JOURNAL OF INFORMATION SCIENCE AND ENGINEERING 40, 1057-1069 (2024)
DOI: 10.6688/JISE.202409_40(5).0009

Multivariate Machine Learning Models for Accurate and Robust Multi-UAV Network Throughput Prediction

WEI JIAN LAU[1,+], JOANNE MUN-YEE LIM[1], CHUN YONG CHONG[2], NEE SHEN HO[3] AND THOMAS WEI MIN OOI[4]

[1]*Department of Electrical and Robotics Engineering, School of Engineering*
[2]*School of Information Technology*
Monash University Malaysia
Bandar Sunway, Selangor, 47500 Malaysia
[3]*Client Computing Group*
Intel Research and Development Ireland Ltd.
Leixlip, W23 N2T7 Ireland
[4]*Network and Edge Group*
Intel Microelectronics Sdn. Bhd.
Penang, 11900 Malaysia
E-mail: wei.lau@monash.edu[+]; joanne.lim@monash.edu; chong.chunyong@monash.edu; nee.shen.ho@intel.com; thomas.wei.min.ooi@intel.com

Anticipatory Multi-Unmanned Aerial Vehicles (UAVs) Network is the key to the realization of high-bandwidth and demanding multi-UAV applications in the future. An accurate and robust Channel Quality Prediction (CQP) model is essential in such anticipatory networks to facilitate the eventual optimization step. However, the models that are proposed in the literature are typically designed for static cellular networks and do not consider robustness or the cross-domain CQP accuracy as a key performance indicator. In this paper, we investigate the efficacy of three different Machine Learning (ML) models in CQP for multi-UAV networks by training them with univariate and multivariate network metrics data curated through OMNeT++ simulations. The models are then evaluated in two-folds via in-domain and cross-domain evaluations to test their accuracies and robustness, respectively. The results from the in-domain evaluations show that multivariate data is key to improving the in-domain performance of the ML models for multi-UAV network throughput prediction, whereas the cross-domain evaluations reveal that more complex models like the Seq2seq are necessary for achieving good robustness against multi-UAV network environments that have different operating conditions, with a maximum improvement in cross-domain CQP performance of 200% over the other implemented ML models.

Keywords: multi-UAV network, channel quality prediction, machine learning, deep learning, time-series forecasting

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are becoming more pervasive and ubiquitous recently with many applications that leverage multi-UAV setups emerging. This phenomenon results in the need for the design of effective and efficient multi-UAV networks. Anticipatory Mobile Networking (AMN) is a promising technique that can be used to realize such multi-UAV network designs. This technique leverages accurate prediction of the future evolution of channel qualities in a network to effectively optimize the network

Received February 10, 2023; revised May 9 & June 28, 2023; accepted July 24, 2023.
Communicated by Chin Ying Liew.
[+] Corresponding author.

resource usage and utilization and improve the network performance and capabilities [1]. AMNs have shown great successes in many network optimization use-cases, especially cellular networks, such as handover [2] and Random-Access Control (RACH) optimizations [3]. However, anticipatory networking remains largely unexplored for multi-UAV networks due to the challenging operating conditions with highly dynamic nodes and intermittent links. Most network optimization methods for a multi-UAV network are reactive, rather than proactive, which significantly hinders their adaptability because the channel quality variations are rapid and have short temporal coherences [4].

Existing Channel Quality Prediction (CQP) models that can be found in the literature are mostly designed for cellular networks [2, 3, 5-7] which exhibit significantly distinct network characteristics when compared to a highly dynamic multi-UAV network, where the latter often exhibit sporadic and intermittent links [4]. More importantly, these models often overlook the robustness of the model in terms of cross-domain CQP accuracy and focus only on the in-domain accuracy [2, 3, 5-10]. This presents a major limitation that prohibits widespread use of CQP models in actual anticipatory networks which is the models' inability to adapt to varying network operating conditions without retraining. This issue is exacerbated in a multi-UAV network due to the time-varying characteristics of the network conditions owing to the node mobilities [4]. Therefore, it is unclear whether the existing models can perform high-accuracy in-domain and cross-domain CQP when deployed in a multi-UAV network.

In our previous work, we have investigated the efficacies of three univariate ML methods with increasing levels of complexity in CQP for multi-UAV networks [11]. This paper presents an extension to our original work, whereby we study and assess the multivariate versions of these models and compare them with the univariate models. The main contributions of the paper are as follows:

- Univariate and multivariate versions of three different ML models with increasing complexity – Random Forest, Long Short Term Memory (LSTM) and Sequence-to-sequence (Seq2seq), and longer prediction horizons are implemented and tested through in-domain evaluations.
- The throughput prediction accuracies of the multivariate ML models in network environments with varying link capacities, relative contention levels and traffic loads are tested through cross-domain evaluations to study their robustness.

2. LITERATURE REVIEW

Data-driven methods utilizing various ML methods are generally more popular compared to analytical methods for CQP in wireless networks due to their black-box design. Table 1 presents an overview of the recent work in CQP that utilizes ML methods.

Table 1 shows that most CQP models proposed in the literature are designed for cellular [2, 3, 5-7] or terrestrial-based Wi-Fi networks [9] where the nodes have low mobilities. This is in contrast with a multi-UAV network where high mobility nodes are prevalent which results in time-varying channel qualities that have shorter temporal coherences. Therefore, a model that is trained using data from cellular or terrestrial networks is not readily transferable to a multi-UAV network. One work [8] has designed a CQP model for next generation 6G vehicular networks which comprises nodes with higher mobilities, but they are still confined to 2-Dimensional mobility models, unlike UAVs in multi-UAV networks. To the best of our knowledge, only one work done in [10] has devised an RNN-based online throughput prediction framework for UAV-to-Ground Control Station (GCS) communications. However, the authors considered only a single-UAV setup, rather than a multi-UAV setup where channel access contention and co-channel interferences are prominent features.

Table 1. Overview of recent work on data driven CQP models (Multi-multivariate, Uni-Univariate).

Network	Ref	Input Data Type	Output	Model	Prediction Horizon	Cross-domain performance?
Vehicular	[8]	Multi	Data rate	ANN, Random Forest (RF), Support Vector Machines	1s	N/A
Cellular	[2]	Multi	Bandwidth	TPA-LSTM	1-3s	N/A
	[3]	Uni	Network traffic	LSTM	1 slot	N/A
	[5]	Multi	Link bandwidth	RF	1s	N/A
	[6]	Multi	Future throughput	LSTM	1s	N/A
	[7]	Multi	Network traffic	LA-ResNet	1s	N/A
Many	[9]	Uni	Received Signal Strength Indicator (RSSI)	DeepChannel (Seq2seq)	10s	N/A
UAV network	[10]	Uni	Throughput	RNN	1s	N/A

Furthermore, the overview also shows that many different ML methods, from classical models to more sophisticated recurrent-based models, have been employed for designing CQP models in recent works. However, these models are often designed with short prediction horizons (1-3s), except for DeepChannel [9], which makes them less ideal for predictive optimizations in an anticipatory network. This is because inferencing and optimization loops with short intervals can introduce large network operations overhead that impacts the overall network performance. Thus, a major gap in the practical deployment of these models regarding the length of the prediction horizon exists as it is desirable to achieve high-accuracy CQP for longer term prediction horizons in anticipatory networks.

Furthermore, all the recent works have focused solely on the in-domain accuracies of the proposed CQP models and overlook cross-domain accuracy, or robustness, of their models. This represents another major gap that exists in the practical deployments of these CQP models in actual networks because it is undesirable to retrain a CQP model with data from the deployment environment as it is computationally expensive and inefficient. This issue is also exacerbated by the highly dynamic network conditions and shorter network lifetime of a multi-UAV network. Therefore, it is important that a CQP model designed for dynamic wireless networks like multi-UAV networks is both accurate for the network environment that it is trained in and robust towards new and unseen network environments. A key focus of this paper is to assess the in-domain and cross-domain accuracies of the models with a moderately long prediction horizon that is beyond one time slot, through the evaluations of three ML methods with univariate and multivariate configurations, so that a proper method can be recommended for future work in CQP for multi-UAV networks.

3. DATASET GENERATION AND ANALYSIS

This section discusses the methodology used to generate and curate the multi-UAV network metrics dataset that is used to train and evaluate the implemented ML models. Aside from that, we also study the correlation between the collected channel quality metrics and the throughput which is the target metric for the CQP models.

3.1 Dataset Generation

OMNeT++ simulator is utilized to generate and curate a comprehensive channel qualities dataset for multi-UAV networks under varying operating conditions [12]. The simulated network consists of ten freely moving member UAVs that are connected and communicating with a dedicated and stationary UAV-Base Station (UAV-BS) via IEEE802. 11g wireless links which mimics actual use-cases where continuous transfer of video feeds or images are required such as in Search and Rescue (SAR) missions [13].

Table 2. Simulation and network parameters.

Parameter	Value	Parameter	Value
Transmit Power	100mW	Background Noise Power	–86 dBm
IEEE 802.11g Channel	1	Antenna Gains (Transmitter and Receiver)	0 dB
Path Loss Exponent	2	Nakagami-*m* shape parameter	4
Mobility Model	Random Waypoint Mobility Model (RWPM)	Max Speed	5 m/s
Contention Level, *N*	Low – 1 UAV Medium – 5 UAVs High – 10 UAVs	Traffic Load, *A*	5Mbps, 10Mbps
802.11g bitrate, *B*	18Mbps, 54Mbps	Traffic Pattern	Constant Bit Rate (CBR)

Each actively transmitting UAV communicates CBR traffic data to a UAV-BS, which generates interference and contention among all transmitting UAVs. From the simulations, a dataset consisting of five network metrics recorded in one second interval over the simulation period is generated. These metrics include the observed throughput, Signal-to-Interference Plus Noise Ratio (SINR), RSSI, delay, and distance.

Another major consideration for the simulations is to simulate and collect data from different instances of the multi-UAV network with varying network operating conditions and parameters. As such, three different parameters are varied across the simulations, including the number of actively transmitting UAVs (*N*) which determine the relative network contention level, the traffic load (*A*), and the data carrying capacities (*B*) of the IEEE 802.11g links. These three parameters are varied because they are commonly affected by the mobilities of the nodes as they move in and out of the communication range of the UAV-BS. At the Physical Layer, the links are subjected to Friss Path Loss [14] and Nakagami-*m* Fast Fading [15]. Furthermore, we assume that the UAV-to-UAV links are in Line-of-Sight (LoS) to simplify the network simulations. All other simulation and network parameters are kept the same throughout all instances of the simulated networks and are tabulated in Table 2.

By varying the three parameters, N, A, and B, a collection of twelve datasets, denoted as $\mathcal{D}_i$, $i \in \{0, 1, \ldots, 11\}$, is curated. Out of these twelve datasets, one dataset is dedicated as the main training dataset which is denoted by $\mathcal{D}_0$, and has the following parameters: N=Medium, A=10Mbps and B=18Mbps. Each multi-UAV network instance is simulated for 10 minutes, except for $\mathcal{D}_0$ which is simulated for 30 minutes as more network metrics data is needed for training and testing the ML models compared to the other instances which are used for evaluation purposes only.

3.2 Data Analysis

After the data collection process, we first study the correlation of the network metrics for the main training dataset, $\mathcal{D}_0$, with the future throughput, which is the prediction target for the CQP models. This study allows us to determine if the multivariate network metrics are significantly correlated with the prediction target as a justification for the selection of the network metrics for training the CQP models. The Pearson correlation scores between each individual metric and the next second of observed throughput are also calculated to quantify the correlation using the following formula,

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \tag{1}$$

where x_i and y_i are two time-series variables that are under investigation whereas $\bar{x}$ and $\bar{y}$ represent the mean of the time-series variables. Furthermore, we also visualize the correlation of the data by plotting a scatter plot of each individual network metric against the next second of observed throughput in Fig. 1 with the Pearson correlation scores shown on top of each scatter plot.

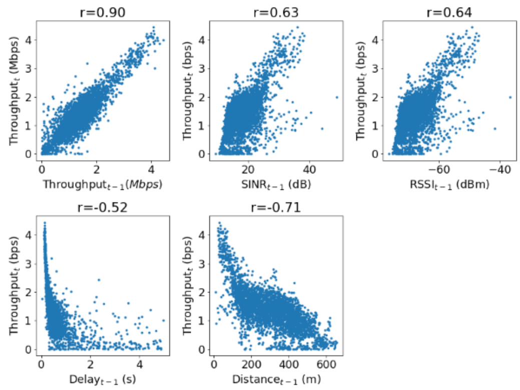

Fig. 1. Scatter plots of the network metrics and the next throughput.

It is observable from Fig. 1 that the current observed throughput has strong positive correlation with the future throughput as the throughput is unlikely to change rapidly from one second to the next. Aside from that, the SINR and RSSI have moderately strong positive correlation with the future throughput. This observation implies that these Physical Layer metrics, which indicate the level of impairments of the wireless links, can also be used to infer the evolution of future throughput. On the other hand, the delay and distance exhibit negative correlation with the future throughput. This observation implies that when the delay experienced by a flow is high or the distance between the nodes is long, it is highly likely that the throughput in the next second will be lower as well.

In summary, we observe that all five of the collected network metrics exhibit moderate to strong positive or negative correlations with the future throughput which reinforces our choice of network metrics to act as input to the CQP models. These observations also give strong merits to only train the models using a simpler univariate dataset due to its already strong positive temporal correlation. However, we argue that the other metrics can also provide useful information to the CQP models through their moderately strong correlations.

3.3 Data Preprocessing

As a first step, windowing is performed on the data to transform them into a dataset of subsets of the five collected network metrics, consisting of $w = 10$ time steps of historical observations and $v = 5$ time steps of prediction targets. The SINR, RSSI, delay, and distance metrics are scaled with min-max scaling to transform the values into the range 0-1. These transformations allow the CQP models to process and learn from data which have similar scales and ranges, as it is beneficial to their training process. Finally, the main dataset, $\mathcal{D}_0$, is split into the training, validation, and test sets via a 7:1.5:1.5 split.

4. MACHINE LEARNING METHODS

This section introduces and details the three ML methods that are implemented in this paper for multi-UAV network throughput prediction. These three models are selected based on their prevalence in recent works [2, 3, 5, 6, 8, 9] and the varying levels of model complexities, which allows us to investigate the level of complexity required to design an accurate and robust CQP model for multi-UAV networks.

4.1 Random Forest (RF)

RF is an ensemble learning-based model [16], comprising a combination of decision trees that are trained using random subsets of the training data that are sampled independently. The forest is then trained through bootstrap aggregating which is an ensemble meta-algorithm that helps to reduce variance and prevent overfitting. In regression tasks, the final prediction from the forest is obtained by averaging the outputs of each constructed tree in the forest.

4.2 LSTM

The main strength of a LSTM network [17] compared to a normal RNN architecture lies in its ability to deal with the vanishing gradient problem that exists for a vanilla RNN where the model fails to capture long time dependencies when the predictions are made. LSTM networks can retain long time dependencies due to the inclusion of multiple logical gates in each of its cells that control the flow of information. In this paper, the LSTM architecture is designed to perform many-to-many predictions because the problem involves multi-step forecasting. The Fully Connected layer has v units, one for each of the prediction time step and have nonlinear activation functions of Rectified Linear Unit (ReLU).

4.3 Seq2seq

Seq2seq model is a Deep Learning (DL) RNN architecture comprising two main components – an encoder and a decoder. In this problem, the encoder receives the historical network metrics, **X**, as the inputs and produces a context vector, ***C***, which represents a summary of the input sequence in the latent space. This context vector is then used to initialize the states of the decoder for predictions. The encoder and decoder are two separate RNNs with LSTM cells as the underlying recurrent units, following the DeepChannel implementation [9]. At the j^{th} input time step, the input from the sequence, x_i^j, is fed into the corresponding LSTM cell which produces an output vector and an internal states vector, comprising of the hidden and cell states, based on the internal states propagated from the previous time step. At the final time step of the input sequence, the internal states vector of the last LSTM cell is treated as ***C***. At the decoder's side, the input to the first decoder LSTM cell is the last observation from the input sequence and its internal state is initialized using ***C*** to generate the LSTM outputs for the current time step. The outputs from the LSTM cells are then propagated through a Fully Connected layer with ReLU activation function to get the prediction for the first-time step in the output sequence, $\hat{y}_i^{t+1}$, where t is the end of the history window. Fig. 2 visualizes the Seq2seq architecture used in this work unrolled in time to show the inputs and outputs of the model, where w denotes the number of historical observations. In this work, we also extend the base architecture of DeepChannel to a multivariate version and study its CQP performance in multi-UAV networks.

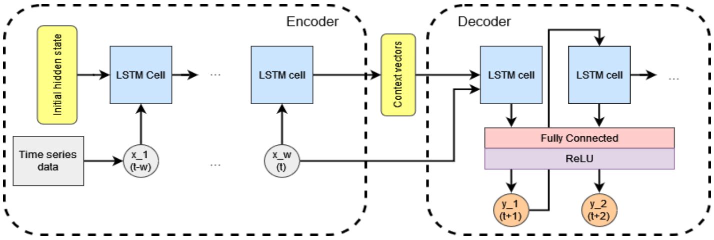

Fig. 2. Seq2seq model unrolled in time.

5. RESULTS AND DISCUSSION

In this section, we describe the setup of the experiments used to evaluate and compare the performances of the CQP models and their variations as introduced in Section 4. The models are compared in two-fold via in-domain and cross-domain evaluations.

5.1 Experimental Setup

Models and hyper-parameters: As discussed in Section 4, three different ML models are implemented, namely RF, LSTM, and Seq2seq models. Specifically, the univariate Seq2 seq model follows the implementation of DeepChannel [9] whereas the multivariate version is an extension to that original model. Grid search is performed for the LSTM and Seq2seq models and the best combination of hyperparameters is tabulated in Table 3. The same hyperparameter settings are used to implement both the univariate and multivariate versions of the two models. On the other hand, the RF model is implemented using the default hyperparameters for the Random Forest Regressor model implemented by the open-source scikit-learn library [18].

Table 3. Hyperparameters for the LSTM and Seq2seq models implemented in this work.

Parameter	LSTM	Seq2seq
Batch Size	32	32
Number of Hidden Layers	3	Encoder: 2, Decoder: 1
Number of Hidden Node	256	Encoder: 256, Decoder: 256
Number of epochs	100	
Optimizer	Adam	
Loss Function	Mean Squared Error	
Initial Learning Rate	0.001	
LR Regularization	Patience = 20, Factor = 0.1	

Metrics: The performances of the models are measured and compared in terms of the Mean Squared Error (MSE) and coefficient of determination, R^2, between the actual and predicted throughput. MSE and R^2 are mathematically expressed as Eqs. (2) and (3), respectively.

$$MSE_i = \frac{1}{v}\sum_{i=1}^{v}(\hat{y}_{t+i}^2 - y_{t+i}^2) \tag{2}$$

$$R_i^2 = 1 - \frac{\sum_{i=1}^{v}(\hat{y}_{t+i} - y_{t+i})^2}{\sum_{i=1}^{v}(\bar{y} - y_{t+i})^2} \tag{3}$$

In Eq. (3), $\bar{y}$ represents the average throughput over the v prediction time steps.

Platform: All the models are trained on a commodity PC with an RTX 2060 GPU, 8-cores CPU and 16GB RAM.

5.2 In-Domain Evaluations

Table 4 presents the in-domain CQP accuracies in terms of the performance metrics of both the univariate and multivariate versions of the three ML models for the in-domain evaluations. From Table 4, it can be observed that the addition of four extra multivariate network metrics in the input, namely SINR, RSSI, delay, and distance helps improve the performance of all ML models, as evident by the improved accuracies between the multivariate and univariate versions of all models. This is because the multivariate data provides the models with more information regarding the current network state to achieve better forecasting performance. In some cases, the improvement is substantial such as the significant reduction in MSE for the Seq2seq model when compared to the univariate version used for Deep Channel [9]. This improvement indicates that the more complex architecture of the Seq2seq model bodes well with the more complex multivariate data. Despite its impressive CQP accuracy, the Seq2seq model has significantly longer inferencing time when compared to the RF model [5, 8] which has a simpler architecture. The results also show that the inferencing time of the models increases with both model and training complexities as the use of multivariate training data results in slight increases in inferencing times across all models as well. From these results, we conclude that multivariate network metrics data is crucial to improving the in-domain prediction accuracy of a CQP model, especially for dynamic multi-UAV networks.

Table 4. In-domain evaluation performances.

Model	RF [5, 8]		LSTM [2, 3, 6]		Seq2seq	
	Uni	Multi	Uni	Multi	Uni [9]	Multi
MSE	0.220	0.210	0.420	0.290	0.955	**0.137**
R^2	0.800	**0.800**	–0.574	–0.096	–2.617	0.48
Inferencing Time (ms)	**0.117**	0.163	0.568	0.573	1.508	1.537

5.3 Cross-Domain Evaluations

Table 5 tabulates the performances of each multivariate ML model in the cross-domain evaluations. The remaining datasets from the set collected through the methodology outlined in Section 3.1, $\mathcal{D}_i$, $i \in \{0, 1, \ldots, 11\}$, are used to perform the cross-domain evaluations. Note that the combination of $B = 18$Mbps, $A = 10$Mbps and $N =$ Medium is missing from Table 5 because it represents the main training dataset, $\mathcal{D}_0$. Therefore, the eleven other multi-UAV network instances utilized for this evaluation represent unseen network operating conditions and environments to the trained CQP models.

Table 5. Cross-domain evaluation performances of the multivariate models in terms of MSE.

B (Mbps)	A (Mbps)	N	RF [5, 8]	LSTM [2, 3, 6]	Seq2seq
18	5	Low	7.86	4.51	**1.01**
		Medium	1.4	0.56	**0.16**
		High	0.7	0.27	**0.14**
	10	Low	8.39	7.05	**1.57**
		High	0.66	0.3	**0.2**
54	5	Low	0.98	0.44	**0.31**
		Medium	2.61	1.34	**0.81**
		High	0.28	**0.09**	0.13
	10	Low	5.03	6.99	**3.48**
		Medium	2.91	3.28	**1.62**
		High	2.93	2.11	**1.2**
Average			**3.07**	**2.45**	**0.966**

It is observable from Table 5 that the multivariate Seq2seq model outperforms the RF [5, 8] and LSTM [2, 3, 6] models, which are commonly used for CQP, in terms of cross-domain CQP accuracies against new network environments in ten out of the eleven tested scenarios, with significantly better average performance. This incredible robustness can be attributed to its more complex architecture with the encoder-decoder structure being more capable of learning deeper temporal representations of the data during the training process. Despite its impressive accuracy in the in-domain evaluations, the RF model [5, 8] exhibits a significant lack of robustness due to its simpler architecture. We argue that strong robustness, on top of high forecasting accuracy, is one of the key features that a CQP model must possess so that it is able to adapt to the ever-changing network environment in real multi-UAV networks. Therefore, a more complex architecture such as the Seq2seq is necessary for designing a robust and accurate CQP model for multi-UAV networks, provided that the trade-off between inferencing complexity and performance is well-balanced.

6. CONCLUSION

A reliable and accurate CQP model is the main component for an effective anticipatory multi-UAV network. In this paper, we implemented and assessed three different ML models, trained using univariate and multivariate network metrics data, to determine the suitable level of model and dataset complexity to achieve high accuracy and robustness. From the in-domain and cross-domain evaluations, it is demonstrated that multivariate input data is crucial to achieving high in-domain accuracy with an improvement of 85% for the Seq2seq model. Furthermore, multivariate models with more complex architectures, like the Seq2seq model, demonstrated impressive robustness by outperforming the other models with a maximum improvement of 200% in certain network environments due to its stronger learning capabilities. The significant differences in CQP performance for the simpler RF model in the in-domain and cross-domain evaluations have demonstrated the need to consider both accuracy and robustness when designing a CQP model for an anticipatory multi-UAV network. Despite the impressive accuracy and cross-domain robustness, the Seq2seq model still exhibits unacceptably high MSE in certain network environments, which can be detrimental in the predictive optimization step that follows. It is proposed that future work can focus on exploring the use of transfer learning techniques with the multivariate Seq2seq model, to develop a more robust CQP model with better cross-domain performance. Furthermore, the results have also shown that the inferencing time of the Seq2seq model is significantly longer than a simpler model which can be a concern in ensuring the real-time performance of a network. One possible way to mitigate this problem is to increase the prediction horizon so that the inferencing loop interval can be increased to reduce the overhead in the network operations.

ACKNOWLEDGEMENT

This work was funded by the Collaborative Research in Engineering, Science and Technology Center (CREST), Intel Microelectronics (M) Sdn Bhd and Department of Electrical and Robotics Engineering, School of Engineering, Monash University Malaysia under the grant number, P05C1-18. The authors would also like to thank CREST for their continuous support in this research (Grant no. P05C1-18).

REFERENCES

1. N. Bui, M. Cesana, S. A. Hosseini, Q. Liao, I. Malanchini, and J. Widmer, "A survey of anticipatory mobile networking: Context-based classification, prediction methodologies, and optimization techniques," *IEEE Communications Surveys & Tutorials*, Vol. 19, 2017, pp. 1790-1821.
2. L. Mei, J. Gou, Y. Cai, H. Cao, and Y. Liu, "Realtime mobile bandwidth and handoff predictions in 4G/5G networks," *Computer Networks*, Vol. 204, 2022, No. 108736.
3. N. Jiang, Y. Deng, and A. Nallanathan, "Traffic prediction and random access control optimization: Learning and non-learning-based approaches," *IEEE Communications Magazine*, Vol. 59, 2021, pp. 16-22.
4. L. Burhanuddin, X. Liu, Y. Deng, U. Challita, and A. Zahemszky, "QoE optimization for live video streaming in UAV-to-UAV communications via deep reinforcement learning," *IEEE Transactions on Vehicular Technology*, Vol. 71, 2021, pp. 5358-5370.
5. C. Yue, R. Jin, K. Suh, Y. Qin, B. Wang, and W. Wei, "LinkForecast: Cellular link bandwidth prediction in LTE networks," *IEEE Transactions on Mobile Computing*, Vol. 17, 2018, pp. 1582-1594.
6. D. Raca *et al*., "On leveraging machine and deep learning for throughput prediction in cellular networks: Design, performance, and challenges," *IEEE Communications Magazine*, Vol. 58, 2020, pp. 11-17.
7. M. Li, Y. Wang, Z. Wang, and H. Zheng, "A deep learning method based on an attention mechanism for wireless network traffic prediction," *Ad Hoc Networks*, Vol. 107, 2020, No. 102258.
8. B. Sliwa, R. Falkenberg, and C. Wietfeld, "Towards cooperative data rate prediction for future mobile and vehicular 6G networks," in *Proceedings of the 2nd 6G Wireless Summit*, 2020, pp. 1-5.
9. A. Kulkarni, A. Seetharam, A. Ramesh, and J. D. Herath, "DeepChannel: Wireless channel quality prediction using deep learning," *IEEE Transactions on Vehicular Technology*, Vol. 69, 2020, pp. 443-456.
10. Y. Jiang, K. Nihei, J. Li, H. Yoshida, and D. Kanetomo, "Learning on the fly: An RNN-based online throughput prediction framework for UAV communications," in *Proceedings of IEEE International Conference on Communications Workshops*, 2020, pp. 1-7.
11. W. J. Lau, J. M.-Y. Lim, C. Y. Chong, H. N. Shen, and T. W. Min Ooi, "Machine learning methods for multi-UAV network throughput prediction," in *Proceedings of International Conference on Computer and Drone Applications*, 2022, pp. 107-112.
12. A. Varga, ''OMNet++,'' in *Modeling and Tools for Network Simulation*, Springer, Berlin, 2010, pp. 35-59.
13. V. Papić, P. Šolić, A. Milan, S. Gotovac, and M. Polić, "High-resolution image transmission from UAV to ground station for search and rescue missions planning," *Applied Sciences*, Vol. 11, 2021, No. app11052105.
14. H. T. Friis, "A note on a simple transmission formula," in *Proceedings of the IRE*, Vol. 34, 1946, pp. 254-256.
15. A. F. Molisch, *Wireless Communications*, 2nd ed., Wiley Publishing, Chichester, UK, 2011.
16. L. Breiman, "Random forests," *Machine Learning*, Vol. 45, 2001, pp. 5-32.

17. S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, Vol. 9, 1997, pp. 1735-1780.
18. F. Pedregosa *et al.*, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, Vol. 12, 2011, pp. 2825-2830.

Wei Jian Lau received the B.Eng. (Hons) in Electrical and Computer Systems Engineering from Monash University in November 2020. He is currently pursuing the Ph.D. degree in Monash University in Wireless Communications on Unmanned Aerial Vehicles (UAV). His research interests include UAV wireless communications, anticipatory networking, artificial intelligence/machine learning and intelligent networks.

Joanne Mun-Yee Lim received her Ph.D. in Engineering from Multimedia University. Her research interests include Internet of Things (IoT), intelligent transportation system (ITS), unmanned aerial vehicle (UAV/Drones), vehicular ad-hoc network (VA-NET), artificial intelligence, machine learning, optimization schemes, robotics design and sustainable Systems.

Chun Yong Chong received the MS and Ph.D. degrees in Computer Science from the University of Malaya, Malaysia, in 2012 and 2016, respectively. His current research interests include software maintenance, software clustering, software remodularization, software fault prediction, and metamorphic testing. He was awarded Marie Skłodowska-Curie Research Exchange Fellowship and visited XLAB d.o.o., Slovenia, as a visiting scholar under the EU Project IDENTITY 690907.

Nee Shen Ho received his MS in Reliable Embedded Systems from University of Leicester in 2013 and Bachelor's degree from Multimedia University in 2004. He is currently a Software Program Manager at Intel Research and Development Ireland working on Intel's next generation artificial intelligence accelerator. He used to coordinate strategic university program engagement for Intel's Malaysia Design Center.

Thomas Wei Min Ooi is currently serving as a Director of Central Solutions Enabling in Intel Network and Edge Solutions Group and the APJ leader for Federal and Industrial Business for Intel Network and Edge Solutions Group. Thomas holds a bachelor's degree in Computer Science, MBA and Doctorate in Business Management.