Machine learning-driven analysis of user bandwidth allocation and performance in 5G heterogeneous network: a survey

Pang Wai Leong[1], Raymond Chia[1], Phang Swee King[1], Goh Hui Hwang[1], Chan Kah Yoong[2], Chung Gwo Chin[2]
[1]School of Engineering, Taylor's University, Selangor, Malaysia
[2]Faculty of Artificial Intelligence and Engineering, Multimedia University, Selangor, Malaysia

Article Info

Article history:

Received Oct 31, 2025
Revised Mar 24, 2026
Accepted Apr 27, 2026

Keywords:

5G heterogeneous network
Machine learning
Network slicing
Resource allocation
User-centric

ABSTRACT

A key foundation of 5G heterogeneous networks (HetNets) is the use of network slicing, which divides bandwidth into multiple logical networks and accounts for each function's requirements. Currently, various machine learning (ML) models are being implemented into the network slicing algorithm to allocate bandwidth dynamically. The network slicing algorithm analyzes the traffic and allocates bandwidth based on the current services using a network-centric approach. However, limited work is found on further studying the impact of user-centric algorithms in bandwidth allocation. This paper presents the network slicing used in 5G and the limitations of these algorithms. A detailed review of user-centric bandwidth allocation algorithms is presented, along with a critical review of ML algorithms for traffic prediction and resource allocation decisions. Finally, the technology gaps and opportunities of the existing works are reported, and the direction for further research of ML in user-centric bandwidth allocation algorithms is tabulated.

Corresponding Author:

Chung Gwo Chin
Faculty of Artificial Intelligence and Engineering, Multimedia University
63100 Cyberjaya, Selangor, Malaysia
Email: gcchung@mmu.edu.my

1. INTRODUCTION

As cellular technology and mobile networks have developed over the years, each generation of cellular technology has aimed to improve. Each generation (1G, 2G, 3G, and 4G) exhibited improvements in capacity, data speed, and coverage. The need for dependable and fast data transmission has been increasing, and data transmission technology has been advancing to fulfill this demand. The latest generation of mobile networks is the 5th generation (5G), which began deployment in 2019 and significantly improved the latency and coverage of data transmission compared to 4G cellular technology [1]. The heterogeneous networks (HetNets) architecture combines multiple types of wireless technology into the same network, such as Wi-Fi, long-term evolution (LTE), and 5G. In 5G HetNets, heterogeneity also arises from the coexistence of multiple cell tiers, including Macro, Micro, Pico, and Femto cells, which differ in coverage radius, transmit power, and deployment density. HetNets improve the coverage and capacity of 5G networks but also increase the number of users in the network. Therefore, multiple studies have been conducted on this topic [2]–[5]. With the ever-growing demand of users, the number of users using 5G in 2023 has reached 1.4 billion and is projected to continue increasing until 5.3 billion individual users by 2029 [2]. This does not include all the extra devices, such as internet of things (IoT) devices, where 30 billion devices are connected to a 5G network [6]. Therefore, the demand for 5G networks is expected to significantly increase over the next few years.

5G promises to satisfy the need for reliable and low-latency data transmissions. 5G is nearly a hundred times faster than 4G. However, as there is explosive growth in the number of users, the amount of bandwidth may be insufficient for data transmission requirements, creating a backlog of data. Therefore, more user equipment (UE) is connected to an access point or base station, which increases the latency and packet loss when transmitting data. Therefore, the user's quality of experience (QoE) degrades as the bandwidth may be insufficient for the users' needs [7]. Numerous studies have been conducted to assess network slicing and resource allocation strategies to enhance QoE [8]–[12], which divide the available bandwidth to perform specific tasks based on network traffic. Currently, the most common division for these network slices is the voice over internet protocol (VoIP), one for video services and a final slice for best-effort services that are not time-sensitive (for example, web browsing or email) [13]–[15]. These slices mainly focus on real-time data transmission to allocate more bandwidth for services that might be unsatisfactory to the user experience when packets are lost or have high latency [16]. Therefore, various network slicing methods are being developed to manage network traffic. Numerous bandwidth management methods have been developed to regulate network traffic or predict network traffic outcomes using machine learning (ML) to effectively allocate bandwidth [13]–[18].

Network slicing methods aim to improve the overall traffic of the network by splitting services based on the traffic used, ensuring that certain services have allocated bandwidth, but do not approach the allocation of resources based on individual users. As new technologies such as the internet of vehicles (IoV) and IoT are being developed, the quality of service (QoS) required by each service will vary [19]. Service-centric resource allocation may not achieve the required fine-grained control of resource allocation. Current resource allocation methods do not consider the QoS satisfaction of individual users, and slices are not made to meet users' expectations [14]. Although many efforts have been made to improve network-centric resource allocation and many algorithms have been designed, these algorithms do not consider the resources that each user needs or their level of satisfaction [18], [20]. Therefore, the proposed survey aims to investigate a user-centric solution to allocate bandwidth to various users based on their QoE requirements.

The survey aims to analyze ML in user-centric bandwidth allocation in 5G HetNets. ML-based algorithms allow the system to learn from its experience without the help of programming. Therefore, it makes the system dynamic in nature, as it learns as more data is obtained and changes depending on the scenario. Today's telecommunications industry uses a wide variety of ML algorithms, but the majority fall into supervised learning (SL), unsupervised learning (UL), or reinforcement learning (RL).

SL is a model that requires the data to be labelled, as the model is targeted to learn specific information from the dataset. Therefore, the ML model studies patterns from a dataset to determine the relationship between the input data and the desired output [21]. The raw and unlabeled datasets supply an unsupervised ML model. The data were then analyzed to create different clusters. The ML model learns general patterns and parallels between data points and then categorizes the data into a group that allows the model to decide based on the data type [13], [22].

RL teaches a model based on feedback. As the model has decision-making capabilities for its actions, we used a data point/reference for its decision. RL model is either rewarded or punished for its actions. Therefore, this model constantly looks for a balance between rewards and exploration in its decision, trying to find the best decisions to achieve the highest rewards [23]. An example algorithm is the Q-learning algorithm, which gives model rewards based on the "Q" value for its decision. This "Q" value is determined by the designer. The "Q" value is determined by the throughput for all users and will gain more rewards for higher throughput.

The HetNet architecture aims to combine various wireless technologies into the same network, and researchers have been investigating methods of coexistence with various wireless communication technologies. Research conducted on the coexistence of LTE and Wi-Fi showed performance degradation as the overall throughput was degraded, reducing the users' QoE [24], [25]. Various studies have been conducted to reduce the degradation of throughput owing to interference from the HetNet system. Several modulation methods have been investigated to find modulation methods that reduce the effects of interference between the technologies [24]. Various schedulers for resource allocation are being tested to improve throughput and spectral efficiency to enhance QoS [25]. These works aim to meet QoS requirements for real-time services such as video and VoIP, in a HetNet environment. Resource allocation methods have been proposed to ensure fairness and high throughput for multiple access methods such as non-orthogonal multiple access (NOMA) [26]. Overall, due to the HetNet architecture degrading the overall throughput and QoE of the users, various studies have been conducted to improve throughput when various signals overlap and interfere with each other.

Existing research and several surveys discuss the usage of network slicing for resource allocation and its benefits. Existing research also considers implementing ML for traffic prediction for optimal network slices. ML techniques for network slicing enhance users' QoE, but a key issue with these studies is the lack of exploration of network overloading situations. Therefore, this survey is motivated to explore user-centric

bandwidth allocation algorithms that can potentially improve the QoE of users under the overloaded network. In addition, the current ML algorithms used in resource allocation and the potential implementation in user-centric resource allocation algorithms have also been explored. The following research questions were intended to be addressed by this survey:
a. What are the existing algorithms developed for user-centric resource allocation?
b. Which research directions are emerging in the study of ML-based algorithms for user-centric resource allocation and network traffic prediction?

The following section reviews the paper, provides a summary of the current work, and delivers an in-depth analysis of highly related studies. First, an overview of network slicing algorithms is introduced, and the current algorithms employed in network slicing are discussed. The survey then analyzed the proposed user-centric algorithms. Performing an in-depth analysis of the two works, as there is a lack of current research being conducted on user-centric resource allocation algorithms. The paper then follows with reviews of the current work being done on ML and the comparisons that are made. Finally, we explored algorithms for managing congestion in 5G HetNets.

2. SURVEY METHODOLOGY

We followed a lightweight systematic review protocol. Digital libraries used were IEEE Xplore, Scopus, and Web of Science. Search strings applied to the title, abstract, or keywords were (“user-centric” OR “QoE-aware” OR “utility-based”) AND (“resource allocation” OR “bandwidth allocation” OR “admission control”) AND (“5G” OR “HetNet” OR “RAN”) AND (“machine learning” OR “deep learning” OR “reinforcement learning”). The timeframe covered is January 2019 to December 2025. Eligible papers included peer-reviewed journal or flagship conference publications in English with a primary focus on user-centric resource allocation (UCRA) or ML-driven allocation relevant to 5G or 6G across the radio access network (RAN), core, or edge. Items were excluded if they focused solely on service-centric slicing without a user perspective, were non-technical, or were not written in English. Screening was performed by evaluating titles and abstracts, followed by full-text assessment. The studies that passed screening were then synthesized thematically.

This survey is motivated by the need to better understand user-centric resource allocation, which refers to decision-making based on individual user utility, priority, context, or economic factors, while incorporating machine learning to support prediction, clustering, and closed-loop control. The study aims to answer two key research questions. First, what types of user-centric resource allocation algorithms have been proposed for 5G heterogeneous networks, and how they differ in terms of assumptions, performance metrics, and outcomes. Second, which families of machine learning techniques are most suitable for prediction, clustering, and real-time control tasks within these algorithms, along with their practical limitations. To address these questions, the survey organizes existing research into a structured taxonomy, provides comparative tables, and includes clarifying figures. It also synthesizes the available evidence into practical guidance while maintaining the integrity of the original descriptive content. Figure 1 summarizes the selection flow.

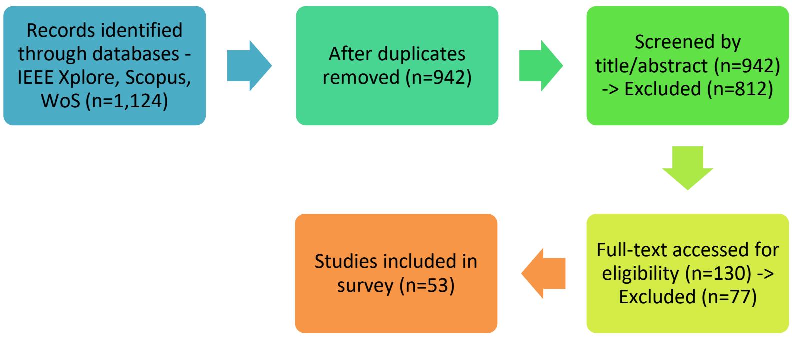

Figure 1. The selection process and screening criteria

3. ANALYSIS OF USER-CENTRIC RESOURCE ALLOCATION

Recent user-centric studies further illustrate practical scenarios in overloaded gNBs [27]–[31]. We group prior works by decision drivers (QoE/utility, economics/market), by ML paradigm (SL/UL/RL), and by deployment locus (edge/D2D), to enable cross-comparison while preserving the details of each study. The overall taxonomy that links ML paradigms, network layers, and UCRA themes is shown in Figure 2.

Research conducted by Chen *et al.* [32] investigated the importance of UCRA for mobile communication and explained the importance of research in this field from an economic perspective. This demonstrates the validity of a UCRA algorithm in which higher-priority users are allocated more resources, while lower-priority users have fewer resources. Using a method called the cumulative distribution function (CDF), they demonstrated that using a UCRA algorithm has the potential to provide a higher overall throughput when there is a high amount of traffic. Demonstrating that when there is more traffic, it might be beneficial to provide higher data rates to users of a higher priority and provide the minimum for users of a lower priority. This work presented the idea of UCRA in 2022 but has researched algorithms that should be used for dynamic allocation.

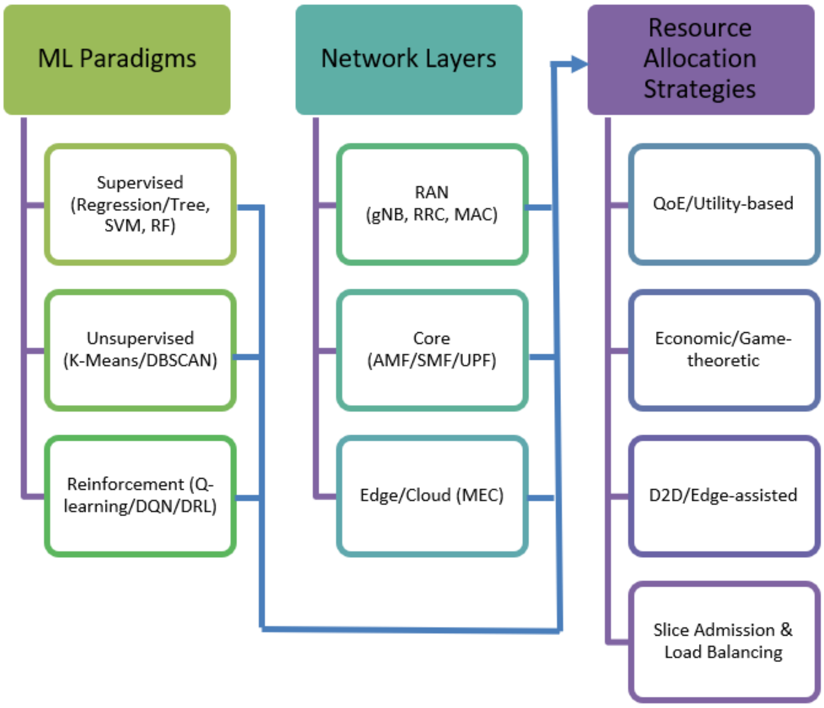

Figure 2. Relationships among ML paradigms, network layers, and user-centric resource allocation themes

3.1. Network slicing in 5G

Before looking into UCRA, one key feature of 5G is network slicing, which can provide a range of services for various types of devices. Unlike other generations of mobile communication, 5G provides three distinct services, i.e., enhanced mobile broadband (eMBB), massive machine-type communication (mMTC), and ultra-reliable low-latency communication (URLLC) [33]. eMBB is used for high-bandwidth services, such as video streaming. The mMTC is mainly used for high amounts of communication between devices, which is mainly needed for IoT devices. URLLC is used for ultra-low-latency communication, such that it is used for autonomous vehicles [34]. The common network slicing method consists of pre-determined layers, i.e., the service instance layer, network slice layer, and resource layer. The main layer that determines the slices is the network slice layer [34]. The network slice layer will have pre-determined slices tailored for each use case, but this is not dynamic. The pre-determined slices can only categorize a group of use cases.

Existing research [34]–[36] investigated network slicing optimization, and research conducted by Dangi and Lalwani [33] explored the use of ML in dividing the slice to dynamically predict the optimal slice. The study examined the use of ML to extract certain features from network traffic and slice the bandwidth based on highly used services. ML techniques include random forest, k-nearest neighbor (KNN), support vector machines (SVM), and decision tree. The network was split into three different optimal slices based on traffic (eMBB, mMTC, and URLLC) using ML algorithms. This is a common network slicing split performed in a HetNet topology to integrate various devices and traffic [37]. It showed that the random forest yielded the most accurate results, but also showed that all algorithms improved the jitter, packet loss and latency without the dynamic split. The proposed method improves network efficiency and can serve the needs of the required services for the user.

Another study was conducted to investigate splitting and generating network slices based on ML [38]. Instead of slicing them into three different slices, the ML model can create multiple new slices. The ability to dynamically generate new slices depends on the users' needs, while ensuring pre-defined QoS requirements for certain services. An SVM is used to react to scenarios while maintaining certain splits based on training. Improvements in latency and capacity were reported with 20 users. However, further research needs to be conducted for higher capacity and dynamic learning. Therefore, further research is being conducted on the use of federated learning (FL) in dynamic network slicing [39]. FL is a type of ML in which SL, such as SVM, can be conducted on an individual device, allowing decentralized ML. Therefore, network slicing needs to be implemented to allocate bandwidth for the transmission/update of the model. FL was implemented in dynamic bandwidth slicing [39]. The main limitation of these proposed methods is the computational resources required for the models, which have high implementation difficulty. This demonstrates the difficulties of implementing dynamic models with network slicing to adapt to individual users' changes in traffic.

It is shown that the network slicing models currently developed show an improvement in terms of overall network efficiency. The model constantly produces accurate predictions of 5G network slices that improve QoS and QoE. Demonstrating the capability of ML models in improving the decisions-making to enhance the network slicing algorithms. It was also shown that these tests were conducted on the overall network traffic after feature extraction and not on individual users. Predictions were made to generalize all users, as the test was performed when the user was grouped into service categories. In addition, these works do not consider the effects when the network is overloaded and only consider the situation in which the network can handle traffic and slice accordingly. This is because network slicing has the same performance for all users in every scenario and does not distinguish between individual users.

3.2. User-centric resource allocation

Utility-weighted prioritization tends to reduce churn and latency but may require fairness constraints for low-battery devices. Therefore, another area that is being researched is user-centric resource allocation, where related work has been conducted [40]–[42]. Compared to network slicing, which divides the network based on what usage is needed the most, user-centric resource allocation focuses on individual user needs and allocates/slices the bandwidth for various users instead of services. Therefore, user-centric resource allocation research has also been investigated, although few studies have been conducted.

Research was conducted to implement a user-centric bandwidth allocation method for video streaming and they investigated using device-to-device (D2D) assisted communication [43]. D2D communication is a form of communication in which data and packets are transferred between UEs, as each piece of equipment acts as a relay node to transmit data to the desired cellular device (CD). An issue with D2D communication is the power efficiency of the user's equipment, as each piece of equipment will be used to transmit data. Therefore, low-battery users will suffer. This is even more prominent with video streaming, as more packets must be transmitted to offer low-latency, high-quality video streaming to improve QoE. Therefore, they presented an algorithm that defines and categorizes the users into "video stream levels" and allocates bandwidth accordingly. They used a method that calculates a utility value that considers the quality, battery life, power usage, and packet loss ratio. Depending on these factors, they are categorized into different priorities/levels based on their needs. The UE with a lower battery life will take help from other D2D devices that act as relay nodes but will be allocated with less bandwidth. In addition, UEs that can act as D2D devices will have a higher bandwidth. The algorithm uses a utility-based multimedia streaming (UAMS) method to categorize the user based on their battery life span and packet-loss ratio. Based on the assigned utility value, the device is categorized as either a D2D relay node or a low-battery user. When the K-means algorithm is used, it determines the D2D device that acts as a relay node for the low-battery user. The D2D relay selection logic is illustrated in Figure 3.

Overall, the algorithm divides the bandwidth used for video streaming based on the UEs' ability to serve as a relay node for D2D. Better video quality and reduced latency are awarded to users who serve as D2D relay nodes. The results show that this method proved to be effective, as it tested the churn rate of inactive users. It was shown that the proposed method provides a 1.06%, 1.59%, and 2% reduction in the churn rate compared to non-adaptive methods. This demonstrates that more users have better QoE with this resource allocation method. Although this method proved to be more effective than traditional resource allocation methods, a few limitations can be seen in the work. First, the research conducted only looked at video streaming services for the division of bandwidth, and further tests can be performed for other services, such as VoIP or email. Another piece of work that can be done is the use of ML in the algorithm. As proven by network slicing algorithms, the ML algorithms can prove to be more effective. Therefore, further work can be performed on the ML algorithms being implemented.

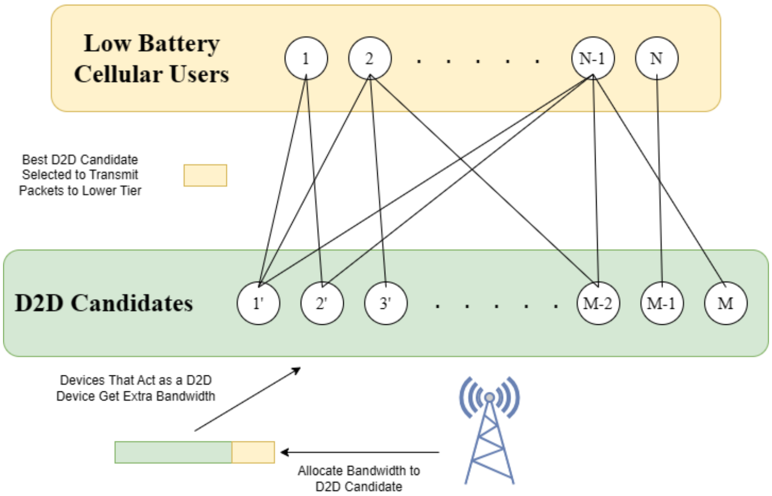

Figure 3. D2D connection decision between the priorities

3.3. Economic and market-driven UCRA

The economic and market-driven UCRA considers the spectrum to be a tradable resource, and decisions reflect the tenant economics on top of the user-level QoS/QoE. Spectrum allocation is processed by a hierarchical decision process framework according to the dynamic market and operators' demands. The framework consists of upper and lower priority tiers. In the upper-priority tier, the infrastructure provider (InP) allocates spectrum across the mobile virtual network operators (MVNOs). At the lower-priority tier, each MVNO then slices its assigned spectrum to individual users according to traffic conditions and QoS requirements. Deep reinforcement learning (DRL) with regulated bidding caps is applied to the upper tier to prevent smaller tenants from being starved of resources while also improving overall spectral efficiency. Figure 4 shows the algorithm framework.

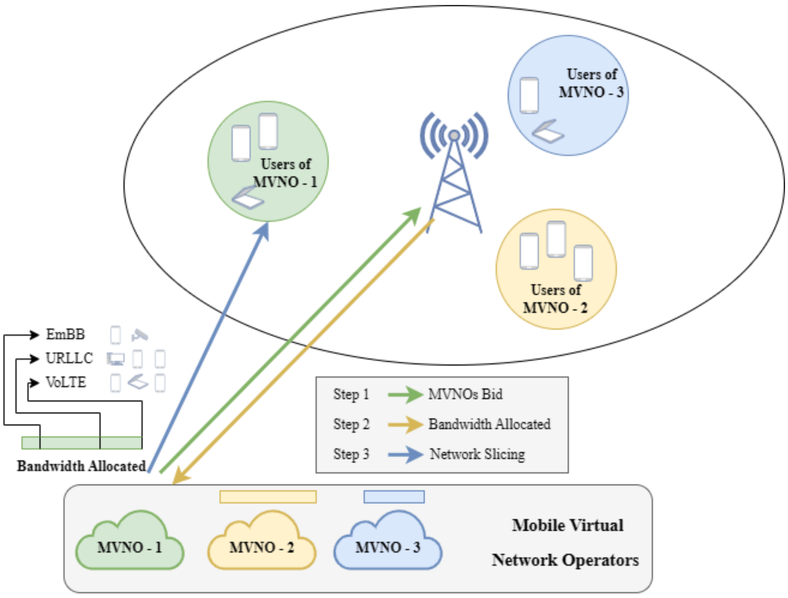

Figure 4. MVNO bidding algorithm framework for resource allocation

Another research split users into priorities based on the MVNOs [44]. MVNOs are service providers that do not own the network infrastructure to which the user is connected. Therefore, the solution proposed will only explore cases when users of different service providers connect to a network infrastructure that does not fall under their own network infrastructure. As more users of various service providers connect to one network infrastructure, the network will be overloaded. Therefore, the users are split into priorities. The paper proposes a two-priority model that uses an upper-priority to allocate resources to the MVNOs and a lower-priority for the MVNOs to slice the network based on the traffic. The MVNOs will bid for the highest amount of bandwidth from the InP, where the highest bid will obtain the most resources and bandwidth, therefore splitting the MVNOs into various groups of a certain amount of total bandwidth. Then the lower priority is where the MVNO will look at the QoS required by their user and slice the network accordingly. Then, using deep Q-network (DQN), which is an algorithm subset of DRL in ML, the DQN will analyze the MVNO bids and network traffic to have an optimal split. The DQN will be used to limit the maximum number of bids that the MVNOs can make. It ensures the lower-bidding MVNOs do not die from starvation (lack of resources) and ensures an optimized allocation of resources.

The DQN and bidding algorithm in the upper priority provided a 5.4% increase in revenue compared to double DQN and a 2.6% increase compared to dueling DQN, as bandwidths are allocated more efficiently based on bids. In addition, it was shown that there is a 0.5-2.7% increase in spectral efficiency in the lower priorities. Overall, the proposed model demonstrated a method of resource allocation based on grouping users based on their service provider and obtained a higher bandwidth when their service provider bids more. Although the method improved spectrum efficiency and QoE, the allocation of resources could be more individualistic. As MVNOs are used to split up users, other methods can be tested to split users into various groups. In addition, further research can be conducted to compare various ML algorithms, as this work only considers DQN as an algorithm for the optimization and prevention of starvation. Therefore, more research can be conducted to compare the various types of ML algorithms.

3.4. Machine learning paradigms for UCRA

5G networks use a variety of ML methods in resource allocation, but each ML algorithm learns in different ways. The performance of SL (prediction), UL (profiling/clustering), and RL (closed-loop control) are compared. Computational complexity, scalability, adaptability, and deploy ability are considered as practical evaluation criteria. Network analysis ML algorithms can forecast network performance and traffic and make decisions based on such forecasts. The models used included regression tree, random forest, k-Means, KNN, Q-learning, deep neural network and DQNs.

Network slicing and Regression Trees were used to predict the outcome by assigning values to the slices [17]. The regression tree model demonstrated is a SL model, as the model was created with the help of previous training. This model is developed in which data are initially fed into the model, where the model is fed data of the optimal response to a certain data traffic scenario. Then, these data are split into two branches based on certain features that the model identifies, and this process is repeated as the branches constantly split and identify features that will be categorized into a type of data traffic. Using this, the ML algorithm can forecast traffic based on the data it is seeing and provides more efficient splits as the throughput is increased by 30%. It was also shown that the regression tree model was better than the other SL models, as it had approximately the same accuracy but reduced training time. Although the regression tree model proved to have over 90% accuracy in prediction, note that SL has a slight failure, as it can overfit the data. As data changes, the model demonstrated might not prove to be as effective.

Another type of ML algorithm that investigated k-means for network traffic management demonstrated the use of UL [45]. K-means takes unlabeled data and splits it into clusters. Each cluster is created by the similarity and disparity between the data patterns. Each cluster of data is created through an iterative method. As data points move between clusters after each iteration to achieve the desired split. The study used k-means to group users into groups based on the usage of services and identified an even split for resource allocation of the cluster to efficiently use each slice. This work showed that using the k-means algorithm provides better performance compared to the standard network slicing algorithm. As the network dynamically searches for similar patterns between users and profiles them into clusters. It improves network traffic management. This study evaluated different ML algorithms, including density-based spatial clustering of applications with noise (DBSCAN), Naïve Bayes, SVM, KNN, and k-means. K-means offers more dynamic resource allocation. However, this study did not include RL algorithms and evaluated only the even-split configurations.

Q-learning for user-centric RAN optimization was also proposed [38]. Q-learning is an RL algorithm that stores Q-values for different actions in a Q-table. The outcome states/decisions will be categorized into Q-values. Subsequently, the ML model will be rewarded if it makes decisions that obtain higher Q-values. The Q-values will update over time based on the network conditions at that time. This research introduces the use of S-zones to determine how to boost signals to certain zones around the base station depending on the services used. The ML model is tasked with determining S-zones based on the usage of services. This work shows that the standard Q-learning algorithm does not significantly increase performance, but its main benefit is that it has lower complexity and can dynamically update changes. A comparative summary of the SL, UL, and RL models applied in UCRA tasks is presented in Table 1.

Therefore, based on the research that has been conducted, ML shows its merits, as it has been presented in prior research. It outperforms inefficient usage of the bandwidth and can dynamically change based on the current data. However, a key limiting factor in the research is the lack of comparison between ML algorithms. The algorithms are mostly compared with non-ML methods or with other similar ML models. More effort is needed to evaluate different ML algorithms for their strengths and weaknesses in network performance and bandwidth allocation.

Table 1. Comparison of ML paradigms mapped to user-centric resource allocation (UCRA) tasks, evaluation metrics, strengths, and limitations

Algorithm/Paradigm	Task in UCRA	Key Metrics	Strengths	Limitations
Regression tree / random forest (SL)	Traffic/QoE prediction	Accuracy, latency	Fast training; interpretable	Needs labels; drift-sensitive
SVM (SL)	Slice decision support	F1-score, delay	Robust to small datasets	Kernel tuning; limited scalability
K-means (UL)	User/service clustering	Throughput, cluster quality	Label-free; simple	K selection; cluster drift
Q-learning (RL)	Admission/control at RAN	QoE, fairness	Low complexity; online learning	Convergence; reward shaping
DQN/DRL (RL)	Slice admission and load balancing	QoE, spectral efficiency	Handles high-dimensional states	Sample complexity; stability

3.5. Edge-assisted and D2D UCRA

We discuss congestion management and the role of edge computing, multi-connectivity, and D2D assistance under overload conditions. Naturally, some studies investigate congestion control for high traffic loads in networks. As congestion control is an important aspect of 5G, HetNets allow various network instances in a single infrastructure to improve QoE [46]. The use of network slicing algorithms in high congestion/overloaded scenarios was evaluated with an 89% reduction in the overall QoE [47]. Even when introducing DQN into the resource allocation, only a 20% increase in QoE can be observed, showing the severity of the overloaded network on user QoE. It is also further demonstrated that network slicing may not be an optional method for solving these issues. The proposed network slicing models from these studies do not indicate an improvement in QoE or QoS [48]–[50]. As these models demonstrated the capabilities to predict high-congestion scenarios with an accuracy of approximately 90% using both reinforcement and SL. This confirms the reliability of the implementation of ML. Although these methods achieve high prediction accuracy, network slicing algorithms are still unable to significantly increase users' QoE.

Therefore, some research considers improving congestion management by applying algorithm schemes with multi-connectivity [51], [52]. A single device can be connected to several cells using multi-connectivity algorithms, which divide heavy traffic among cells. Other works propose deploying additional small cells to support high congestion. The use of a user-centric association between various small base stations was proposed [53]. The DQN model was used to associate individual UE with another base station that offers the highest resources. The methods demonstrated an 80% improvement in the overall throughput under overloaded situations with 50 UEs, as the network traffic was balanced between nodes. However, these methods have a main limitation. They are difficult to implement in real-world situations, as high resources are required to create multiple nodes in a dense area. Therefore, it was proposed by researchers [43], [44], and [53] to study a user-centric resource allocation method for congestion control, as user-centric algorithms perform better than network-centric algorithms. The differences between QoE-based, economic, DRL-based, and clustering-based UCRA schemes are summarized in Table 2.

Table 2. Thematic comparison of user-centric resource allocation schemes, representative studies, network settings, reported outcomes, and key observations

Theme	Representative Study	Setting	Reported Outcome	Limitations
QoE/Utility-based allocation	D2D-assisted video UAMS	HetNet video streaming	↓ churn 1–2%, ↓ latency	Relay incentive vs battery fairness
Economic/Market-based allocation	Two-priority DRL + bidding	MVNO over shared RAN	↑ revenue 2.6–5.4%, ↑ Spectral Efficiency 0.5–2.7%	Starvation avoidance via bid caps
RL-based control	User-centric association (DRL)	Ultra-dense millimeter wave (mmWave)	↑ throughput (simulation)	High deployment complexity; coordination overhead
UL-based clustering	Adaptive slicing via k-means	Mixed traffic	↑ QoS/QoE compared to static slicing	Cluster robustness required

4. DISCUSSION AND CRITICAL SYNTHESIS

The survey highlights several significant insights regarding the use of ML-based UCRA in 5G heterogeneous networks. Each ML paradigm contributes differently to prediction, classification, and real-time control tasks. SL methods demonstrate strong capability in forecasting traffic levels and slice requirements. These make them suitable for proactive admission control and resource planning. UL methods provide advantages when grouping users or services based on patterns in traffic behavior or QoE requirements. RL techniques are particularly effective for continuous and adaptive decision-making in environments where network conditions and user demands change rapidly.

A consistent finding is that service-centric slicing strategies perform poorly under congested network conditions when compared with UCRA approaches. Service-centric allocation treats all users within a slice as a single group, which results in insufficient differentiation among users with distinct QoE needs. In contrast, UCRA methods that incorporate user utility, contextual information, and priority attributes. These demonstrate better performance in terms of fairness, throughput, and resilience during overload. This observation is supported by several RL-based UCRA studies that adjust admission or resource-allocation decisions in real time. These studies report improvements in spectral efficiency, throughput, and user QoE, particularly when the network is subject to heavy traffic.

The practical deployment of ML within UCRA presents several important challenges. Many ML models have high computational demands, and this complexity can limit deployment at the base station or user-equipment level. Operators also require some level of interpretability in decision-making to ensure trust in resource management. Fairness is an important consideration because certain approaches naturally assign higher priority to specific user groups. Low-priority or low-battery users may experience starvation or degraded service quality without safeguards.

The review also reveals several research gaps that are common across studies. Current ML-based methods are not sufficiently robust against disturbances in training data, such as noise, anomalies, or adversarial manipulation. Most resource-allocation models focus primarily on the radio-access network. Practical implementation requires consistent coordination across the radio-access network, the core network, and edge-computing environments. Another emerging direction is the potential shift toward semantic or goal-oriented communication, which redefines resource allocation around user intent rather than raw traffic characteristics. Lightweight and interpretable ML models are also needed to support deployment closer to the network edge, where hardware resources are more limited. Overall, the synthesis shows that ML-based UCRA provides a strong potential for improving user-level QoE in the overloaded 5G heterogeneous networks. At the same time, several technical and operational challenges must be addressed to achieve reliable, efficient, and fair deployment in the real systems.

5. CONCLUSION

A review of existing works demonstrates a few research gaps and the future direction of research to develop new algorithms. Most of the existing works focused on network slicing to improve the network performance by allocating bandwidth based on which services are being used. However, the overloaded network condition is not evaluated in these works. Congestion control is an important aspect of the 5G HetNets because various devices are being connected to one infrastructure. Therefore, user-centric methods are currently being developed to allocate resources to the user. ML models are a promising method to be implemented in algorithm prediction and decision-making. They improve the performance of the 5G network, but it is difficult to identify the optimal ML model for user-centric algorithms. Existing works have not conducted a holistic approach in evaluating various ML algorithms, especially comparing SL, UL and RL.

6. FUTURE DIRECTION

Therefore, further research can be conducted to fill the gaps in the current research. The user-centric resource allocation algorithm that uses user priorities with low resource requirements can be designed to improve congestion control. In addition, various ML algorithms can also be explored in a user-centric resource allocation algorithm to identify the best ML algorithm that provides the best decision to improve QoE and QoS. Overall, further research can be conducted on a ML-based user-centric resource allocation algorithm to improve congestion control in the 5G HetNet infrastructure.

ACKNOWLEDGEMENT

We would like to express our gratitude to the Ministry of Higher Education (MOHE) for providing funding for this project.

FUNDING INFORMATION

This research was supported by the Ministry of Higher Education (MOHE) through the Fundamental Research Grant Scheme (FRGS/1/2024/ICT06/TAYLOR/02/1).

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Pang Wai Leong	✓	✓					✓		✓			✓	✓	✓
Raymond Chia	✓	✓				✓		✓	✓					
Phang Swee King			✓		✓	✓			✓		✓			
Goh Hui Hwang		✓	✓				✓			✓				
Chan Kah Yoong				✓		✓				✓				
Chung Gwo Chin	✓								✓	✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Since this is a review article, the authors confirm that the data supporting the findings of this study are cited within the article. No new data were created or analyzed in this study.

REFERENCES

[1] R. I. Rony, E. Lopez-Aguilera, and E. Garcia-Villegas, "Dynamic spectrum allocation following machine learning-based traffic predictions in 5G," *IEEE Access*, vol. 9, pp. 143458–143472, 2021, doi: 10.1109/ACCESS.2021.3122331.
[2] E. Gures, I. Shayea, M. Sheikh, M. Ergen, and A. A. El-Saleh, "Adaptive cell selection algorithm for balancing cell loads in 5G heterogeneous networks," *Alexandria Engineering Journal*, vol. 72, no. 72, pp. 621–634, 2023, doi: 10.1016/j.aej.2023.04.012.
[3] S. A. Khan, I. Shayea, M. Ergen, A. A. El-Saleh, and M. Roslee, "An improved handover decision algorithm for 5G heterogeneous networks," in *15th IEEE Malaysia International Conference on Communications: Emerging Technologies in IoT and 5G, MICC 2021 - Proceedings*, 2021, pp. 25–30, doi: 10.1109/MICC53484.2021.9642076.
[4] R. Gatti, G. B. Arjun Kumar, K. N. Sunil Kumar, S. Palle, and T. R. Gadekallu, "Optimal resource scheduling algorithm for cell boundaries users in heterogenous 5G networks," *Physical Communication*, vol. 55, 2022, doi: 10.1016/j.phycom.2022.101915.
[5] M. U. Iqbal, E. A. Ansari, S. Akhtar, M. Farooq-I-Azam, S. R. Hassan, and R. Asif, "Optimal learning paradigm and clustering for effective radio resource management in 5G HetNets," *IEEE Access*, vol. 11, pp. 41264–41280, 2023, doi: 10.1109/ACCESS.2023.3268543.
[6] I. Chakour, C. Daoui, M. Baslam, B. Sainz-De-Abajo, and B. Garcia-Zapirain, "Strategic bandwidth allocation for QoS in IoT gateway: predicting future needs based on IoT device habits," *IEEE Access*, vol. 12, pp. 6590–6603, 2024, doi: 10.1109/access.2024.3351111.
[7] J. S. Perez, S. K. Jayaweera, and S. Lane, "Machine learning aided cognitive RAT selection for 5G heterogeneous networks," in *2017 IEEE International Black Sea Conference on Communications and Networking, BlackSeaCom 2017*, 2018, vol. 2018-January, pp. 1–5, doi: 10.1109/BlackSeaCom.2017.8277675.
[8] F. O. Okello, V. Oduol, C. Maina, and A. Apiyo, "Improvement of 5G core network performance using network slicing and deep reinforcement learning," *International Journal of Electrical and Electronics Research*, vol. 12, no. 2, pp. 493–502, May 2024, doi: 10.37391/ijeer.120222.
[9] I. Ullah, H. El Sayed, S. Malik, and A. Manzoor Ahmed Khan, "Performance evaluation of quality of experience aware mobility management in heterogeneous cellular networks," *IEEE Access*, vol. 12, pp. 97994–98003, 2024, doi: 10.1109/ACCESS.2024.3426991.
[10] A. A. Simiscuka, A. Yaqoob, and G. M. Muntean, "FRADIS: A machine learning-based multipath solution for differentiated services in a network slicing-enhanced delivery environment," in *IEEE International Symposium on Broadband Multimedia Systems and Broadcasting, BMSB*, 2024, pp. 1–6, doi: 10.1109/BMSB62888.2024.10608237.
[11] D. Yan, B. K. Ng, W. Ke, and C. T. Lam, "Deep reinforcement learning based resource allocation for network slicing with massive MIMO," *IEEE Access*, vol. 11, pp. 75899–75911, Jan. 2023, doi: 10.1109/ACCESS.2023.3296851.
[12] K. B. Ajeyprasaath and P. Vetrivelan, "A hybrid machine learning approach for improvised QoE in video services over 5G wireless networks," *Computers, Materials and Continua*, vol. 78, no. 3, pp. 3195–3213, 2024, doi: 10.32604/cmc.2023.046911.
[13] O. Aouedi, K. Piamrat, S. Hamma, and J. K. M. Perera, "Network traffic analysis using machine learning: an unsupervised

approach to understand and slice your network," *Annales des Telecommunications/Annals of Telecommunications*, vol. 77, no. 5–6, pp. 297–309, Nov. 2022, doi: 10.1007/s12243-021-00889-1.

[14] M. H. Abidi *et al.*, "Optimal 5G network slicing using machine learning and deep learning concepts," *Computer Standards and Interfaces*, vol. 76, p. 103518, Jun. 2021, doi: 10.1016/j.csi.2021.103518.

[15] N. Salhab, R. Langar, and R. Rahim, "5G network slices resource orchestration using machine learning techniques," *Computer Networks*, vol. 188, p. 107829, Apr. 2021, doi: 10.1016/j.comnet.2021.107829.

[16] N. Suganthi *et al.*, "Enhancing 5G network performance through effective resource management with network slicing," *International Journal of Electrical and Computer Engineering*, vol. 14, no. 4, pp. 4721–4731, Aug. 2024, doi: 10.11591/ijece.v14i4.pp4721-4731.

[17] N. Salhab, R. Rahim, R. Langar, and R. Boutaba, "Machine learning based resource orchestration for 5G network slices," in *Proceedings - IEEE Global Communications Conference,* 2019, pp. 1–6, doi: 10.1109/GLOBECOM38437.2019.9013129.

[18] M. Setayesh, "Machine learning-based algorithms design for network slicing, federated learning, and 360° video streaming in wireless systems," Thesis, Department of Applied Science, Faculty of Electrical and Computer Engineering, University of British Columbia, 2024.

[19] M. Raeisi and A. B. Sesay, "Handover reduction in 5G high-speed network using ML-assisted user-centric channel allocation," *IEEE Access*, vol. 11, pp. 84113–84133, Jan. 2023, doi: 10.1109/ACCESS.2023.3297982.

[20] S. Saibharath, S. Mishra, and C. Hota, "Joint QoS and energy-efficient resource allocation and scheduling in 5G network slicing," *Computer Communications*, vol. 202, pp. 110–123, Mar. 2023, doi: 10.1016/j.comcom.2023.02.009.

[21] S. Mathur, Y. Chaba, and A. Noliya, "Performance analysis of support vector machine learning based carrier aggregation resource scheduling in 5G mobile communication," *Procedia Computer Science*, vol. 218, pp. 2776–2785, Jan. 2022, doi: 10.1016/j.procs.2023.01.249.

[22] M. Mina, "Performance prediction and enhancement of 5G networks based on linear regression machine learning," *Eurasip Journal on Wireless Communications and Networking*, vol. 2023, no. 1, Aug. 2023, doi: 10.1186/s13638-023-02282-z.

[23] Z. Tong *et al.*, "Dynamic user-centric multi-dimensional resource allocation for a wide-area coverage signaling cell based on DQN," *Frontiers of Information Technology and Electronic Engineering*, vol. 24, no. 1, pp. 154–163, Jan. 2023, doi: 10.1631/FITEE.2200220.

[24] Y. J. I. A. Yaqoob, W. L. Pang, S. K. Wong, and K. Y. Chan, "Performance evaluation of video streaming on LTE with coexistence of Wi-Fi signal," *Bulletin of Electrical Engineering and Informatics*, vol. 8, no. 3, pp. 890–897, Sep. 2019, doi: 10.11591/eei.v8i3.1580.

[25] J. I. A. Y. Yaqoob, W. L. Pang, S. K. Wong, and K. Y. Chan, "Enhanced exponential rule scheduling algorithm for real-time traffic in LTE network," *International Journal of Electrical and Computer Engineering*, vol. 10, no. 2, pp. 1993–2002, 2020, doi: 10.11591/ijece.v10i2.pp1993-2002.

[26] O. Abuajwa, M. Roslee, Z. B. Yusoff, L. L. Chuan, and P. W. Leong, "Resource allocation for throughput versus fairness trade-offs under user data rate fairness in NOMA systems in 5G networks," *Applied Sciences (Switzerland)*, vol. 12, no. 7, Mar. 2022, doi: 10.3390/app12073226.

[27] R. Chia, W. L. Pang, S. King Phang, H. Hwang Goh, and K. Yoong Chan, "Machine learning-driven analysis of user bandwidth allocation and performance in 5G network," *IEEE Access*, vol. 13, pp. 173081–173095, 2025, doi: 10.1109/ACCESS.2025.3615398.

[28] R. Chia, W. L. Pang, H. H. Goh, W. H. Tee, K. Y. Chan, and G. C. Chung, "Analysis of user bandwidth allocation and performance in 5G heterogeneous network," *Proceedings of ICRAIE.* 2025, pp. 171–176, doi: 10.1109/icraie65839.2025.11239191.

[29] M. P. Kunasegran, W. L. Pang, and S. K. Phang, "Optimising resource allocation in 5G networks: Balancing URLLC and eMBB traffic under gNB congestion," in *Proceedings of MECON 2025*, 2025, pp. 1–6, doi: 10.1109/mecon67253.2025.11277096.

[30] M. P. Kunasegran, W. L. Pang, and S. K. Phang, "SLA-aware DRL for joint slice admission control and load balancing in multi-service 5G RAN," in *Proceedings of ICRAIE 2025*, 2025, pp. 207–212, doi: 10.1109/icraie65839.2025.11239148.

[31] W. H. Chow *et al.*, "Design of user-centric QoS provisioning scheme in 5G network," *Journal of Engineering Science and Technology (23rd EURECA 2024 Special Issue)*, pp. 28–50, 2026.

[32] J. Chen, B. Qian, Y. Xu, H. Zhou, and X. Shen, "Towards user-centric resource allocation for 6G: An economic perspective," *IEEE Network*, vol. 37, no. 2, pp. 254–261, 2023, doi: 10.1109/MNET.115.2200027.

[33] R. Dangi and P. Lalwani, "Feature selection based machine learning models for 5G network slicing approximation," *Computer Networks*, vol. 237, p. 110093, Dec. 2023, doi: 10.1016/j.comnet.2023.110093.

[34] N. Kumar and A. Ahmad, "Machine learning-based QoS and traffic-aware prediction-assisted dynamic network slicing," *International Journal of Communication Networks and Distributed Systems*, vol. 28, no. 1, pp. 27–42, 2022, doi: 10.1504/ijcnds.2022.120298.

[35] A. Fayad, "Optimization of 5G and beyond networks for cost- and energy-efficiency," Dept. of Telecommunications and Media Informatics, Faculty of Electrical Engineering and Informatics, Budapest University of Technology and Economics, 2024.

[36] S. Urooj, R. Arunachalam, M. A. Alawad, K. Narayan Tripathi, D. Sukumaran, and P. Ilango, "An effective model for network selection and resource allocation in 5G heterogeneous network using hybrid heuristic-assisted multi-objective function," *Expert Systems with Applications*, vol. 248, p. 123307, Jan. 2024, doi: 10.1016/j.eswa.2024.123307.

[37] E. Ataeebojd, M. Rasti, and M. Latva-Aho, "Network selection and resource allocation for coexistence of eMBB and URLLC services in a 6G multi-band HetNet," *IEEE Transactions on Green Communications and Networking*, vol. 9, no. 3, pp. 1179–1194, Jan. 2025, doi: 10.1109/TGCN.2024.3481281.

[38] S. K. Kasi, U. S. Hashmi, S. Ekin, A. Abu-Dayya, and A. Imran, "D-RAN: A DRL-based demand-driven elastic user-centric RAN optimization for 6G & beyond," *IEEE Transactions on Cognitive Communications and Networking*, vol. 9, no. 1, pp. 130–145, Feb. 2023, doi: 10.1109/TCCN.2022.3217785.

[39] A. F. Y. Mohammed, J. Lee, and S. Park, "Dynamic bandwidth slicing in passive optical networks to empower federated learning," *Sensors*, vol. 24, no. 15, p. 5000, Aug. 2024, doi: 10.3390/s24155000.

[40] Y. Su, Z. Gao, X. Du, and M. Guizani, "User-centric base station clustering and resource allocation for cell-edge users in 6G ultra-dense networks," *Future Generation Computer Systems*, vol. 141, pp. 173–185, 2023, doi: 10.1016/j.future.2022.11.011.

[41] P. G. Burguera, H. Al-Tous, and O. Tirkkonen, "Distributed user-centric cell-free massive MIMO with architectural constraints," in *2024 Joint European Conference on Networks and Communications and 6G Summit, EuCNC/6G Summit 2024*, 2024, pp. 541–546, doi: 10.1109/EuCNC/6GSummit60053.2024.10597006.

[42] M. Salma, "User-centric slicing with functional splits in 5G cloud-RAN," Thesis, Sorbonne Université, pp. 1–113, Jan. 2021.

[43] P. K. Barik, C. Singhal, and R. Datta, "D2D-assisted user-centric adaptive video transmission in next generation cellular networks," *Physical Communication*, vol. 56, p. 101944, Feb. 2023, doi: 10.1016/j.phycom.2022.101944.

[44] G. Chen, X. Zhang, F. Shen, and Q. Zeng, "Two tier slicing resource allocation algorithm based on deep reinforcement learning and joint bidding in wireless access networks," *Sensors*, vol. 22, no. 9, p. 3495, May 2022, doi: 10.3390/s22093495.

[45] S. Saini, S. K. Garg, P. P. Singh, A. Ali, and A. Pandey, "Enhancing QoS of network traffic based on 5G wireless networking using machine learning approaches," in *Communications in Computer and Information Science*, vol. 1672 CCIS, 2022, pp. 3–15.

[46] S. Khan, A. Hussain, S. Nazir, F. Khan, A. Oad, and M. D. Alshehr, "Efficient and reliable hybrid deep learning-enabled model for congestion control in 5G/6G networks," *Computer Communications*, vol. 182, pp. 31–40,2022, doi: 10.1016/j.comcom.2021.11.001.

[47] V. Saravanan *et al.*, "Design of deep learning model for radio resource allocation in 5G for massive IoT device," *Sustainable Energy Technologies and Assessments*, vol. 56, p. 103054, Mar. 2023, doi: 10.1016/j.seta.2023.103054.

[48] S. E. A. Alnawayseh, W. T. Al-Sit, and T. M. Ghazal, "Smart congestion control in 5G/6G networks using hybrid deep learning techniques," *Complexity*, vol. 2022, pp. 1–10, Oct. 2022, doi: 10.1155/2022/1781952.

[49] L. J, K. T, and J. Lloret, "A novel architecture of intelligent decision model for efficient resource allocation in 5G broadband communication networks," *ICTACT Journal on Soft Computing*, vol. 13, no. 3, pp. 2986–2994, Apr. 2023, doi: 10.21917/ijsc.2023.0420.

[50] M. B. Alshawki, I. Ahmed Najm, and A. Khalaf Hamoud, "Congestion control prediction model for 5G environment based on supervised and unsupervised machine learning approach," *IEEE Access*, vol. 12, pp. 91127–91139, Jan. 2024, doi: 10.1109/ACCESS.2024.3416863.

[51] J. J. Hernández-Carlón, J. Pérez-Romero, O. Sallent, I. Vilà, and F. Casadevall, "A deep q-network-based algorithm for multi-connectivity optimization in heterogeneous cellular-networks," *Sensors*, vol. 22, no. 16, 2022, doi: 10.3390/s22166179.

[52] X. Ba, "QoS-forecasting-based intelligent flow-control scheme for multi-connectivity in 5G heterogeneous Networks," *IEEE Access*, vol. 9, pp. 104304–104315, 2021, doi: 10.1109/access.2021.3099824.

[53] Q. Xue, Y. Sun, J. Wang, G. Feng, L. Yan, and S. Ma, "User-centric association in ultra-dense mmWave networks via deep reinforcement learning," *IEEE Communications Letters*, vol. 25, no. 11, pp. 3594–3598, Aug. 2021, doi: 10.1109/LCOMM.2021.3108013.

BIOGRAPHIES OF AUTHORS

Pang Wai Leong is an associate professor at Taylor's University, Malaysia. He has 20 years of teaching and industry experience. He possesses a diverse range of professional qualifications, including a Professional Engineer (Ir.) from the Board of Engineers Malaysia (BEM), membership in the Institution of Engineers Malaysia (MIEM), and Senior Membership in the Institute of Electrical and Electronics Engineers (SMIEEE). He is a certified Industry 4.0 Architect. He has made significant research contributions, particularly in wireless communication, IC design, and smart systems. His work has been extensively published in renowned journals and proceedings, and he has received numerous awards for his research excellence. He can be contacted at email: waileong.pang@taylors.edu.my.

Raymond Chia was born in Penang, Malaysia, in 2004. He is currently pursuing the Bachelor of Engineering (B.Eng.) degree in electrical and electronic engineering at Taylor's University, Malaysia. His research interests include machine learning, artificial intelligence, wireless communication, and embedded systems. During his internship, he conducted research on artificial intelligence applications in computer vision and image identification, where he contributed to developing algorithms for image classification and object detection. Currently, as part of his final year project, he is researching machine-learning-driven user-centric resource allocation algorithms aimed at optimizing network performance in wireless communication systems. He can be contacted at email: raymondchenjet.chia@sd.taylors.edu.my.

Phang Swee King received the B.Eng. and Ph.D. degrees in electrical engineering from the National University of Singapore (NUS), in 2010 and 2014, respectively. He is currently a Programme Director with Taylor's University, Subang Jaya, Malaysia. He has authored numerous publications, including a book chapter in the Handbook of Unmanned Aerial Vehicles, multiple peer-reviewed journals and international conference proceedings. His research interests include system design of unmanned aerial systems (UAS), modelling and flight controller design, indoor navigation, and trajectory optimization. He was a recipient of the Best Paper Award (Guan Zhao-Zhi Award) in the 33rd Chinese Control Conference, Nanjing, China (2013); the Finalist of the Best Paper Award in the 14th IEEE International Conference on Control and Automation, Alaska, USA (2018); and IET Commendable Paper Award in 13th International Engineering Research Conference (2019). He is currently also the Deputy Director of the Digital Innovation & Smart Society Impact Laboratory, Taylor's University. Student teams from his research laboratory have won numerous UAS related competitions, including the Champion for the AIRBUS Innovation Fun Day 2019 in Kuala Lumpur, Malaysia; and the Champion for the CDIO Drone Academy Challenge 2018 in Kanazawa, Japan. He can be contacted at email: sweeking.phang@taylors.edu.my.

Goh Hui Hwang is a professor at the Taylor's University, Malaysia. He is a practicing electrical consultant and registered electrical energy manager. His technical interests and expertise include electrical engineering, power systems, renewable and sustainable energy, embedded power generation, wavelet analysis, load shedding, and data mining. He has been dedicating his profession to leading various research projects, putting his focus on fostering innovation, development, and testing of new technologies that can be used to address sustainable energy issues in the developing world. He has won medals from many international expos, for the significant contributions of his innovations to the progress and welfare of the community. He can be contacted at email: jonathan.goh@taylors.edu.my.

Chan Kah Yoong is a professor at the Multimedia University (MMU), Malaysia. He obtained his Ph.D. in electrical engineering from Jacobs University Bremen in Germany. His research areas are in smart materials and devices including smart glasses/windows, solar cells, transparent electronic materials and devices, microelectronics and nanotechnology, IoT smart farming technologies, solar energy harvesting applications, and recent renewable green technologies as well as CO_2 reduction technologies. He also serves as a Chairperson for a Research Center of Advanced Devices and Systems (CADS). He can be contacted at email: kychan@mmu.edu.my.

Chung Gwo Chin obtained the Master of Engineering Science (M.Eng.Sc.) from Multimedia University, Malaysia in 2009. He then received his Doctor of Philosophy from the same university in 2017. He is currently an assistant professor at the Faculty of Engineering, Multimedia University in Malaysia. His research area includes the field of wireless communications, especially in digital signal processing, and interference suppression. He is currently extending his research field to internet of things (IoT) and machine learning. He is also a member of International Association of Engineers (IAENG), Institute of Advanced Engineering and Science (IAES), International Computer Science and Engineering Society (ICSES) and The Institute of Research Engineers and Doctors (IRED). He has received several medals at the Research Innovation Commercialization & Entrepreneurship Showcase (RICES), Invention Exhibition (iNVENTX), and Multimedia University Engineering Conference 2024 (MECON 2024) from the year 2018 till 2024. He has vast experience in being a project leader in both national and university research grants such as the Skim Geran Penyelidikan Eksploratori (ERGS) (2013-2015), Fundamental Research Grant Scheme (FRGS) (2023-2026), Mini Fund (2018-2019) and IRFund (2021-2023). He can be contacted at email: gcchung@mmu.edu.my.