Intelligent Reflecting Surfaces Aided Millimetre Wave Blockage Prediction For Vehicular Communication

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***Abstract*—The ability of millimeter-wave (mmWave) to deliver gigabit throughput has led to its widespread adoption in Fifth Generation (5G) networks. However, mmWave links between Base Station (BS) and users can be easily obstructed by obstacles. In vehicular networks with dynamic environments and mobile users, the mmWave link blockage issue is even more pronounced. In order to preserve the mmWave link in the vehicular network, it is necessary to predict blockages. For blockage prediction, sensor information from Lidar, Radar, and cameras has been considered. Nonetheless, these non-radio frequency methods necessitate the use of additional equipment and signal processing, which raises the implementation cost and complexity. The existing literature also considers the use of BS and user's Radio Frequency (RF) signatures to predict blockage. However, users' mobility has not been taken into account. An Intelligent Reflecting Surface (IRS), on the other hand, has been viewed as a promising method for providing an alternate path by reflecting the mmWave signal between the BS and user in order to improve the reliability of vehicular networks. Therefore, this research investigates the IRS-assisted blockage prediction in order to determine the future link status in the vehicular environment with respect to user mobility. The proposed solution employs a number of active elements that are randomly distributed on the IRS to obtain the RF signatures. Furthermore, it utilises Machine Learning (ML) techniques to learn the pre-blockage wireless signatures, which can predict future blockages. The results indicate that the proposed method can predict blockages between a single IRS and a moving user with a greater than 98 percent accuracy up to one second before they occur.**

***Index Terms*—Intelligent reflecting surfaces, millimetre wave, blockage prediction, machine learning, wireless signatures.**

I. Introduction

Millimetre-wave (mmWave) wavelength has been utilised in Fifth Generation (5G) and Sixth Generation (6G) to achieve greater spectral efficiency thanks to its higher bandwidth. It can provide a high data rate in excess of gigabits to enable technologies such as holographic telepresence, unmanned aerial vehicles, extended reality, and a variety of other common applications. In waves that require Line-of-Sight (LoS) for communication, the characteristics of shorter wavelength result in high propagation losses and high penetration losses [1]. Due to the highly dynamic nature of the vehicular environment, these disadvantages are exacerbated in vehicular networks, particularly in terms of their reliability and latency. Moreover, in highly dynamic vehicular networks, sudden blockages may render the status of the link unpredictable [2].

To facilitate Non-Line-of-Sight (NLoS) links in mmWave communications between users and Base Station (BS), an Intelligent Reflecting Surface (IRS) has been introduced to add additional scattering paths that extend the communication range and enhance the reliability [3]. The IRS is a cost-effective metasurface with low material costs and low energy consumption [4]. It can be installed on walls or buildings to reflect incident signals and provide an alternate path for NLoS users, thereby significantly enhancing the network's availability. In addition, the IRS can be combined with Machine Learning (ML) techniques to enable sensing in vehicular networks and further close the Ultra-Reliable Low-Latency Communication (URLLC) gap in vehicular networks. These ML techniques are data-driven, natural decision-making tools that can be used to perform sophisticated cognitive tasks [5].

Although it is crucial to be able to predict mmWave link blockage in vehicle networks, conventional techniques such as greedy algorithms and game theory are unable to do so [2]. ML, however, can be used to predict link blockages, as demonstrated by references [6], [7], and [8]. Specifically, deep learning models were developed by training various types of sensory data, including Radar, Lidar, and vision-aided data, to predict link blockages. Nevertheless, such models require the installation of additional sensors and hardware. In addition, [6] uses vision-aided data and wireless data for future blockage prediction; however, this requires the implementation of a sophisticated method with multiple combined deep learning models, combining Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) with Gated Recurrent Units (GRU). Furthermore, Long Short-Term Memory (LSTM) Networks is a family of RNN which has been utilised in [7] for Radar-aided future blockage prediction. In addition, the accuracy of each of the aforementioned papers also varies between 87% and 90%, which is notable but could still be improved.

Since wireless information can be easily captured by IRS with sparse active elements [9] or BS, it is worthwhile to investigate the creation of deep learning models using wireless information for future blockage prediction in vehicular networks with high mobility users. The most recent paper, [10], identifies pre-blockage wireless signatures by observing the received power over time and then feeding them as training data for ML models. The pre-blockage wireless signature is a received signal pattern that occurs prior to the blockage since the approaching moving obstacle, such as a moving vehicle between a stationary BS and a stationary user, causes the scattered ray to change. However, users with high mobility have not been considered in this paper, which could affect the network's reliability due to rapidly changing channels [2]. Moreover, [11] has utilised a dual band system in its blockage prediction with a sub-6 GHz transceiver, but it can only predict very near future link blockage and only takes indoor environment into account.

This research, inspired by [9], enables an IRS with a few active elements and both variants of RNNs (GRU and LSTM) for future blockage prediction, which can predict the blockage with high accuracy and low Root Mean Square Error (RMSE) before the NLoS occurs. Simulation results demonstrated that the proposed solution predicts blockages with nearly 98% accuracy up to one second before NLoS occurrence.

Notation: We use the following notation: $\mathbf{A}$ is a matrix, $\mathbf{a}$ is a vector, a is a scalar, and A is a set. $\mathbf{A}^T$, $\mathbf{A}^*$ are the transpose and Hermitian (conjugate transpose) of $\mathbf{A}$. $[a]_n$ is the nth element of $\mathbf{a}$. $\mathbf{A} \circ \mathbf{B}$ is Hadamard product of $\mathbf{A}$ and $\mathbf{B}$. $N(\mathbf{m}, \mathbf{R})$ is a complex Gaussian random vector with mean $\mathbf{m}$ and covariance $\mathbf{R}$. $\mathbb{E}[\cdot]$ is to denote expectation. $\mathbf{vec}(\mathbf{A})$ is a vector whose elements are the stacked columns of matrix $\mathbf{A}$.

II. System and Channel Model

A. System Model

Consider a communication system represented by Fig. 1, where a BS communicates with a vehicular user with the assistance of an IRS. However, the IRS-user link can be blocked by obstacles, e.g., busses or trucks. For simplicity, we assume that the BS and vehicle user have equipped with a single antenna while the IRS is equipped with M antennas. Orthogonal Frequency-Division Multiplexing (OFDM) based system is adopted with number of subcarriers, K. $\mathbf{h}_{BU,k} \in \mathbb{C}$ is defined as a direct channel between the BS and the user. Then, adopting from [9], $\mathbf{h}_{B,k}$ and $\mathbf{h}_{U,k} \in \mathbb{C}^{M \times 1}$ are defined as uplink channels between BS and user to IRS at the k^{th} subcarrier. By reciprocity, the transpose of the uplink channels, $\mathbf{h}_{U,k}^T$ and $\mathbf{h}_{B,k}^T$, are downlink channels. The interaction matrix of the k^{th} subcarrier, $\mathbf{\Psi}_k \in \mathbb{C}^{M \times M}$, is the interaction characteristic of the incident signal from the transmitter at IRS. The transmitted signal, s_k is sent over k^{th} subcarrier from the BS to user which satisfies the total power constraint $\mathbb{E}|s_k|^2 = P_T/K$, with P_T as the total transmit power. Then received signal at the user's end with received noise, $n_k \sim N_{\mathbb{C}}(0, \sigma_n^2)$ is expressed as:

$$y_k = \mathbf{h}_{U,k}^T \mathbf{\Psi}_k \mathbf{h}_{B,k} s_k + \mathbf{h}_{BU,k} s_k + n_k \tag{1}$$

Since it is assumed that the direct channel is insignificant in this case, it can be disregarded. The receive signal can then be expressed as:

$$y_k = \mathbf{h}_{U,k}^T \mathbf{\Psi}_k \mathbf{h}_{B,k} s_k + n_k \tag{2}$$

The diagonal structure of the interaction matrix, $\mathbf{\Psi}_k$, may be layered in a reflection beamforming vector, $\psi_k \in \mathbb{C}^{M \times 1}$, due to the assumption that only phase shifters implemented in IRS components are used. The same applied to all subcarriers, $\psi_k = \psi, \forall k$. Therefore, it may be expressed in Hadamard product form as follows:

$$y_k = (\mathbf{h}_{U,k} \circ \mathbf{h}_{B,k})^T \psi_k s_k + n_k \tag{3}$$

B. Channel Model

This work assumes a geometric channel model in which the channel vector of the uth user at the k^{th} subcarrier is given by:

$$\mathbf{h}_{B,k} = \sum_{d=0}^{D-1} \sum_{\ell=1}^{L} \alpha_\ell e^{-\frac{j2\pi k}{K} d} p(dT_S - \tau_\ell) \mathbf{a}(\theta_\ell, \phi_\ell) \ , \tag{4}$$

where L is the total number of channel paths and $\alpha_\ell, \tau_\ell, \theta_\ell, \phi_\ell$ are the ℓ^{th} channel path's path gains, which include path losses, the delay, the azimuth and elevation arrival angles, respectively. T_S stands for sampling time and D for the length of the cyclic prefix, with the assumption that DT_S is less than the maximum delay. The downlink IRS-user channel $\mathbf{h}_{U,k}$ can be defined similarly. To accomodate for the variations of both channels, $\{\mathbf{h}_{B,k}\}_{k=1}^K$ and $\{\mathbf{h}_{U,k}\}_{k=1}^K$, over time, we employ a block fading channel model in which the channel is considered to be constant throughout the coherence time, T_C.

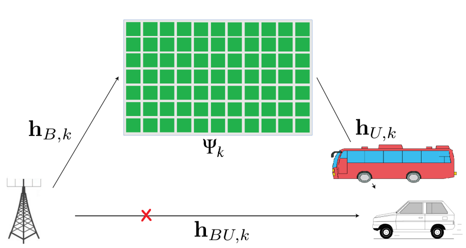

Fig. 1. The selected simple scenario for IRS-aided future blockage prediction.

III. Problem Formulation

The problem involves anticipating whether a blockage may occur in the near future at the IRS-user link. Due to its proximity to the user, the IRS can therefore play a significant role in sensing the environment or preemptively predicting a blockage in this scenario. When the single-antenna user transmits a pilot signal to the IRS employing [9] compressed sensing with ML technique, the channel vector power is sampled from a few randomly distributed active elements on the IRS. The number of the active elements, $\bar{M}$, that are randomly distributed on the IRS with a total number of elements, M, is equal to the multiplication of the number of horizontal elements, M_h and vertical elements, M_v. These active elements are receiving the channel vector of each x-axis coordinate while the moving vehicle is sending an omni-directional pilot signal with a single antenna to IRS. $\mathbf{G}_{IRS}$ is an $\bar{M} \times M$ selection matrix selecting entries from the original channel vector that correspond to the IRS active elements. $\mathbf{G}_{IRS} = [\mathbf{I}]A$, where A defines the set of indices of the active elements, and $\mathbf{I}$ is the identity matrix corresponding to the IRS active elements. Hence, the IRS sampled channel vector, $\mathbf{h}_{U,k} \in \mathbb{C}^{\bar{M}\times 1}$ at the k_{th} subcarrier is written as below:

$$\bar{\mathbf{h}}_{U,k} = \mathbf{G}_{IRS}\mathbf{h}_{U,k} \tag{5}$$

Let $\hat{\bar{\mathbf{h}}}$ denote the noisy sampled channel vector from the user's pilot signal. It can be written as below, where $w_k \sim N_{\mathbb{C}}(0, \alpha_n^2 \mathbf{I})$ is the received noise vector at the IRS active elements:

$$\hat{\bar{\mathbf{h}}}_{U,k} = \mathbf{G}_{IRS}\mathbf{h}_{U,k} + w_k \tag{6}$$

Then, the sampled received channel vector power, $\hat{\bar{\mathbf{P}}}_{U,k} \in \mathbb{C}^{\bar{M}\times 1}$ at k^{th} subcarrier is defined as below:

$$\hat{\bar{\mathbf{P}}}_{U,k} = |\hat{\bar{\mathbf{h}}}_{U,k}|^2 \tag{7}$$

We define $t \in \mathbb{Z}$ as the index of the discrete time instance and $f[t] = 0, 1$ as the link status at the t^{th} time instance. $f[t] = 1$ denotes a blocked link, i.e., the LoS route between the transmitter and receiver is obstructed, whereas $f[t] = 0$ denotes an unimpeded link. Moreover, if at that instance time, t, the single-antenna user transmits a pilot signal to the IRS, the channel vector power is sampled from a few randomly distributed active elements on the IRS. For every t instance, the IRS active elements will receive these pilots signal and estimate the sampled channel vector power. Then, concatenated sampled channel vector power at the t^{th} time interval, $\hat{\bar{\mathbf{P}}}(t)$, is defined as below:

$$\hat{\bar{\mathbf{P}}}(t) = \mathbf{vec}([\hat{\bar{\mathbf{P}}}_{U,1}(t)\ , \hat{\bar{\mathbf{P}}}_{U,2}(t) \ldots\ , \hat{\bar{\mathbf{P}}}_{U,K}(t)]) \tag{8}$$

To facilitate ML training and prevent data loss, the received channel vector power is normalised with a MIN-MAX scaler to the range [0, 1]. Hence, normalized channel vector power, $\hat{\bar{\mathbf{P}}}_{norm}(t)$, is defined as below:

$$\hat{\bar{\mathbf{P}}}_{norm}(t) = \frac{\hat{\bar{\mathbf{P}}}(t) - \min \hat{\bar{\mathbf{P}}}(t)}{\max \hat{\bar{\mathbf{P}}}(t) - \min \hat{\bar{\mathbf{P}}}(t)} \tag{9}$$

Let T_o denote the observational time window. Then, the sequence of these sampled channel vectors power for the previous time instances which is in the observation window, $t - T_o + 1\ , \ldots t$, is then combined into S_{uo} defined as:

$$S_{uo} = \hat{\bar{\mathbf{P}}}_{norm}(t+n)_{n=1-T_o}^{0} \tag{10}$$

Given inputs, the target of this study is to predict the blockage link status in future time instance, T_p. B_{T_p} represents the future link status within T_p instance, and it is defined as below:

$$B_{T_p} = \begin{cases} 0, f[t+n_p] = 0\ \forall n_p \in \{1, \ldots, T_p\} \\ 1, \text{Otherwise} \end{cases} \tag{11}$$

where 0 indicates no obstacles and 1 indicates a blockage in front of the IRS. When the predicted link status, $\hat{B}_{T_p}$, is obtained, the objective is to optimise the prediction's accuracy and reduce RMSE by developing ML models with appropriate architects and training them with a sequence of sampled channel vectors power.

IV. Proposed Solution

Informed by [9], this study enables an IRS with a small number of active elements and both types of RNN (GRU and LSTM) for future blockage prediction, which can predict the blockage with high accuracy and low RMSE before the NLoS occurs. As stated in [10], since pre-blockage wireless signature may be noticed in receive power, it can be utilised to anticipate future blockages. Consequently, ML may utilise the sequence of channel vectors power to predict the future NLoS link between the IRS and user. This signature is proposed for use in predicting future link blockage in mmWave systems. Due to the complexity of these characteristics, we employ ML to learn and exploit them.

To allow the neural network to learn the time sequence of observed channel vectors power, the GRU network design depicted in Fig. 2 from [10] is employed. The model comprises initially of GRU with **q**-layers, followed by feedforward Fully Connected layers, including the output layer. However, the activation functions of the prediction component layers are strictly linear.Similarly, this approach, as shown in Fig. 2 can be applied to the LSTM model. Instead of GRU, we replace them with LSTM networks in the **q**-layers. We employ Mean Square Error (MSE) loss for the blockage prediction problem as training fuction:

$$l_{MSE} = \sum_{t=1}^{T} (p_t - \hat{p}_t)^2 \tag{12}$$

where p_t and $\hat{p}_t$ are the blockage probability of the link status. There are two link statuses, 0 and 1. Then, RMSE is defined as below:

$$RMSE = \sqrt{l_{MSE}} \tag{13}$$

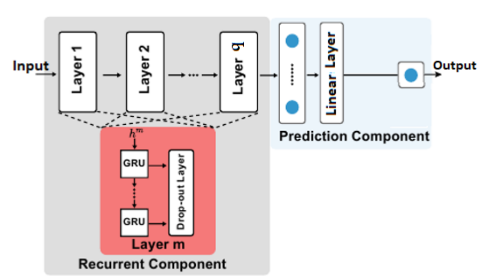

Fig. 2. The adopted GRU architect model to predict the link status [10].

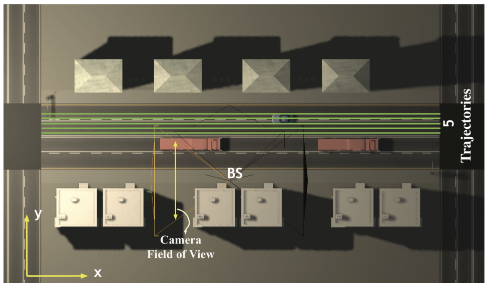

Fig. 3. The selected scenario, "colo_cam_blk", in ViWi Dataset Generation Framework [12].

V. Experimental Setup

The scenario takes place in an urban area surronded with buildings. Due to rush-hour traffic, two buses are unable to move and are acting as obstacles between the moving vehicles and the IRS. In addition, the BS is installed at the top left, beside the traffic light. We designate "BS" as the IRS in Fig. 3, and the user's vehicle moves along five of these trajectory paths, which total 5000 points. It is assumed that the moving vehicle is travelling at 32.04 km/h while transmitting omnidirectional pilot signals with a single antenna (10 ms every 0.089 m). This scenario's dataset is generated by the Vision-Wireless (ViWi) framework for dataset generation [12]. It is named "colo_cam_blk" as shown in Fig. 3. It has high-fidelity synthetic wireless data samples generated by ray-tracing software, Remcom Wireless Insite. In addition, 10% of the sequences are selected as test sets, and they are excluded from training (70%) and validation (20%) sets from a total of 5000 samples in order to further improve the model and validate if there are any training-related biases.

Using the system model defined in Section II, we utilise the IRS to predict future blockage links between the IRS and the user of a moving vehicle. The IRS adopts a Uniform Plannar Array (UPA) structure with 32×32 ($M = 1024$) antennas at the mmWave 60 GHz setup. The spacing between antenna elements is set to half the wavelength, where λ is the antenna's operating wavelength. The remaining parameters of the adopted ViWi dataset are summarised in Table I.

TABLE I
The ViWi Dataset Parameters

Dataset Parameter	Value
Frequency band	60 GHz
Active IRS	1
Number of IRS Antennas	$(M_x, M_y, M_z) = (32, 1, 32)$
Active users	From 1 to 5000
System bandwidth	125MHz
Number of OFDM subcarriersr	64
Number of OFDM sampling factor	1
Number of OFDM limit	64
Number of channel paths	{1, 20}
Antenna spacing	0.5λ

VI. Performance Evaluation

With active elements embedded on the IRS, the noisy channel vectors power can be estimated by receiving the pilot signal from the user moving at each point. Then, we feed the sequence, S_{uo}, to the ML model to predict the blockage. Let S denotes the total of the sample size. Hence, the accuracy can be calculated as below:

$$Accuracy = \frac{1}{S}\sum_{s=1}^{S} \mathbb{1}(B_{T_p}^{(s)} = \hat{B}_{T_p}^{(s)}) \ , \tag{14}$$

where $\mathbb{1}$ is the indicator function, and $B_{T_p}^{(s)}$ and $\hat{B}_{T_p}^{(s)}$ are the target link status and predicted link status within future time instances of T_p in the problem respectively.

By increasing the number of active elements, $\bar{M}$, in the IRS surface with 32x32 elements, the LSTM model is trained and converged with better performance metrics, higher accuracy, and lower RMSE value, which is validated with the test set as depicted in Fig. 4 when only the strongest channel path, L, is considered and with a time instance of 400 ms. Moreover, when a more realistic scenario with multiple channel paths due to building reflections or other reflective surfaces is considered, the performance decreases as the number of channel paths, L, considered increases.

Furthermore, to compare the performance of the GRU model and the LSTM model, the performance metrics of both models are evaluated when L equals 20 based on the future blockage prediction time instance, T_p, using the test set depicted in Fig. 5 and Fig. 6 for RMSE and accuracy. The GRU model can predict future blockages one second before NLoS between the IRS and the moving vehicle or user with high accuracy, 99.17%, and a low RMSE value, 0.0875, whereas the LSTM model achieves accuracy of 98.96% and RMSE value of 0.105. Observing both performance metrics, the GRU model performs slightly better than the LSTM model with an increase in T_p. The best-trained GRU model for future blockage predictions can predict 400 ms before NLoS occurs with an accuracy of 99.37% and a low RMSE value of 0.0707. It performs slightly better than the LSTM model when

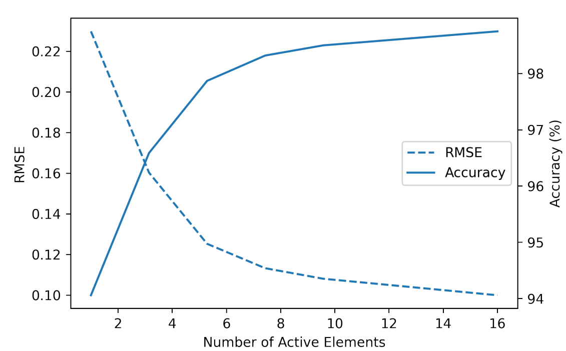

Fig. 4. The LSTM model blockage prediction RMSE value and accuracy versus the number of active elements when L=1 and T_p= 400 ms.

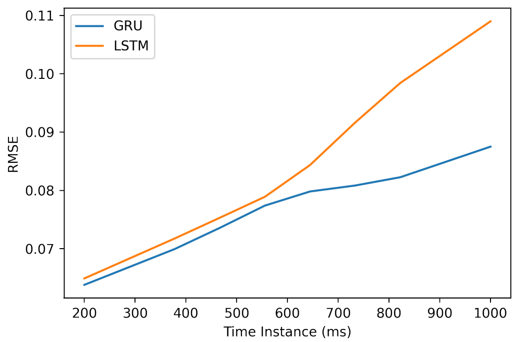

Fig. 5. Comparison between the GRU model and the LSTM model in RMSE value versus future time instance.

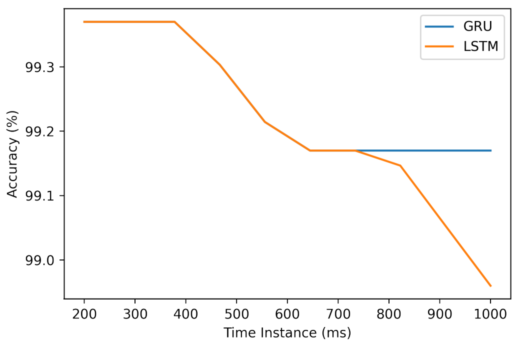

Fig. 6. Comparison between the GRU model and the LSTM model in accuracy versus future time instance.

predicting future blockages. With a high degree of accuracy, 99.17%, and a low RMSE value of 0.0876, the GRU model can predict future blockages between IRS and a moving vehicle user.

Additionally, Table II provides a summary of the findings for all research mentioned that take a proactive approach to blockage prediction.

VII. Conclusion

This study found that IRS-assisted vehicular network blockage prediction with ML techniques can attain significant outcomes with enhanced accuracy and low RMSE. The ability of the model to predict future blockages improves as the number of active elements increases. However, the performance decreases as the number of channel paths considered increases. Furthermore, these results suggest that a system assisted by the IRS is able to predict the future status of links. Although the GRU model and the LSTM model have been very similar in terms of their performance, this may not be the case with larger datasets and more variables considered in the equations.

In future research, multiple IRSs can be incorporated into scenarios employing cooperative techniques to improve the reliability of vehicular networks. Furthermore, mobility of obstacles can be taken into consideration for more realistic simulations.

TABLE II
Summary of all future blockage prediction results for comparison.

Paper No.	Sensory Data Types	ML Model	Instance (ms)	Accuracy (%)
[6]	Vision-aided and wireless	CNN & GRU	Near Future	≈ 86
[7]	Radar	LSTM	1000	>90
[8]	Lidar	CNN	1000	>80
[10]	Wireless data	CNN	830	>65
[10]	Wireless data	GRU	830	>65
Proposed LSTM	Wireless data	LSTM	1000	>98
Proposed GRU	Wireless data	GRU	1000	>99

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References

[1] C. De Alwis, A. Kalla, Q.-V. Pham, P. Kumar, K. Dev, W.-J. Hwang, and M. Liyanage, "Survey on 6g frontiers: Trends, applications, requirements, technologies and future research," *IEEE Open Journal of the Communications Society*, vol. 2, pp. 836–886, 2021.

[2] F. Tang, Y. Kawamoto, N. Kato, and J. Liu, "Future intelligent and secure vehicular network toward 6g: Machine-learning approaches," *Proceedings of the IEEE*, vol. 108, no. 2, pp. 292–307, 2019.

[3] C. De Lima, D. Belot, R. Berkvens, A. Bourdoux, D. Dardari, M. Guillaud, M. Isomursu, E.-S. Lohan, Y. Miao, A. N. Barreto *et al.*, "Convergent communication, sensing and localization in 6g systems: An overview of technologies, opportunities and challenges," *IEEE Access*, 2021.

[4] Q. Wu, S. Zhang, B. Zheng, C. You, and R. Zhang, "Intelligent reflecting surface aided wireless communications: A tutorial," *IEEE Transactions on Communications*, 2021.

[5] H. Gacanin and M. Di Renzo, "Wireless 2.0: Toward an intelligent radio environment empowered by reconfigurable meta-surfaces and artificial intelligence," *IEEE Vehicular Technology Magazine*, vol. 15, no. 4, pp. 74–82, 2020.

[6] G. Charan, M. Alrabeiah, and A. Alkhateeb, "Vision-aided dynamic blockage prediction for 6g wireless communication networks," in *2021 IEEE International Conference on Communications Workshops (ICC Workshops)*. IEEE, 2021, pp. 1–6.

[7] U. Demirhan and A. Alkhateeb, "Radar aided proactive blockage prediction in real-world millimeter wave systems," *arXiv preprint arXiv:2111.14805*, 2021.

[8] S. Wu, C. Chakrabarti, and A. Alkhateeb, "Lidar-aided mobile blockage prediction in real-world millimeter wave systems," *arXiv preprint arXiv:2111.09581*, 2021.

[9] A. Taha, M. Alrabeiah, and A. Alkhateeb, "Enabling large intelligent surfaces with compressive sensing and deep learning," *IEEE Access*, vol. 9, pp. 44 304–44 321, 2021.

[10] S. Wu, M. Alrabeiah, C. Chakrabarti, and A. Alkhateeb, "Blockage prediction using wireless signatures: Deep learning enables real-world demonstration," *arXiv preprint arXiv:2111.08242*, 2021.

[11] M. Alrabeiah and A. Alkhateeb, "Deep learning for mmwave beam and blockage prediction using sub-6 ghz channels," *IEEE Transactions on Communications*, vol. 68, no. 9, pp. 5504–5518, 2020.

[12] M. Alrabeiah, A. Hredzak, Z. Liu, and A. Alkhateeb, "Viwi: A deep learning dataset framework for vision-aided wireless communications," in *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*. IEEE, 2020, pp. 1–5.