Analysis and study of Deep Reinforcement Learning based Resource Allocation for Renewable Powered 5G Ultra-Dense Networks

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Abstract

The frequent handover problem and playing ping-pong effects in 5G (5th Generation) ultra-dense networking cannot be effectively resolved by the conventional handover decision methods, which rely on the handover thresholds and measurement reports. For instance, millimetre-wave LANs, broadband remote association techniques, and 5G/6G organizations are instances of group of people yet to come frameworks that request greater security, lower idleness, and dependable principles and correspondence limit. One of the critical parts of 5G and 6G innovation is believed to be successful blockage the board. With further developed help quality, it empowers administrator to run many systems administration recreations on a solitary association. To guarantee load adjusting, forestall network cut disappointment, and give substitute cuts in case of blockage or cut frustration, a modern pursuing choices framework to deal with showing up network information is require. Our goal is to balance the strain on BSs while optimizing the value of the information that is transferred from satellites to BSs. Nevertheless, due to their irregular flight characteristic, some satellites frequently cannot establish a connection with Base Stations (BSs), which further complicates the joint satellite-BS connection and channel allocation. SF redistribution techniques based on Deep Reinforcement Learning (DRL) have been devised, taking into account the randomness of the data received by the terminal. In order to predict the best capacity improvements in the wireless instruments of 5G and 6G IoT networks, a hybrid algorithm for deep learning is being used in this study. To control the level of congestion within a 5G/6G network, the suggested approach is put into effect to a training set. With 0.933 accuracy and 0.067 miss rate, the suggested method produced encouraging results.

Keywords:
IoT Networks, Accuracy, Satellite-BS, Communication Model, Congestion Control, Deep Reinforcement Learning, 5G/6G Technology, Broadband Wireless.

I. Introduction

Internet of Things has grown so quickly in recent years, current mobile communications technology is unable to match the long-distance, low-power consumption, and numerous connection needs of IoT node equipment (Najm, M. 2018). This gave rise to the creation of the Low-Power Wide Area Networks (LPWANs), a broad name for communication technologies appropriates for multi-connection, long-distance, low-power, and low-bandwidth Internet of Things connections.

LoRa, NB-IoT, RPMA, Sigfox, LTE-M, among other wireless networking technologies are all included in LPWAN. They can be separated into two groups based on whether authorization is necessary.

Since its invention, LoRa has been extensively utilized in the uncontrolled frequency band due to its great transmission range and low consumption of electricity in the Internet of Things. Many organizations and corporations with network needs prefer it because of its inexpensive implementation cost and on-demand deployment, as opposed to NB-IoT, which requires operators consent. LoRa provides more benefits than other communication technologies, particularly when it comes to situations requiring low power consumption, large transmission distances, and weak signals (T. Rahem, 2017).

As a result, the STINs establish a new standard for seamless communication. In the meantime, there is a sharp increase in the demand for high-quality audio, video, and other multimedia services. As a result, a new dilemma has emerged: how to effectively manage the resources of STINs to give customers improved Internet services.

A critical technology that influences STIN performance is resource allocation. However, power allocation, radio spectrum allocation, and other related topics are the main subjects of research. Furthermore, not much research has been done on the joint channel allotment and satellite association. An aggressive market strategy to address the problem of user identification in satellite-drone networks. Using the distributed belief propagation technique, heterogeneous networks' user association problem is addressed. Investigated user connection of the upward links in heterogeneous systems and assured users' data transmission rate by applying the augmented Lagrange approach and maximization-minimization theory (M. Y. Aalsalem, 2018). Employed a multivalent reinforcement learning approach to optimize user associate strategy while taking user service requirements in diverse cellular networks into account. Nevertheless, these methods are inappropriate in STINs.

The main reasons are as follows:

(1) Users in the previously mentioned network situations are inside the conversation range of BSs when optimizing the user association problem. In other words,

Manuscript received January 5, 2024
Manuscript revised January 20, 2024
https://doi.org/10.22937/IJCSNS.2024.24.1.26

consumers are always protected by at least a single BS. However, because satellites connect with BSs via the Line-of-Sight (LoS) method, many satellites in STINs are unable to link to them.

(2) The process of communication between satellites and base stations is fragmented rather than continuous due to the satellites' regular movement.

(3) A significant impact on the STINs' performance is the load balancing of the BSs. Certain BSs will reach capacity ahead of scheduled if the load balancing of BSs is ignored. STIN performance is harmed by this as well (M. Saleem, S. Abbas 2022). But the literature mentioned above doesn't take into account the BSs' load balance.

One of the key components of the new generation of information technology is the Internet of Things (IoT) and associated technologies. Smart factories, smart homes, intelligent transportation, and the Internet of cars are some of the common IoT application scenarios. An increasing number of Internet of Things (IoT) devices are now connected thanks to the quick development of networking, computing, and technology for communication. In addition to the usual fixed equipment, the Internet of Things also encompasses a vast number of mobile consumer devices. Additionally, there is a lot of need for time-sensitive typical apps and mobile traffic (R. Dong, C. 2019).

The Internet of Everything is facilitated by 5G networks' high speed, low latency, and all-encompassing network characteristics, which is an essential foundation for the high calibre of big data business and communication services in IoT application scenarios.

The next generation of wireless networks will demand large device access, high data rates, and enormous volumes of mobile traffic that the 5G low band, midland, in & LTE (Long-Term Evolution) tiny cell approaches cannot handle.

For this reason, in our research, we use the extremely high-frequency sector and the power source ultra-dense the deployment methodology of 5G networks(A. Sunny, S. Panchal, 2017). The millimetre wave technique is part of the 5G key techniques in Ultra-Dense Networks (UDN). In a two-layer cellular network architecture, the number of access users and network throughput are enhanced by the extremely dense deployment of tiny cells. Additionally, mobile users' QoS (Quality of Service) needs are met.

Nonetheless, frequent handover and the ping-pong effect are caused by the short cover and network access constraints of small cells, which have a direct impact on the continuity and quality of communications in 5G ultra large networks. The frequently handover and ping-pong effect cannot be effectively resolved by the classic handover decision methods, which rely on a transfer threshold and measurement report(Y. Chen, J. Li, 2016).

The SA-PER handover choice method is suggested as a way to decrease needless handovers and enhance QoS by combining analysis of stay time with the concept of state awareness method. Three steps make up the wireless network handover management process: gathering information, making a handover decision, and carrying out the handover. The majority of research projects focuses on enhancing the handover decision technique. Several transfer decision criteria and effective handover decision procedures determine the best candidate cellular in the transfer decision process.

Additionally, the evaluation criteria include things like throughput, playing ping-pong impact, radios link failure rate, and handover rate, among others. The prioritised experience replay and stay time are chosen as the new transition criterion and handover approach, respectively, in this study.

5G is the fifth advancement in cellular networks. The world is embracing a brand-new wireless technology. According to 5G wireless technology, many more users will benefit from multi gigabit per secondly peak speeds of data, incredibly quick reaction times, increased reliability, (A. Khalili, S. Akhlaghi, H. 2020) [2020], large network volume, extended accessibility, and other dependable user experiences. New sectors can be connected, performance and efficiency are improved, and new user experiences are made feasible.

It is guessed that another 6G innovation will arise inside the following decade because of the fast improvement of 5G applications and the developing requirement for rapid correspondence organizations. 5G means to easily associate various implanted sensors in nearly anything by downsizing velocity of information, power, and development, giving extremely thin and reasonable association decisions(N. Zhao, Y.-C. Liang, D. 2019).

With the ability to support applications like virtual and Augmented Reality (AR), instant messaging, continuous cognitive ability, the Internet of Things, or current mobile usage scenarios, 6G systems are anticipated to be more varied than their predecessors. According to a number of sources, the technology known as 6G might be accessible by 2030. more security, lower latency, safer standards, and more transmission efficiency are needed for millimeters-wave LANs, broadband wireless network plans, and 5G or 6G networks. Effective congestion control, which enables operators to route numerous networks instance on the same arrangements for enhanced service quality, is one of the key features of 5G and 6G technology.

The utilization of computerized reasoning and profound learning are fundamental to reconfigure and work on a 5G/6G innovation routine in light of the monstrous amount of information. Clog in 5G and 6G organizations might be overseen by carrying out AI into systems administration advancements. AI will assume a significant part in forming correspondences in the future because of its expected viability when applied to complex issues.

When combined with conventional congestion control mechanisms, machine learning is a pragmatic and widely applicable solution used to handle the demands with 5G Internet of Things (IoT) network. Many industries, such as smart towns, e-Health, and environmental surveillance, are using the 5G environments to perform better.

Traditional congestion control systems can use machine learning as a suitable and workable solution to satisfy 5G network requirements. In order to improve congestion management, this work employs deep learning and naive Bayes prediction(V. Mnih, K. Kavukcuoglu, D. 2015).

In 5G and 6G networks, machine learning algorithms have gained popularity for their ability to forecast optimal control of congestion. Machine learning works best when it comes to analyzing data and forecast the outcome of certain events using readily available sample inputs. This allows for the creation of suitable models that help decision-makers make the best choices. Artificial intelligence encompasses machine learning, which is an aspect of deep learning. One aspect of machine learning is automated decision-making. Deep learning, on the other hand, is a feature that computers have that mimic the architecture of the human brain to enable autonomous thought and behaviour. Because deep learning requires a smaller processing capacity than machine learning, it usually requires less ongoing human interaction.

A. Objectives

- Examine the use of DRL algorithms to optimize energy consumption in 5G ultra-dense networks that are fulled by renewable sources of energy.
- Examine how resource allocation strategies based on DRL can improve 5G ultra-dense networks' overall performance.
- Create plans that can effectively distribute resources in real-time while taking network demands and variations in energy supply into account.

II. LITERATURE REVIEW

(Sharma, N. 2022) The implementation of dense the fem within the ultra-dense network structure of this has been suggested as a potential solution to the issue of the increasing demand for cellular services. The challenge of allocating resources optimally among densely distributed Femto-Cell Base Station (FBSs) in a random manner might be difficult due to significant interferences. A two-stage cluster-based allocation of resources technique has been presented in order to get over these interferences and achieve effective resource allocation. Initially, an effective dynamic clustering technique grounded in unsupervised learning is suggested, which divides the FBSs into an ideal number of clusters while maintaining a balance in the traffic load within each cluster.

(Anzaldo, A., 2023) Denitrification of the network is an appropriate way to increase the capacity of upcoming mobile networks. However, the performance of Ultra-Dense Networks (UDNs) will be negatively impacted by the deployment of large low-power base stations that share the radio spectrum due to increasing disturbance. For decades, proposals for Resource Allocation (RA) have been developed to handle the data traffic and Quality of Service (QoS) demands of mobile customers while avoiding detrimental interference. However, the RA problem has grown more complicated as mobile apps demand higher data rates, more bandwidth, and ultra-reliable latency as networks change. In comparison to conventional approaches, Machine Learning (ML) methods have recently been investigated to dramatically lower the computationally challenging nature of RA problems and enhance overall UDN performance.

(Zhao, S. 2023) The 5G (5th Generation) mobile wireless communication network comprises two exemplary application scenarios: computing at the edge and the IIoT (Industrial Internet of Things). Consequently, this article examines the resource allocation strategies for these two common cases and suggests a resource allocation strategy that uses the DRL algorithm and is energy-efficient while also improving network performance and lowering operating costs. First, in accordance with edge computing characteristics, an allocation of resources model for user satisfaction with service (QoS) ensure is designed, with the needs of mobile users serving as constraints, and the goal of minimizing overall energy efficiency.

(Peng, T., 2022) The ultra-dense networks (UDN) technology is frequently used to meet the rapidly increasing demands on wireless networks. While UDN technology has the potential to expand network capacity, it also introduces significant InterCell Interference (ICI). Unfortunately, the limitations of the systems in place prevent the current solutions from functioning well in such complicated situations. The article proposes an interference-oriented allocation of radio resources framework with numerous uses, near-perfect offline training, high compatibility, and the ability to provide accurate, consistent, and fast performance feedback's as a solution to the problem. An effective approach for regression-based interference modelling is suggested to assist the framework, since its application stems from accurate interference identification. Once the interference mechanism has been thoroughly examined, the suggested algorithm has the ability to effectively and precisely simulate user interference with just the information gathered from active wireless networks.

(Gao, S., 2020) Caching method for Smaller Base Stations (SBSs), which typically have limited capacity, is essential for ultra-dense network with wireless backhaul to handle huge high data rate requirements. We use Maximum-Distance Segmented (MDS) coding in a cooperative caching method, taking advantage of Reinforcement Learning (RL) to deal with the unknown time variations in the content popularity profile. In order to optimize the long-term predicted cumulative traffic load that is serviced directly by the SBSs with requiring access to the macro base station, we model the MDS codes based collaborative caching as a Markov chain of decisions. This allows us to capture the demand dynamics. First, we use Q-learning to integrate cooperative MDS coding and determine the most effective approach for a small-scale system for the specified problem.

(Tinh, B. T., 2022) In response to the growing need for Fifth Generation (5G) mobile networks to have greater coverage and capacity, ultra-dense networks, or UDNs, have been used to address critical issues. It has been projected that the widespread use of UDNs will break the basic deadlocks of beyond 5G or Sixth Generation (6G) network and provide many more orders magnitude increases than are now possible with current technologies. Nonetheless, it is well known that developing a mathematical technique to maximize system performance while adhering to strict radio resource limits is extremely difficult. Existing UDNs' system-level performance optimization is often carried out by using numerical simulations, which can be very time-consuming and challenging in the context of 6G with very high densities. Therefore, creating a practical mathematical model for improving the 6G UDNs is imperative.

(Mughees, A., 2020) In light of global efforts to reduce energy waste and adopt more environmentally friendly technologies, wireless network energy efficiency is more important than ever. Research and network design are crucial since next-generation networks, like 5G, are being created with increased energy efficiency in mind. Many administrations, for example, further developed versatile broadband, huge machine-type correspondence, ultra-dependability, and low inertness, are expected to be given by the 5G organization. The 5G organization has formed into a multi-facet framework that uses the utilization of various mechanical progressions to give a wide scope of remote administrations to clients to meet such a broadened set of prerequisites.

(Gorla, P., 2022) The deployment of a multi modal ultra-dense network with a variety of topographical use cases is what the telecommunications system will require in the future. But in 5g and beyond, this rise in ultra-denseness presents a number of difficulties for resource allocation, necessitating a precise prediction based on learning. This research provides a novel architecture for Mobile Edge based provisioning of resources to User Equipment (UEs) utilizing Distributed Learning with Machine Learning (DML) and Federated Learning (FL). With the use of Kolmogorov tests, this work develops unique correlation-based processes across UEs for Distributed and Distributed Machine Learning applications that predict SNR. The Kolmogorov test correlations of the distribution determine the degree of Independence and Exactly Distributed (IID) -ness among the modelled variables and assess the global model's accuracy in resource provisioning.

(Nguyen, V. 2020) By 2020, there will be more than 50 billion devices connected to the Internet, and by 2019, there will be more than 11.5 billion mobile devices. These astounding growth rates are expected to continue rising over the coming decades, which will undoubtedly result in huge demand for universal communication in terms of traffic. During 2016 and 2021, it is predicted that the amount of data traffic would almost quadruple. Of this, 75% of the traffic will come from non-PC devices, and 42% of all connection will be used for M2M communication amongst the more than 10 billion smart items. By 2030, the Fifth-Generation (5G) wireless networks—which are being propelled by the explosive expansion of mobile Internet—should offer 1000 times more data throughput than current networks.

(Chen, J., 2022) In the field of unmanned aerial vehicle (UAV) networks, the distribution of resources for Mobile Edge Computing (MEC) has been a popular study topic. Unlike other works, this paper takes into account a scenario of multi-UAV assisted uplink communication and explores an energy-saving resource allocation problem while taking into account Mobile Users' (MUs') transmit power limitations and system latency resulting from computation and transmission. It is established that the issue is a difficult time-series data mixed-integer non-convex programming problem. That is, deeper Reinforcement Learning (DRL) is used to optimize UAV movement and MU connection in order to reduce system latency and energy consumption.

III. METHOD

The primary objective of this examination project is to make a blockage the executive's model that will work on the usage of the open organization assets and diminish clog in 5G organizations. To deal with the intricacy of gauging the ideal limit of the 5G organization, a brilliant system is advanced(J. Qiu, J. Lyu, 2020).

The main goal of this suggested congestion control strategy is to minimize network congestion on 5G and 6G networks by optimizing the utilization of the resources that are currently accessible. This technique stands out due to its hybrid deep learning, which is currently under development at the moment. Figure 1 below displays the suggested model.

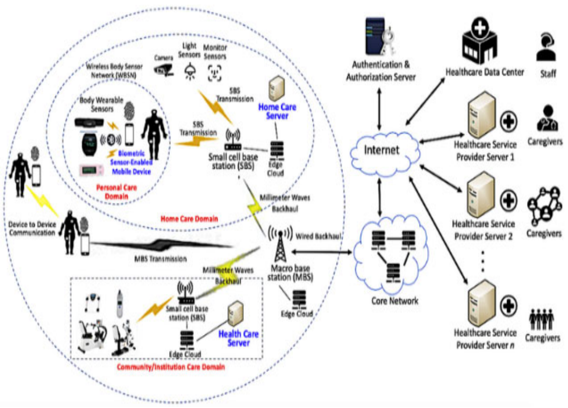

Fig. 1 Model of System.(J. Qiu, J. Lyu, 2020) .

A. Channel Model

The features of the wireless channel are described by the MBS and SBS channel models in 5G UDN. The user-defined route loss of a wireless linked cell is as follows:

$$PL_{ij} = \begin{cases} 33.2 + 24\lg(f) + 30\lg(d_{ij}) + X, \ \textit{it is macro cell}, \\ 33.2 + 24\lg(f) + 31.8\lg(d_{ij}) + X, \ \textit{it is small cell} \end{cases} \quad \text{...1}$$

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}, \quad \text{...2}$$

$$SINR = 10.\log\left(\frac{P_S}{P_I + P_N}\right), \quad \text{...3}$$

$$Th = W * log_2\left(1 + \frac{P_2}{P_I + P_N}\right), \quad \text{...4}$$

Data collection is the initial stage, which gathers information from the input parameters and enters it into a database(J. Pei, P. Hong, M. 2020). Next, utilizing choosing features, handling values that are missing, moving averages, and normalization, the database's stored data is per-processed to reduce the noise.

Next, using the SVM method and Naïve Bayes, the information that has been processed is sent to the training model.

$$k = H\widetilde{o\iota} + \zeta, \quad \text{...5}$$

$$H\widetilde{O\iota} - k + \zeta = 0. \quad \text{...6}$$

$$\vec{T}.\bar{t} + \zeta = 0. \quad \text{...7}$$

$$T = \frac{\tilde{o}i}{|t|} + \frac{k}{|t|}, \quad \text{...8}$$

$$||t|| = \sqrt{\widetilde{O^2_{\iota}}_{+} k^2_{+} \dots\dots\dots\dots t^2_{\zeta}}. \quad \text{...9}$$

$$\cos(\theta) = \frac{\widetilde{O\iota}}{||t||} \ and \cos(u) = \frac{K}{||t||}, \quad \text{...10}$$

$$\acute{A}(T,\zeta,\mu) = \frac{1}{2}\ T.T - \sum_{i=1}^{t} \mu_i[M:(T.t + \zeta) - 1], \text{...11}$$

$$\nabla_T \acute{A}(T,\zeta,\mu,) = T - \sum_{i=1}^{\tau} \mu_i \{M:(T.t + \zeta) - 1]\text{...12}$$

$$\nabla_\zeta A\acute{A}(T,\zeta,\mu,) = -\sum_{i=1}^{\tau} \mu_i M_i = 0. \quad \text{...13}$$

The hyperplane will only be available once, after which we can use it for prediction. Where the function of the hypothesis is:

$$c(T_i) = \begin{bmatrix} +1 if T.t + \zeta \geq 0 \\ -1 if T.t + \zeta \geq 0 \end{bmatrix}. \quad \text{...14}$$

Therefore, the core task of the algorithm used by SVM is to find a hyperplane that can accurately disseminate the data and identify the best one, also known as the optimum hyperplane.

The training output is then saved on the cloud and verified to see if the learning conditions are met; if otherwise, it is revised, and so on. The Fused Machine Learning (FML) technique receives the trained patterns. It is the responsibility of FML to combine the predictions from both algorithms using a fuzzy inference method. To achieve more accuracy and improved decision-making, FML combines machine learning with a decision level fusion technique. Figure 2 demonstrates the suggested model's performance graphically in good, satisfactory, and poor, using yellow, blue, and green colouring, correspondingly.

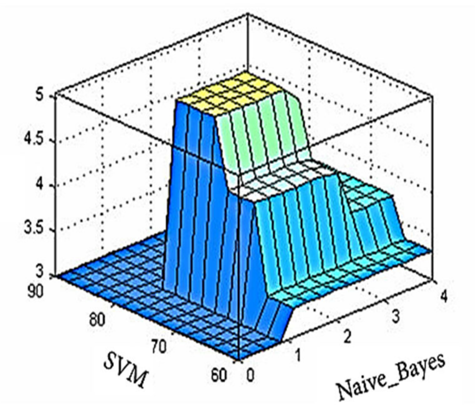

Fig. 2 Visual Display of the Suggested Model Performance.(J. Pei, P. Hong, M. 2020).

B. Action Space

The user chooses at as the prospective cell to handover during network time slot t. With A= {0, 1, 1, 2,}, the prospective cell the index set to UDN is expressed. Macro cells are indexed 0 to 9, while tiny cells are indexed 0 to 9. Mobile users choose which task to handover during each time slot t. The best candidate cell is chosen if a handover is required(Jiang and X. Zhu, 2020).

IV. RESULTS AND DISCUSSION

This study presents an intelligent system that uses a fused artificial intelligence technique to more effectively and accurately predict 5G congestion. The suggested method is used on a dataset.

Using SVM and Naïve Bayes algorithms, a real-time cyberattack is predicted for a total of 7558 occurrences. Additionally, for both training and validation reasons, the dataset is split into trained founds of 70% (5291 items) and 30% (2267 samples)(H.-X. Peng 2021) . The algorithms follow different parameters utilized in the performance computation with other indicators:

$$Sensitivity = \frac{\sum True\ positive}{\sum Condition\ positive}, \quad \textbf{...15}$$

$$Specificity = \frac{\sum True\ negative}{\sum Condition\ Negative}, \quad \textbf{...16}$$

$$Accuracy = \frac{\sum True\ positive + \sum True\ positive}{\sum Condition\ Negative}, \quad \textbf{...17}$$

$$Miss - Rate = \frac{\sum False\ Negative}{\sum Condition\ Position}, \quad \textbf{...18}$$

$$Fallout = \frac{\sum False\ Positive}{\sum condition\ Negative}, \quad \textbf{...19}$$

$$Likehood\ Positive\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ ratio}, \textbf{..20}$$

$$Likehood\ Negative\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ ratio}, \quad \textbf{...21}$$

$$Positive\ Prrdictive\ Value = \frac{\sum True\ Positive}{\sum Predicted\ Condition\ Negative}, \quad \textbf{...22}$$

$$Negative\ Prrdictive\ Value = \frac{\sum True\ Positive}{\sum Predicted\ Condition\ Negative}, \quad \textbf{...23}$$

Table 1 SVM-based suggested model training for 5G congestion prediction.

Table 1 5G congestion prediction (SVM). (H.-X. Peng 2021.

PROPOSED MODEL TRAINING	
True positive	False positive
1988	366

PROPOSED MODEL TRAINING	
False negative	True Negative
103	2834

Table 2 illustrates how the suggested model forecasts infiltration during the validation stage(R. Arshad, H. ElSawy, S. 2017). Accordingly, a total of 2267 results were used for validation, broken down into 1064, 1203 positive, and negative samples.

Table 2 prediction of 5G congestion (SVM).(R. Arshad, H. ElSawy, S. 2017)

PROPOSED MODEL VALIDATION	
True positive	False negative
936	128

PROPOSED MODEL VALIDATION	
False negative	True negative
95	1108

The suggested system for predicting 5G capacity during the training phase is displayed in Table 3. 5291 samples total—2383, 2908 positive samples and 2908 negative samples—are used in the training process.

Table 3 Naive **Bayes forecast of 5G congestion.**

PROPOSED MODEL TRAINING	
True Positive	False Positive
1910	423

PROPOSED MODEL TRAINING	
False negative	True negative
183	2725

Table 4 illustrates how the suggested model anticipates 5G congestion throughout the validation stage. 2267 samples are used for validation; they are split into 1132, 1135 positive, and 1135 negative samples, respectively (Y. Z. H. Wang, X. Yang, 2020) .

Table 4 Naive **Bayes forecast of 5G congestion.**(Y. Z. H. Wang, X. Yang, 2020).

PROPOSED MODEL TRAINING	
True positive	False positive
912	220

PROPOSED MODEL TRAINING	
False negative	True negative
119	1016

The presentation of the proposed framework as far as responsiveness, particularity, exactness, miss rate, and accuracy during preparing is shown in Fig. 3 (SVM), where it brings about upsides of 0.911, 0.950, 0.089, 0.093, and 0.844, individually.

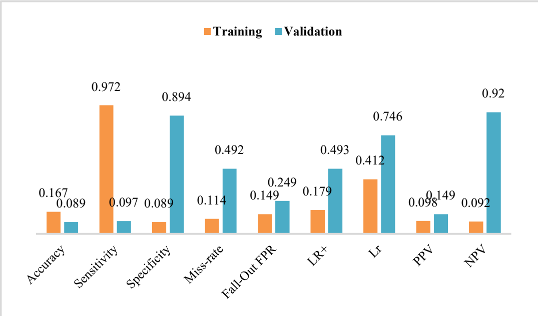

Fig. 3 Control the model's performance throughout the training and validation process (SVM).(Y. Z. H. Wang, X. Yang, 2020) .

Figure 4 (Naïve Bayes) illustrates how the suggested system performs in terms of sensitivity, specificity, accuracy, miss rate, and precision during training, with results of 0.876, 0.913, 0.852, 0.916, and 0.802, respectively(L. W. W. Sun, J. Liu, 2021) .

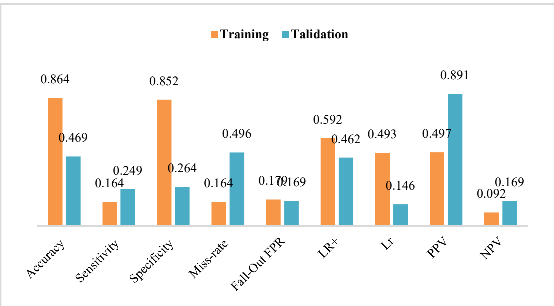

Fig. 4 suggested system using many statistical metrics for both training and validation (Naïve Bayes).(L. W. W. Sun, J. Liu, 2021) .

Additionally, Table 5 displays a comparison of the suggested system's performance, revealing that the miss rate and Naïve Bayes accuracy are 0.149 and 0.851, respectively. That is 0.901 and 0.099 in SVM, respectively. It is shown that the suggested fusion-based technique performs better in terms of accuracy (0.933) and miss rate (0.067).

Table 5 suggested system utilizing SVM and Naïve Bayes algorithms. (Q. Liu, C. F. Kwong, S. Wei, L 2021) .

Naïve Bayes	**Accuracy**	0.198
	Miss rate	0.149
SVM	**Accuracy**	0.09
	Miss rate	0.098
Proposed Fusion-Based ML approach	**Accuracy**	0.939
	Miss rate	0.067

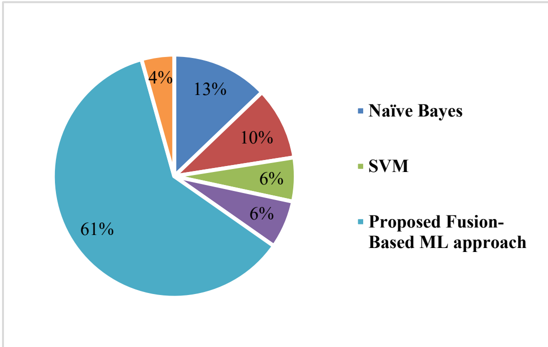

Fig. 5 suggested system utilizing SVM and Naïve Bayes algorithms.

The primary target of this examination is to come up with blockage the board procedures for 5G and 6G organizations to stay away from clog and improve the utilization of the assets that are by and by accessible in these organizations (Q. Liu, C. F. Kwong, S. Wei, L 2021). For the cutting edge remote organizations in homes and business undertakings, 5G and 6G organization correspondence is a difficult yet important errand.

One significant trouble confronting the examination local area is making a smart settling on decisions structure for approaching organization traffic to check load adjusting, limit network correspondence calamity, and give one more in the event of devastating or overcapacity conditions (M. Cicioğlu, 2021).

This study proposed a model that used a half breed profound learning way to deal with gauge the best clog in 5G organizations, consequently tending to the trouble of 5G blockage control. The suggested strategy can improve network efficiency and yield superior results in terms of 0.067 miss rate and 0.933 accuracy (G. Gódor, Z. Jakó, Á. 2015).

V. CONCLUSION

The study found that in 5G ultra-dense networks, the suggested SA-PER handover judgement approach decreased the frequency of handovers and the ping-pong effect. The communication services are provided with improved and upgraded quality and continuity. The frequently handing and ping-pong effect were lessened by the state-aware technique and the evaluation of cell dwell time.

The simulation results demonstrate that our created algorithm is capable of decreasing the data collision rate between LoRa nodes as their number increases, and that their energy usage approaches the minimum distance. Real-time data transmission from satellites to terrestrial networks is required for some applications. Nevertheless, throughout the snapshot, the majority of satellites are unable to communicate with BSs. As a result, getting the real-time data produced by satellites onto terrestrial networks is difficult.

A tiny portion of the lost packet phenomena will take place in LoRa nodes as a result of the DRL algorithm's preliminary characteristics.

Future work

We anticipate improving the LoRa loss of packets scenario much more in the future. Additionally, as satellite-based cooperative communication becomes more developed, research on joining multi mode communication optimization will grow in importance.

VI. REFERENCES

[1] Najm, M. Ismail, T. Rahm, and A. Al Razak, “Wireless implementation selection in higher institution learning environment,” Journal of Theoretical and Applied Information Technology, vol. 67, pp. 477–484, 2014.

[2] T. Rahem, M. Ismail, I. A. Najm, and M. Balfaqih, “Topology sense and graph-based TSG: efficient wireless ad hoc routing protocol for WANET,” Telecommunication Systems, vol. 65, no. 4, pp. 739–754, 2017.

[3] M. Y. Aalsalem, W. Z. Khan, W. Gharibi, M. K. Khan, and Q. Arshad, “Wireless Sensor Networks in oil and gas industry: recent advances, taxonomy, requirements, and open challenges,” Journal of Network and Computer Applications, vol. 113, pp. 87–97, 2018.

[4] M. Saleem, S. Abbas, T. M. Ghazal, M. A. Khan, N. Sahawneh, and M. Ahmad, “Smart cities: fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques,” Egyptian Informatics Journal, vol. 23, 2022, In Press.

[5] R. Dong, C. She, W. Hardjawana, Y. Li, and B. Vucetic, “Deep learning for hybrid 5G services in mobile edge computing systems: learn from a digital twin,” IEEE Transactions on Wireless Communications, vol. 18, no. 10, pp. 4692–4707, 2019.

[6] A. Sunny, S. Panchal, N. Vidhani et al., “A generic controller for managing TCP transfers in IEEE 802.11 infrastructure WLANs,” Journal of Network and Computer Applications, vol. 93, pp. 13–26, 2017.

[7] Y. Chen, J. Li, W. Chen, Z. Lin, and B. Vucetic, “Joint user association and resource allocation in the downlink of heterogeneous networks,” IEEE Transactions on Vehicular Technology, vol. 65, no. 7, pp. 5701–5706, 2016.

[8] A. Khalili, S. Akhlaghi, H. Tabassum, and D. W. K. Ng, “Joint user association and resource allocation in the uplink of heterogeneous networks,” IEEE Wireless Communications Letters, vol. 9, no. 6, pp. 804–808, 2020.

[9] N. Zhao, Y.-C. Liang, D. Niyato, Y. Pei, M. Wu, and Y. Jiang, “Deep reinforcement learning for user association and resource allocation in heterogeneous cellular networks,” IEEE Transactions on Wireless Communications, vol. 18, no. 11, pp. 5141–5152, 2019.

[10] V. Mnih, K. Kavukcuoglu, D. Silver et al., “Human-level control through deep reinforcement learning,” Nature, vol. 518, no. 7540, pp. 529–533, 2015.

[11] Sharma, N., & Kumar, K. (2022). Energy Efficient Clustering and Resource Allocation Strategy for Ultra-Dense Networks: A Machine Learning Framework. IEEE Transactions on Network and Service Management.

[12] Anzaldo, A., Rodríguez, M. D., & Andrade, Á. G. (2023). Intelligence-learning driven resource allocation for B5G Ultra-Dense Networks: A structured literature review.

[13] Zhao, S. (2023). Energy efficient resource allocation method for 5G access network based on reinforcement learning algorithm. Sustainable Energy Technologies and Assessments, 56, 103020.

[14] Peng, T., Guo, Y., Wang, Y., Chen, G., Yang, F., & Chen, W. (2022). An interference-oriented 5G radio resource allocation framework for ultradense networks. IEEE Internet of Things Journal, 9(22), 22618-22630.

[15] Gao, S., Dong, P., Pan, Z., & Li, G. Y. (2020). Reinforcement learning based cooperative coded caching under dynamic popularities in ultra-dense networks. IEEE Transactions on Vehicular Technology, 69(5), 5442-5456.

[16] Tinh, B. T., Nguyen, L. D., Kha, H. H., & Duong, T. Q. (2022). Practical optimization and game theory for 6G ultra-dense networks: Overview and research challenges. IEEE Access, 10, 13311-13328.

[17] Mughees, A., Tahir, M., Sheikh, M. A., &Ahad, A. (2020). Towards energy efficient 5G networks using machine learning: Taxonomy, research challenges, and future research directions. Ieee Access, 8, 187498-187522.

[18] Gorla, P., Keerthivasan, V., Chamola, V., &Guizani, M. (2022). A Novel Framework of Federated and Distributed Machine Learning for Resource Provisioning in 5G and Beyond using Mobile-Edge SCBS. IEEE Transactions on Network and Service Management.

[19] Nguyen, V. D., Duong, T. Q., &Vien, Q. T. (2020). Emerging techniques and applications for 5G networks and beyond. Mobile Networks and Applications, 25, 1984-1986.

[20] Chen, J., Cao, X., Yang, P., Xiao, M., Ren, S., Zhao, Z., & Wu, D. O. (2022). Deep reinforcement learning based resource allocation in multi-uav-aided MEC networks. IEEE Transactions on Communications, 71(1), 296-309.

[21] J. Qiu, J. Lyu, and L. Fu, “Placement optimization of aerial base stations with deep reinforcement learning,” in ICC 2020-2020 IEEE International Conference on Communications (ICC),, pp. 1–6, Dublin, Ireland, 2020.

[22] J. Pei, P. Hong, M. Pan, J. Liu, and J. Zhou, “Optimal VNF placement via deep reinforcement learning in SDN/NFV-enabled networks,” IEEE Journal on Selected Areas in Communications, vol. 38, no. 2, pp. 263–278, 2020.

[23] Jiang and X. Zhu, “Reinforcement learning based capacity management in multi-layer satellite networks,” IEEE Transactions on Wireless Communications, vol. 19, no. 7, pp. 4685–4699, 2020.

[24] H.-X. Peng and X. Shen, “Multi-agent reinforcement learning based resource management in MEC- and UAV-assisted vehicular networks,” IEEE Journal on Selected Areas in Communications, vol. 39, no. 1, pp. 131–141, 2021.

[25] R. Arshad, H. ElSawy, S. Sorour, T. Y. Al-Naffouri, and M.-S. Alouini, “Velocity-aware handover management in two-tier cellular networks,” IEEE Transactions on Wireless Communications, vol. 16, no. 3, pp. 1851–1867, 2017.

[26] Y. Z. H. Wang, X. Yang, and C. Wei, “METRE measurement task recommendation for energy-efficient handover in dense networks,” in GLOBECOM 2020 - 2020 IEEE Global Communications Conference, pp. 1–6, Taipei, Taiwan, 2020.

[27] L. W. W. Sun, J. Liu, N. Kato, and Y. Zhang, “Movement aware CoMP handover in heterogeneous ultra-dense networks,” IEEE Transactions on Communications, vol. 69, no. 1, pp. 340–352, 2021.

[28] Q. Liu, C. F. Kwong, S. Wei, L. Li, and S. Zhang, “Intelligent handover triggering mechanism in 5G ultra-dense networks via clustering-based reinforcement learning,” Mobile Networks and Applications, vol. 26, pp. 27–39, 2021.

[29] M. Cicioğlu, “Multi-criteria handover management using entropy-based SAW method for SDN-based 5G small cells,” Wireless Networks, vol. 27, no. 4, pp. 2947–2959, 2021.

[30] G. Gódor, Z. Jakó, Á. Knapp, and S. Imre, “A survey of handover management in LTE-based multi-tier femtocell networks: requirements, challenges and solutions,” Computer Networks, vol. 76, pp. 17–41, 2015

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