated that LSTM is an effective prediction technique for wireless channel quality assessment in different mobility patterns. The LSTM is a modified version of the common time-series deep learning Recurrent Neural Network (RNN) algorithm, but LSTM can effectively overcome the vanishing problem of RNN by implementing a forget gate. Specifically, the LSTM is composed of a memory cell, an input gate, an output gate and a forget gate. The cell stores values over arbitrary time intervals. The three gates regulate the flow of information into and out of the cell, representing information flow between the LSTM cells.

In this study, we applied a time series LSTM deep learning technique to forecast the RSSI for 802.11n (2.4 GHz, 5 GHz) and 802.11p networks. To decrease the complexity of design, we proposed that the channel quality of C-V2X is fixed over the simulation period. The RSSI must exceeds the specified receiver sensitivity of the targeted vehicle, otherwise the signal will be discarded. We build a LSTM sequence-to-sequence model that predicts the channel quality of the target RAT at next time T. At each time step, a q-dimensional vector $\xi(t)$ is passes as input to LSTM model with q components, where q is the quality measure at T. As the system depend only on the past value $\xi(s), s < T$, the output value is presenting the predicted value for next time.

LSTM used in this paper is the standard sequence-sequence LSTM as shown in Figure 9 and can be modelled by the following recursive equations (2)-(7):

$$i_t = \sigma(x_t U^i + h_{t-1} W^i)$$  \hspace{1cm} (2)
$$f_t = \sigma(x_t U^f + h_{t-1} W^f)$$  \hspace{1cm} (3)
$$o_t = \sigma(x_t U^o + h_{t-1} W^o)$$  \hspace{1cm} (4)
$$C_t = \tanh(x_t U^c + h_{t-1} W^c)$$  \hspace{1cm} (5)
$$C_t = \sigma(f_t \odot C_{t-1} + i_t \odot C_t)$$  \hspace{1cm} (6)
$$h_t = \tanh(C_t) \odot o_t$$  \hspace{1cm} (7)

where $\sigma(x) = \frac{1}{1 + e^{-x}}$, $W^i, W^f, W^o, W^c$ are linear transformation matrices, $i_t; f_t; o_t$ are gating vectors, $c_t$ is cell memory state vector, and $h_t$ is a state output vector.

For convenience, the LSTM prediction is performed as follows:

$$\xi(Q, t) = L(\xi(Q, t))$$  \hspace{1cm} (8)
where \( L(U(t)) \) means the input has been passed through above equations. The minimization technique used in this paper is MSE, where \( Q \) and \( H \) is the input and output sequences, respectively and \( Q \neq H \). \( Q \) is composed of different measurement inputs namely RSSI pick up time (Simtime), x-axis position vehicle \((V_x)\), the real distance between the vehicle and the particular RAT (distance), \(TTL\), noise \((n)\), and RSSI. Figure 10 depicts the linear data correlation analysis between the input sequence. It is clear that RSSI is high correlated with the geographical information of the vehicle.

![FIGURE 9. Structure of LSTM cell.](image)

![FIGURE 10. LSTM input sequence correlation.](image)

A set of predicted LSTM output sequence at time \( \zeta(t) \) is used to predict RSSI values, if the predicted value exceeded the RSSI threshold \( \gamma \) of \( k_i \), then this RAT included in \( k_i \) reliable list for further RAT selection procedures. The LSTM parameters are illustrated in Table 4. The dataset generation procedures are as follows:

1. As an initial step, the dataset is generated using the network simulator NS-3.31, and it contains the position of the vehicle and its current RSSI for each RAT.

2. The previous dataset was validated using LSTM deep learning method, where 70% of the input sequence is used for the training session, and 30% for validation.

3. There are numerous ways of storing the trained models that can be used later. The benefit of storing such models is that each time we need to make predictions on a new dataset, we only need to load a pre-trained model and make a predictive analysis instead of repeating the process all over again. In our proposed model, the weights of each RAT at each 1 m distance are saved in Keras H5 format [64] and later used for any future prediction using the symmetrical load weight’s function.

4. We repeat the prediction procedure on the saved model, H5 model, taking 100% of the input sequence of each vehicle at each RAT, and then the predicted value of RSSI is stored in CSV file format.

5. Finally, when the predicted value of RSSI is required, our model passes only the position in which the current node (vehicle) is located to CSV file store to fetch the predicted value of each RAT according to the current location and send it back to NS-3 module.

6. The predicted RSSI is validated by minimizing the mean square error (MSE) using equation (9).

\[
MSE = \frac{1}{QH} \sum_{k=1}^{H} \sum_{q=1}^{Q} (\zeta(H, Q) - \zeta(H, Q))^2
\]

**E. UTILITY FUNCTIONS**

To select the appropriate RAT for vehicles, a complex approach is required. In this approach, vehicles need to search the available access network and choose the most efficient RAT that achieved the targeted V2X service requirements. Four utility functions are considered in our proposed scheme, namely remaining bandwidth, queueing backlog, network cost, and connectivity.

1) **REMAINING BANDWIDTH UTILITY FUNCTION**

While the connection probability of a vehicle is increasing for the most efficient RAT, we need to raise the awareness for the communication continuity of other vehicles so they can plan to connect to this targeted RAT. Due to this, the remaining bandwidth of the targeted RAT need to be calculated as one the selection criteria. In this paper, Wi-Fi-based RSU is implemented with a proportional-fair model for throughput acquisition for different users. Meanwhile, the Wi-Fi channel is shared by vehicles under a contention-based mechanism, where the theoretical maximum throughput is equal or less than the remaining bandwidth. Thus, if the number of vehicles
that are attached to the RAT is known, the remaining bandwidth can be calculated as [56]:

$$b^i_v = \frac{R^i_v}{\hat{n}^i}$$  \hspace{1cm} (10)

where $R^i_v$ is the PHY rate of vehicle $v$ from $k_i$ and $\hat{n}$ is the number of vehicles that are simultaneously connected to this $k_i$ where $\hat{n}eV = \{V_1, V_2, \ldots V_N\}$. Figure 11 shows that the remaining bandwidth is exponentially decreasing when the number of connected vehicles is increased.

For a simultaneous downlink communication in C-V2X, eNB allocates orthogonal channel to each vehicle without interference. The theoretical rate for each vehicle is calculated using equation (11), where $WL$ is the eNB bandwidth in MHz, $K$ number of sub-channels that can be allocated to a vehicle at time slot $t$, $p$ is the mean transmission power, $g$ is the transmission gain, $n_o$ is the background noise density [57].

$$b^C_{V2X} = \frac{WL}{K} \log_2 \left(1 + \frac{pg}{W_L n_o}\right)$$  \hspace{1cm} (11)

Furthermore, high traffic V2X services such as video sharing or sensor vision require a high bandwidth, while safety services need less bandwidth [53]. We used the utility function proposed in [41], which has been proven to be twice related to autonomous vehicles are expected to contribute to the overall performance of the network [58]. Today, services related to autonomous vehicles are expected to contribute huge transferring packets while they are moving on the road.

Queueing delay at $k_i$ is determined stochastically, where all packets delivered from vehicles follow a Poisson distribution with specified rate. Similarly, each vehicle generates packets according to Poisson distribution $P(x) = \frac{\rho^e \rho^v}{x!}$. The packet arrival traffic is given by:

$$A(\tau, t) = (\rho_A (t - \tau) + U)^+$$  \hspace{1cm} (16)

where $\rho_A$ is the packet arrival rate started from $\tau$ seconds till $t$, $U$ is the burstiness measure parameter of each V2X service, $\rho_A > 0$, $U \geq 0$, and $t \geq \tau \geq 0$. Note that $(X)^+ = 0$ when $X < 0$. Otherwise, $(X)^+ = X$. The service rate at $k_i$ is dependent on the data rate value $b^i_k$ assigned to $k_i$ in its physical layer, and it is given as:

$$S(\tau, t) = (\rho_S (t - \tau) - t_{assoc})^+$$  \hspace{1cm} (17)

where $\rho_S$ is the packet service rate started from $\tau$ seconds till $t$, $t_{assoc}$ is the association time when the vehicle started transferring packets to $k_i$ after acknowledgment process and Address Resolution Protocol (ARP) is performed. Particularly, we consider in our simulation $\rho_S \triangleq b^i_k$. In our proposed scheme, three queue buffers are allocated to the three deployed services at each $k_i$ to increase the reliability of the network and to avoid large queueing delay in case of high density packet transfer use-case.

The accumulated queue backlog at $k_i$ for service $S$ is the remaining packet arrival curve deducted from packet service curve as follows:

$$B(\tau, t) \geq \max_{\tau \in [0, t]} [A(\tau, t) - S(\tau, t)]$$  \hspace{1cm} (18)

The $B(\tau, t)$ should be either equal or greater than the deduction due to uncertainty in the network [59]. Each vehicle transfers its packets to targeted RSU, where practically some of them are processed locally, while some are sent to cloud or another point, and the rest are backlogged in the
queue for a specific queue time before dequeuing. The queue time $Q_k^S(t)$ is dependent on the medium access control of the targeted RATs and their real-time channels conditions. Varying the queue time will impact the overall performance of the network and affects the vehicular application. In the proposed approach, a different queue time is assigned to each RSUs. This queue time is calculated using a stochastic approach, where the queue time is directly proportional to either the packet arrival or burst rate. In our simulation, burst rate is equal to all targeted service and assumed to be zero for simplicity purpose, but the arrival rate differs according to the type and the time that the request message (RM) arrives.

$$Q_k = \frac{1}{\rho_s - \rho_A} - \frac{1}{\rho_s}$$  \hspace{1cm} (19)$$

To stabilize the system and reduce the packet loss $\rho_A < \rho_S$. A linear utility function is implemented to quantify the impact of queueing delay at $k_i$ for service $\int$ as follows:

$$U(Q_k) = 1 - (U(Q_k^S))$$  \hspace{1cm} (20)$$

where

$$U'(Q_k) = \begin{cases} \frac{Q_k}{Q_{k_{\text{max}}}}, & 0 \leq Q_k \leq Q_{k_{\text{max}}} \\ 1, & Q_k \geq Q_{k_{\text{max}}} \end{cases}$$  \hspace{1cm} (21)$$

Note that $Q_{k_{\text{max}}}$ is the maximum allowable delay that is adjusted according to the simulation scenario. If the queueing delay exceeds this value, the packet will be dropped and discarded. Figure 12 depicts the queueing structure for the proposed SOLMC scheme. Three service queue levels are assigned for each $k_i$, where our scheme encourage the vehicle to select $k_i$ that has the lowest queue backlog at its queue service level.

4) TTL UTILITY FUNCTION
Calculating TTL value for each $V$ is important to estimate the connectivity time under the radio coverage of $k_i$. For TTL calculation, first, we calculate the maximum time-to-leave $TTL_{\text{max}}$ of each $k_i$. $TTL_{\text{max}}$ is calculated by dividing the full communication coverage $2D_s$ by the vehicle speed $s_j$ as follow:

$$TTL_{\text{max}} = \frac{2D_s}{s_j}$$  \hspace{1cm} (24)$$

Secondly, we estimate the instantaneous $TTL_i$ at current vehicle position as follows:

$$TTL_i = \frac{D}{s_j}$$  \hspace{1cm} (25)$$

where $D$ is the distance between the $j^{th}$ vehicle location $\psi_j(x) \triangleq \{\psi_x^j, \psi_y^j, \psi_z^j\}$ and the predefined position of each RAT $k_x$ at x-axis and it is calculated as follows:

$$D = \begin{cases} D_x + D_s, & \psi_x^j < k_x \\ D_x - D_s, & \psi_x^j > k_x \\ |\psi_x^j - k_x| \end{cases}$$  \hspace{1cm} (26)$$

3) COST UTILITY FUNCTION
The cost is calculated by multiplying the cost of a bit at each RAT by the maximum number of bits that the V2X service can share. The cost/bit utility function is related to the queue backlog, where $c$ refers to the cost of the deployed RAT, and $c_{\text{max}}$ refers to the maximum cost of the V2X service. The cost of C-V2X is adjusted to the highest cost compared to Wi-Fi RATs.

Figure 13 illustrates the cost utility function value for different RATs. The maximum cost is given by:

$$U(c) = 1 - U'(c)$$  \hspace{1cm} (22)$$

where

$$U'(c) = \begin{cases} c, & 0 \leq c \leq c_{\text{max}} \\ 1, & c \geq c_{\text{max}} \end{cases}$$  \hspace{1cm} (23)$$

FIGURE 13. Utility function of Cost for each RAT.
\[ D_s = \sqrt{r^2 - (h_k^j - h_v^j)^2} \] (28)

Figure 14. illustrates TTL calculation of \( j \)th vehicle based on its position. \( h_k^j \), \( h_v^j \), and \( r \) are the height of \( j \)th vehicle, the height of \( i \)th RAT, and communication coverage of \( i \)th RAT, respectively.

Finally, the TTL is calculated based on the direction of movement \( d_j \), as follows:

\[ TTL = \begin{cases} TTL_i, & d_j > 0 \\ TTL_{\text{max}} - TTL_i, & d_j < 0 \end{cases} \] (29)

The utility function of TTL is proposed as in [41] where it is twice differentiable, monotonic, concavity-convex and guarantee the following conditions:

\[ u(TTL) = 0, \quad \forall TTL \leq TTL_{\text{min}} \] (30)

\[ u(TTL) = 1, \quad \forall TTL \geq TTL_{\text{max}} \] (31)

\[ u(TTL_{\text{mid}}) = 0.5, \quad \forall TTL = TTL_{\text{mid}} \] (32)

where \( TTL_{\text{mid}} = \frac{TTL_{\text{max}} + TTL_{\text{min}}}{2} \), and \( TTL_{\text{min}} \) is the minimum time that is required to deliver all V2X service packets from the source to the destination that is computed by dividing the maximum number of packets of service \( S \) by the packet rate specified for this service.

\[ u(TTL) = \begin{cases} 0 & TTL < TTL_{\text{min}} \\ \left( \frac{TTL_{\text{mid}}}{TTL_{\text{min}}} \right)^2 & TTL_{\text{min}} \leq TTL \leq TTL_{\text{mid}} \\ \frac{1}{1 + \left( \frac{TTL_{\text{mid}}}{TTL_{\text{max}} - TTL_{\text{mid}}} \right)^2} & TTL_{\text{mid}} \leq TTL \leq TTL_{\text{max}} \leq TTL_{\text{max}} & TTL_{\text{max}} \end{cases} \] (33)

The TTL illustrates the link expiration time between the vehicle and the deployed RAT, and it is part of the reliability evaluation in this study. We divided the distance zone to 3 satisfaction areas namely low, moderate, and high satisfaction as shown in Figure 15.

5) COMPUTATION OF UTILITY FUNCTION LIST

Based on the four utility functions adopted in this paper to measure the service preference at each deployed RAT, Algorithm 2 in Figure 16 shows the process of utility function list computation to fetch the \( UL(k)^i \) at \( k_i \) for each \( S \), where \( UL(k)^i \triangleq \{ U(b)^i, U(QW)^i, U(C)^i, U(TTL)^i \} \). In other words, a MCDM approach is used to assist in the process of optimum RAT selection.

6) FINAL SCORE CALCULATION AND PROBLEM FORMULATION

In this section, we will present the proposed problem and its constraints. For each RM received by RSO, different V2X use-cases usually call for different QoS requirement,
which can bring different initial weights and utility levels for each deployed RAT. Our objective is to maximize the overall network throughput for each vehicle with different objective constraints. In this paper, the utility function is deployed with different constraints. The on-time queue length for each deployed RAT is considered as well. The proposed utility function has monotonic properties, where each utility function monotonically increases or decreases at each RAT for each service.

In this paper, a conditional utility function is proposed with an attribute dominance condition property. The conditional property reduces the number of utility assessment when for each service.

for each deployed RAT is considered as well. The proposed constraint constraints. In this paper, the utility function is deployed with different constraints. The on-time queue length for each deployed RAT is considered as well. The proposed utility function has monotonic properties, where each utility function monotonically increases or decreases at each RAT for each service.

The SOLMC algorithm can be divided into three main phases as shown in Figure 18. Phase 1 refers to the AHP hierarchical analysis stated in Algorithm 1, where the weights for the selected criteria will be used as input to Phase 2. Phase 2 refers to the MCDM method given in Algorithm 2. Meanwhile, Phase 3 is the computation of final selection score based on the utility functions of LSTM in Algorithm 3.

The simulation procedures are summarized below:

1) While $v_j$ moves on the initial training session as depicted in Figure 19, LSTM module gathering the RSSI input sequences mainly position of $v_j$, distance to $k_i$, speed of $v_j$, current RSSI, to its encoder side until the number of inputs reach 200 records.
2) Step 1 is repeated for each $k_i$
3) Online LSTM predicts the next RSSI of $v_j$ for each $k_i$, the predicted outputs are stored in a data structure beside $v_j$ mobility information.
4) For each V2X use-case, AHP is used to quantify the requirement of the use-case to numerical weights. The pairwise metric comparison is mainly based on the importance scale between selected criteria.
5) At RSO and after receiving $RM$ from $v_j$, RSO collects network measurements list $\mathbb{N} = \{Z_1, Z_2, \ldots, Z_k\}$ for all $k_i$, where $Z_i$ contains a selection attributes list of $k_i$ namely available bandwidth $b_i$, queueing delay bound, cost $c_i$, TTL for the vehicle that raised this RM.
6) RSO utilize algorithm 1 and $W_S$ which contains the weight of relative importance of each selection attributes, to compute the initial weight list of $k_i$ conducting each $S_i$.
7) According to the utility functions of each selection criteria, compute the utility value of each selection metrics for the raised $S_i$ and at the current vehicle context which raised by $RM$.
8) RSO send initial $CP$ to $v_j$ that includes the computed values of utility functions and the initial weight list of $k_i$ conducting each $S_i$. N.
9) Compute the utility function of predicted RSSI using equation (29) right utility. Rank the final scores of throughput utility function from maximum to minimum using equation (29) left utility. We will use the highest utility value; the second highest will keep for future work.
10) The final optimum RAT index, $P_i^k$, is computed using equation (29). The $v_j$ is connected to $k_i$ that has maximum $P_i^k$. RSO updates $k_i$ information list such as the number of attached users, current queue size for each $S_i$.

The proposed problem $P$ can be solved in at most time complexity $O(kn)$, where $k$ is the number of RATs deployed in the scenario, while $n$ is the number of steps that are required from the vehicles to find the best RAT, depending on the number of selection criteria that are used in the proposed SOLMC algorithm. In the simulation, storing the predicted RSSI values in CSV files and retrieving them when they are required, can simplify the best RAT search and reduce the time complexity in the LSTM module. Therefore, SOLMC
ensures that RAT selection procedures are completed before the vehicle leaves the road segment.

IV. PERFORMANCE EVALUATION OF PROPOSED SOLMC RAT SELECTION ALGORITHM

A. SIMULATION SCENARIO

Figure 19 shows the simulation scenario of a two-lanes bidirectional road with a length of 1000 m and a width of 6 m. In the simulation scenario, there are three road segments ($RS_1$, $RS_2$, $RS_3$). $RS_1$ and $RS_3$ contains each of the DSRC, Wi-Fi 2.4 GHz and Wi-Fi 5 GHz RATs. Meanwhile, the C-V2X eNB is located at the center of $RS_2$ and has a communication radius that covers for the whole scenario.

As mentioned in Section III, each vehicle can communicate to several RATs. At any moment of simulation time, each vehicle can access all deployed RATs with different performance. For example, a vehicle $v_1$ on road segment $RS_2$ can communicate to the four deployed RATs at the same time, while it moves from $RS_2$ toward $RS_3$. Meanwhile, vehicle $v_2$ at the edge of $RS_3$ can communicate to the eNB, rather than the nearest Wi-Fi 2.4 GHz. This is the case if the Wi-Fi has the maximum initial weight, but its predicted channel quality is below the required threshold. Therefore, the final selection profile will be allocated to another RAT (C-V2X).

Note that at the beginning of the simulation, the LSTM training session is performed until 200 measurements for each RATs are received by the LSTM module as presented in Figure 18.

The simulation parameters of the overall and the four deployed RATs are listed in Table 5 and Table 6, respectively. The QPSK modulation scheme is selected for DSRC and C-V2X to ensure reliability. The cost of the deployed use-case is adjusted, where the safety application has the lowest cost, theinfotainment has the highest cost, while the traffic efficiency application has the moderate cost. Furthermore, the maximum queuing delay for the safety application is very stringent and restricted, so the RAT selection scheme should select the RAT that has the lowest queue backlog.

The simulation is conducted in NS-3.31, where the LSTM simulation is performed using the Keras V.2 module. WiFi, WAVE, and LTE NS-3 modules are used when performing the simulation. The simulation scenario is such that the vehicle is in coverage areas of four RATs (IEEE802.11p, Wi-Fi 802.11n 2.4 GHz, 802.11n 5 GHz, and LTE C-V2X). At any time of the simulation, any vehicle can raise RM to handover to a new RAT. In the simulation, the RM is triggered periodically (every 30 meter) in the evaluation process and after the vehicle moves toward a specific distance. The simulation is repeated 50 times to obtain the average performance measurements.

Three methods are considered for the RAT selection: without-RSSI prediction, Nearest-RAT [6], and the proposed SOLMC. The without-RSSI prediction method applies the proposed RAT selection approach in Figure 18 without implementing LSTM, which predicts the RSSI values. It only considers the multi-criteria method in its RAT selection process, and it does not consider the predicted RSSI values in its selection. The Nearest-RAT method considers the distance between the surrounding deployed RAT. It selects the nearest RAT according to equations (24) to (26). Meanwhile, the SOLMC scheme is a service-oriented joint LSTM-based multi-criteria RAT selection in V2I networks that was proposed in Section III. SOLMC considers predicted RSSI values in its RAT selection process, and utilizes queue management over all deployed RAT for queue length reduction.

B. EFFECT OF QUEUEING DELAY

Different maximum queueing delay bound is assigned for each $k_i$ to vary the impact between deployed RATs, namely 500 ms, 600 ms, and 700 ms for DSRC, Wi-Fi 2.4 GHz, and Wi-Fi 5 GHz RATs. Meanwhile, the C-V2X eNB is located at the center of $RS_2$ and has a communication radius that covers for the whole scenario.

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The simulation is conducted in NS-3.31, where the LSTM simulation is performed using the Keras V.2 module. WiFi, WAVE, and LTE NS-3 modules are used when performing the simulation. The simulation scenario is such that the vehicle is in coverage areas of four RATs (IEEE802.11p, Wi-Fi 802.11n 2.4 GHz, 802.11n 5 GHz, and LTE C-V2X). At any time of the simulation, any vehicle can raise RM to handover to a new RAT. In the simulation, the RM is triggered periodically (every 30 meter) in the evaluation process and after the vehicle moves toward a specific distance. The simulation is repeated 50 times to obtain the average performance measurements.

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Figure 20 evaluates the effect of maximum queueing delay on the overall network performance. The maximum queueing delay is adjusted in the simulation scenario to determine how much the maximum time that the transferred packet can stay in the queue buffer before it is discarded. Hence, any packet is stored in a buffer queue until it is transferred to its destination. Congestion on the network is the main reason for packets waiting in the queue buffer. It can be seen
that as the maximum allowable queueing delay increases, the average throughput of all participated vehicles over the overall network is enhanced. Up to 7% throughput increase can be obtained when we consider queue management in our proposed scheme at a queueing delay time $Q_W=10$ ms. Meanwhile, a 3.5% throughput enhancement is obtained at queueing delay time $Q_W=100$ ms.

We considered $Q_W=10$ ms to represent a very restricted queueing delay limit such as for safety use-case, whilst $Q_W=100$ ms is a long queueing delay limit that can be used for an infotainment use-case. In addition, a 2% throughput enhancement occurs when increasing the maximum queue waiting time from $\text{Max}Q_W=10$ ms to $\text{Max}Q_W=100$ ms. This is because the packet drop policy when the packet buffer becomes full is activated after 100 ms. Thus, the packets stay
longer in the buffer queue before they are transmitted to the destination.

In terms of queue stabilization over all deployed RATs excluding the C-V2X eNB, Figure 21 shows how the proposed algorithm SOLMC reduces the queue length over the first 20 s of the simulation time while maintaining the targeted QoS. At time = 10 s, a queue reduction ratio between applying SOLMC and nearest-RAT algorithm to select the optimum RAT is as follows: 18% at IEEE 802.11n located at 5 GHz at RS1, 28% at IEEE 802.11n at 5 GHz located at RS3, and 15% at IEEE 802.11p/DSRC at RS3.
at RS3, 5% at IEEE 802.11n at 2.4 GHz located at RS1, 71% at IEEE 802.11n at 2.4 GHz located at RS3, 90% at IEEE 802.11p/DSRC located at RS1, and 51% at IEEE 802.11p/DSRC located at RS3. The figure shows that significant queue length reductions are achieved in our proposed SOLMC scheme. This is due to the consideration of the queueing delay bound at each RAT before the execution of RAT selection.

### C. PDR ENHANCEMENT

Packet delivery ratio represents the reliability verification of the deployed RAT. The RAT with a highest PDR denotes the most reliable RAT for the targeted V2X use-case. Figure 22 illustrates the comparison of PDR performance for several RAT selection techniques. As shown in the figure, the IEEE 802.11n at 5 GHz that has been assigned a higher 40 MHz bandwidth in the simulation scenario, outperforms the other WiFi RATs for SOLMC and without RSSI-based prediction RAT selection schemes. In all cases, the PDR of C-V2X gives the highest reliability performance. Moreover, the figure shows multi-RAT network gives the benefit of distributing the traffic load over all RATs in the simulation. Figure 23 depicts the PDR improvement of our proposed network compared to the nearest-RAT method over several vehicle speeds. In a nearest-RAT approach, only the nearest RAT will be used as the selection criteria, without considering the RAT’s capability to deal with the received messages. Therefore, severe packet drops will occur, either due to a full queue buffer or limited available bandwidth. As the speed increases, the delivery period decreases, and therefore the packet loss will also gradually decrease. On average, 95% of packets are delivered successfully when the vehicles move at a speed of 10 m/s. When the nearest-RAT algorithm is applied at this speed, only 92.73% of PDR is achieved. This indicates that our proposed algorithm enhances the PDR by 13.3% at a speed of 10 m/s, while an average enhancement of the overall PDR is 20.4%. Moreover, when without-RSSI is applied to SOLMC, meaning with no LSTM prediction technique, at speed 10 m/s, only 94% of PDR is achieved. This indicates that our proposed algorithm enhances PDR by 1% at speed 10 m/s when utilizing the RSSI predicted values, while an average enhancement of the overall PDR is 6%.
D. THROUGHPUT IMPROVEMENT

Throughput measurement is an important metric for any V2X use-case, as it shows how the packets are delivered from source to destination smoothly. Figure 24 shows the average throughput over all participating vehicles in the scenario for SOLMC, without-RSSI, and nearest-RAT algorithms. It can be seen that IEEE802.11n at 5 GHz and C-V2X contributed more throughput on the network compared to other RATs. In addition, as the vehicle speed increases, the throughput decreases. This is because when the vehicle leaves the RAT coverage before the carrier sense procedure is completed, the selection of a new RAT association will occupy a part of the channel access. This results in the increase of the channel collision probability. In Figure 24c of nearest-RAT algorithm, RAT occupancy is based on which is the closest RAT, so it is not necessary to select the RAT with the highest bandwidth as what is happened in SOLMC. Theoretically, IEEE 802.11n at 5GHz (with 40 MHz bandwidth) has a peak data rate of 150 Mbps, which is higher than all other deployed Wi-Fi RATs. Moreover, C-V2X shows a high throughput satisfaction for all, thus it is selected as a backup RAT when other RATs cannot satisfy the service requirements.

The network total throughput in Figure 25 compares the proposed SOLMC scheme against the without-RSSI, and nearest-RAT approaches. The simulation results show that our intelligent proposed algorithm SOLMC increases the network throughput. This is because SOLMC selection method considers the quality of the targeted RAT prior to initiating the final selection profile. Up to 47.5% enhancement in the total throughput is achieved by the SOLMC scheme compared to the nearest-RAT selection approach.

E. MULTI-RAT SATISFACTION AND UTILIZATION PERFORMANCE

Two methods are performed to validate SOLMC: 1) RAT satisfaction and 2) Average $k_i$ utilization. $k_i$ satisfaction measures the transmission efficiency of the targeted $k_i$. In general, the satisfaction percentage measured the throughput achieved compared to theoretical throughput for each $k_i$:

$$\text{Satisfaction}(\%) = \frac{\text{measured throughput}}{\text{theoretical throughput}} \times 100\% \quad (46)$$

From Figure 26, SOLMC has a satisfaction ratio of 97% and 98% for scenarios with a vehicle speed of 10 m/s and 15 m/s, respectively. When the vehicle speed increases, the satisfaction of SOLMC decreases to 92%, 83%, and 78% for speed from 20, 25 and 30 m/s, respectively. It is worth mentioning that the SOLMC scheme satisfies the V2X use-case requirements in terms of throughput by 43% compared to the traditional RAT selection, i.e. the nearest RAT. In addition, a 3.5% satisfaction enhancement is achieved when RSSI is predicted before RAT selection.

In Figures 27a and 27b, the average RAT utilization is measured for 12 vehicles and 24 vehicles in the 1km road
scenario. RAT utilization ratio defines the percentage of how many vehicles select this RAT over the total number of vehicles. From the figure, three points could be summarized: (1) no RAT is utilized more than 50% in both figures, (2) the overall network load is fairly distributed over all deployed RATs, and (3) RATs that have the higher bandwidth contribute more to sharing the data, particularly, the V2X use-case. The IEEE 802.11p/DSRC with the lowest data rate, contributes the least utilization compared to the other RATs.

F. LSTM PERFORMANCE VALIDATION
The RMSE is used to determine the loss ratio of each RSSI prediction for each RAT. The achieved accuracies for RSSI forecasting are 98.2%, 97.1%, and 98.15% for IEEE 802.11p/DSRC, Wi-Fi IEEE 802.11n at 2.4 GHz and IEEE 802.11n 5 GHz, respectively. One feature of LSTM is predicting a sequence in time series as shown in Figure 28, which will be utilized in our scheme to predict future RSSI for each RAT.

V. CONCLUSION
In this paper, we developed an intelligent multi-criteria multi-service network selection in V2X networks, known as SOLMC multi-RAT selection scheme. Furthermore, we high-
light the importance of a dynamic optimum RAT selection that allows vehicles to communicate with the road infrastructure and disseminate real-time conditions information. In our proposed scheme, the V2X use-cases are quantized based on several selection factors using AHP. Then, each RAT satisfaction is computed using different shape utility functions. Deep learning LSTM is utilized in this study to forecast the incoming RSSI for the deployed RAT, which is then assigned to the RAT selection profile. Each vehicle receives a selection profile based on its current location and by implementing SOLMC, it can select the optimum RAT that satisfies its preferences. Simulation results show the proposed SOLMC improves the reliability of packet delivering ratio compared to when the conventional Nearest-RAT scheme. Moreover, significant throughput enhancement is achieved by SOLMC against the nearest-based RAT selection. In our future work, a hybrid LSTM-CNN combined RSSI prediction shall be considered to predict the optimum RAT that can satisfy the targeted V2X use-case. CNN can be utilized to extract network features, while LSTM can be implemented for time series prediction. Combining both methods should improve the prediction of the network conditions over varying vehicle mobility models.

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