A Survey of power allocation techniques in NOMA: Research challenges and Future directions

Krupa Dave[1], Ashish Kothari[2]
[1]Research scholar, Department of Electronics and Communication, Atmiya University, Rajkot
[2]Professor,Department of Electronics and Communication, Atmiya University, Rajkot

Abstract:
Non-orthogonal multiple access, often known as NOMA, is one of the viable ways to big capacity radio access. It provides a number of desired features, including better spectrum efficiency, making it an appealing choice. This piece places a focus on power-domain NOMA, in which successive interference cancellation (SIC) and superposition coding (SC) are the most essential functions at the transmitter and receiver, respectively. Following an analysis of many standard power allocation methods and the restrictions they impose, the authors of this article go on to describe a variety of innovative power distribution techniques that are based on machine learning. Approaches that are based on machine learning and deep learning produced performance that was considerably near to the optimal in terms of total capacity, although having significantly lower computing costs. Optimal performance would be attained by having the most overall capacity. Discussion of a number of potential future research avenues based on the use of deep learning in NOMA systems is the last step of the process.
Keywords: Deep learning, Power allocation, Non-orthogonal multiple access (NOMA), Machine learning, Successive interference cancellation (SIC).
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1. Introduction

NOMA provides a high level of spectral efficiency in the power domain, which is one of the reasons why it is seen as a potentially useful strategy for meeting the needs of fifth-generation (5G) cellular networks. NOMA provides a service that is accessible to several users all at the same time and on the same frequency. The modulated data from each user's transmission is superimposed by the base station during the downlink and merged before transmission. Each user's broadcast has a unique power level. After that, on the receiving end, each user implements an interference cancellation approach, which may include sequential interference cancellation, in order to differentiate each message from the overlaid signal (SIC). Extensive calculations are required for interference cancellation mechanisms at the receiver [11] and complicated calculations are required for power allocation coefficients at the transmitter [12]. These are two of the primary barriers that prevent the deployment of NOMA at present time.

The mobility of the user population being serviced adds an additional layer of complexity to the problems that must be solved using computing. This study genuinely tackles the issue of power distribution at the transmitter for downlink NOMA systems in order to circumvent the computer limitations. The use of deep learning as well as more conventional methods for regression analysis is shown in [8].

NOMA makes accessible a wide variety of strategies for the distribution of electricity. There are several significant factors, some of which include channel gain, signal-to-noise ratio (SNR), distance from transmitters, fairness index, and the need to improve energy efficiency. At the transmitter, an efficient approach for allocating power is applied, which results in SIC that is very close to being perfect. After power has been allocated, the signal that is supposed to be delivered to the consumers is multiplied at the transmitter by the power index, and then it is either merged or overlaid before it is sent as a signal. When the signals are received by numerous users who are sharing the same resource, they are treated as a strong user signal since they are recognized by multiple users at the same time. The user with the strongest signal is used to produce a new signal, which is then subtracted from the signal that was received in case it was not the desired signal. This procedure will continue until all users are able to read the signals that are specific to them. This is the fundamental concept of SIC [2].

The conventional solutions to this optimization issue are unstable and insufficient for collecting proper channel assignments, which therefore hinders the performance of the NOMA system. Recently, the framework of machine learning has gained recognition as an effective technique that can be applied into wireless communication systems, hence enhancing the system architecture of these communication systems. Deep learning improves overall performance by using the nonlinear relationships included in training data to their utmost potential. This allows the data to be used more effectively. This work, which is inspired by the potential of deep learning, presents a complete investigation of the function that deep learning plays in power allocation in NOMA systems [24].

Both machine learning and fifth-generation (5G) wireless communications are considered separate fields of study for some reason, despite the potential benefits that may result from combining the two. In point of fact, a number of recently developed networking paradigms, such as location-based services [20], mobile edge caching [10], [11], context-aware networking [7], big data analytics [24], [25], mobile edge computing [11][13], and network traffic control, have already demonstrated the impact that machine learning can have on mobile and wireless network communications.

Learning using machine systems is particularly useful for challenging issues that have hand-tuning-intensive solutions or for situations that have no conventional answer at all. It is possible to find solutions to these problems by exchanging traditional software with complicated rule lists for machine learning algorithms that automatically learn from previous experiences. One of the most notable distinctions between machine learning (ML) and cognitive algorithms is that the former does not need time-consuming and costly hand-crafted feature engineering. Automatic feature extraction eliminates this requirement. In general, a job using machine learning may include finding patterns that a professional might miss, detecting anomalies, predicting likely outcomes, adapting to changing settings, gaining insights into complicated issues with tons of data, and other similar activities. [33].

The preceding is how the entire article is organized.

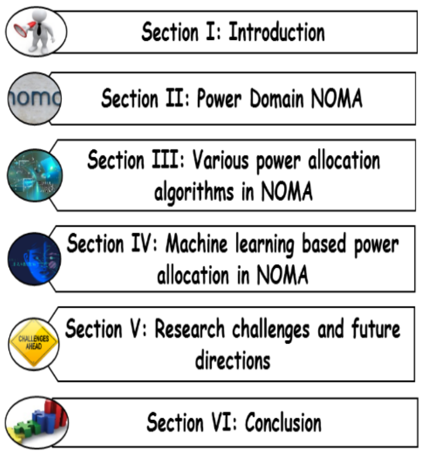

Figure 1: The preceding is how the entire article is organized

All sections comprise the remaining part of this article are as below: In Section II, the concepts of power domain NOMA have been addressed.Conventional power allocation in NOMA systems is presented in section III. Machine learning-based power allocation problems are presented in part IV. This review is at the edge of new technologies because the research for it focused on very recent studies in the field. Section V explores recent research constraints and future directions. Section VI draws conclusion.

2. POWER DOMAIN NOMA

There are a great number of NOMA solutions available; nevertheless, they may mostly be split up into two distinct types. Figure 1 provides a basic classification of the many NOMA techniques that are currently in use. Multiplexing may be accomplished in the code domain with code-domain NOMA, in contrast to the power domain with power-domain NOMA, which does it in the power domain. Code-domain NOMA operates in a manner that is very similar to that of basic code division multiple access (CDMA) systems [15], in that it shares the whole pool of time and frequency resources. On the other hand, the user-specific spreading sequences that are used in code-domain NOMA are either sparse sequences or non-orthogonal cross-correlation sequences that have a low correlation coefficient. Additional classes that may be classified into this one include sparse code multiple access (SCMA) [8, 9], low-density spreading CDMA (LDS-CDMA) [4, 5], and low-density spreading-based OFDM (LDS-OFDM). [18]

LDS-CDMA is able to reduce the effect that interference has on each chip in basic CDMA systems thanks in large part to the use of low-density spreading sequences. Before being transmitted on a number of subcarriers, the information symbols in LDS-OFDM are first scattered over low-density spreading sequences as in LDS-CDMA. LDS-OFDM is a hybrid technology that combines LDS-CDMA with OFDM. SCMA is a code-domain NOMA technique that was developed not too long ago and is based on LDS-CDMA. When bit mapping and bit spreading are combined, as they are in LDS-CDMA, the information bits may be directly converted to separate sparse code words [31]. This is in contrast to the LDS-CDMA method. There are a number of other multiple access algorithms, such as pattern division multiple access (PDMA) and spatial division multiple access (SDMA), which are closely related to NOMA [11–14]. There are many different domains in which PDMA might be used. On the transmitter side, the first step that PDMA takes to generate non-orthogonal patterns is to boost variety while simultaneously reducing overlaps between various users. After that, the multiplexing is executed either in the spatial domain, the code domain, or a combination of the two domains. The primary CDMA systems served as an important source of motivation for the development of the SDMA operating model. In lieu of user-specific spreading sequences, SDMA uses user-specific channel impulse responses as the method for separating the multiple users (CIRs).

This strategy is extremely beneficial in situations in which the number of users on the uplink is much more than the number of similar reception antennas in the base station. On the other hand, an overwhelming majority of customers find it difficult to precisely forecast the CIR. Because of the concept of software-defined radio for multiple access (SDR-MA), several NOMA approaches are able to coexist with one another [15]. This technology provides a flexible configuration of participating multiple access methods, which enables a wide variety of services and applications to be run on 5G networks. It is essential to bear in mind that the aforementioned list, despite the fact that it provides some insights into the many different forms of NOMA, is not complete. The primary emphasis of this research is placed on power-domain NOMA. [31].

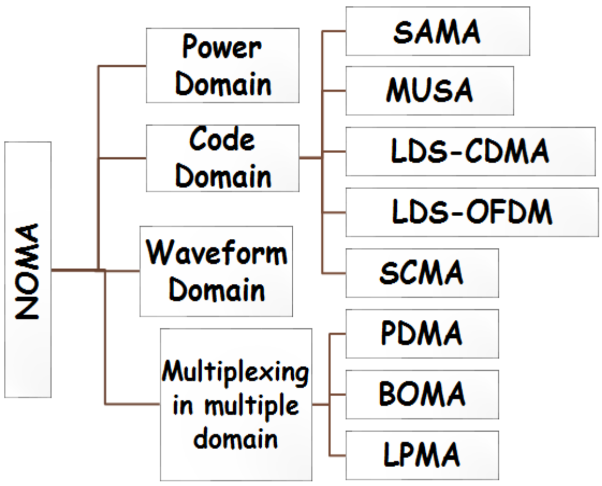

Figure 2: Power domain NOMA

Power allocation in NOMA: Both the downlink and the uplink systems are susceptible to the NOMA notion of assigning distinct power coefficients [16], with the only exception of situations in which SIC operation is used. The SIC process is maintained on the receiving side of the downlink NOMA system, in contrast to the uplink NOMA system, which executes SIC at the location of its transmitter. The NOMA design is closely related to the process that involves selecting the pair of users to be multiplexed across a certain subchannel and allocating the power levels consistent with their channel constraints [15]. This process involves selecting the pair of users to be multiplexed across a certain subchannel.

In uplink NOMA, it was frequently thought that paired users in a single sub-channel would each have their own distinct channel conditions. The user who had the worst channel circumstances would want to pair with the user who had the best channel conditions. In an uplink NOMA system, there are two users that are multiplexed. User 1 represents the strong user, which is a user that has favorable channel conditions, while user 2 represents the weak user (i.e., a user with poor channel condition). In an uplink NOMA, the Base Station (BS) decodes the signal from user 1 first, and then it decodes the signal from user 2 by subtracting it from the signal that is being superimposed [15].

In the case of downlink NOMA, assuming there are two users and one sub-channel, this suggests that user 2 is the weak user and user 1 is the strong user. User 1 conducts SIC, which is provided a low power level in order to decode User 2's signal and then cancel User 2's signal [15]. This is done so that User 1 may then cancel User 2's signal. User 2, in contrast, is provided with a high power level, is free from executing SIC, and is only needed to decode its signal by treating User 1's signal to be interference [14].

3. Various Power allocation Algorithms in NOMA:

Different power levels are allotted to users who share a sub-channel according to power allocation. As a result, the power allocated to each user multiplexed across a certain sub-channel was distributed among them. For NOMA, there are numerous power allocation algorithms, each of which is described below:

Fixed Power Allocation (FPA): On sub-channel c, paired users share power according to a predetermined ratio. Anytime only a portion of a sub-power channel's is given to one user and the remainder is given to another [16].

Fractional Transmit Power Allocation (FTPA): For the multiplexed pair of users, FTPA is employed, which offers an optimal option. Channel conditions are used in power allocation in contrast to Fixed power allocation [16].

Full Search Power Allocation (FSPA): After an exhaustive search, the power levels of user pairs that share a certain sub-channel are presented in FSPA. This approach achieves its desired outcome by generating every possible combination of power levels, which leads to a solution that is superior yet challenging to compute. Taking into account a multiplexed pair in sub-channel c, all possible sets of power levels that are dependent on the channel conditions of each pair are created. This makes it possible to choose the ideal set of power levels based on the system's performance gain [16].

FTPA with Improvements (I FPGA): The FTPA decay factor, which in this context acts as an exponent, fluctuates depending on the channel gain for I-FTPA. This is because the FTPA decay factor functions as an exponent. This method has a reduced bit error rate compared to orthogonal frequency division multiple access (OFDMA), no-overlapping frequency division multiple access (NOMA-FPA), and no-overlapping frequency division multiple access (NOMA FTPA) (BER). Even though it has a superior capacity to adapt to the conditions of the channel, more caution has to be taken while selecting the different decay factors. The accuracy of detection for each user is impacted by a variety of variables that deteriorate with time. The requirements of the user may be modified in accordance with the application in question. In contrast to FTPA, where this adjustment is never made, the decay factor may be modified to take into account the various channels. I-FTPA performs much better than FTPA does in NOMA [17].

Generalized Power Allocation (GPA): In NOMA, the distribution of power is handled with the help of this uncomplicated method. The notion of GPA is shown via the equation (1). [17]

$$Pi = \frac{n!}{i! \times (n-i)n!} \times Ci \qquad (1)$$

where C is the choice factor, which is given by

$$C = P^{1/n} - 1, \quad P = \sum_{i=1}^{n} Pi$$

Optimal Power Allocation (OPA):

This strategy maximizes the throughput of the system as well as the total rate overall, despite specific restrictions placed on the fairness index. First, the desired fairness index is selected, and then the power matrix is initialized with all of the values that might possibly be used. Iterative calculations are performed to determine the fairness index and capacity for each possible combination of PAs. In the event that the fairness index is lower than the value that is wanted, capacity is reset to zero. Each calculated capacity value is evaluated in relation to the initial maximum capacity, which was set at zero. When the computed capacity value is higher than the maximum capacity, the maximum capacity value is adjusted to reflect the computed capacity value at the current time [18].

Particle Swarm Optimisation (PSO) based Particle Approximation:

Particle swarm optimization, often known as PSO, is an optimization approach that involves moving a huge population of particles throughout the search space until an optimum solution is found. The starting placements of these particles are picked at random. The PSO algorithm takes into consideration the population size as well as the channel gain. It is a process that repeats itself in which each particle is given a random starting location, the best possible position for that particle, and the position that best characterizes the swarm as a whole. Either until a condition is met or for a certain number of times, iterations will be carried out until one of these two outcomes occurs. At each iteration, both the position and the velocity of a particle are modified in order to optimize the fitness function and get the best possible results. In the case of PA and NOMA, the fitness function is determined by the amount of power efficiency that may be increased. After that, the optimum location of the swarm is updated to reflect the most effective approach to share the available power among the users. The vector of final allotted powers is thus what the PSO algorithm produces as its output. The result of the PSO method is thus a vector of the powers that have been finally allocated [19].

Target SNR-based PA: When PA is being utilized, the signal-to-interference-plus-noise ratio (SINR) should be optimized for strong users and should be over the minimum level for weak users. In addition to this, it is presumable that both the transmitter and the receiver are aware of the information about the ideal channel condition (CSI). In order to execute PA, you will need to consider the noise variance, channel gain, target SNR, and symbol power. The user who has a high gain receives the power factor with the lowest value, while the user who has a low channel gain receives the power factor with the greatest value. This method has the benefit of ensuring quality of service (QoS) since it generates PA parameters while also taking goal SNR and channel gain into consideration [16].

Eigenvalue-based power allocation is a method that provides a more precise characterization of the channel's capacity. H. Eigenvalue-based power allocation Because of the Channel Gain Matrix's intricacy, its magnitude square is the one that is used. This matrix makes use of the singular value decomposition technique. After then, the disparity in channel gain between users 1 and 2 is calculated in order to determine which of the two is superior in terms of the channel. [17] A user pair is defined as a collection of users who share the same channel in their communication.

According to this method, the rate of the system is determined by the sub-channel and the strength of the transmissions. I. User Classification and Preference Ranking Algorithm Following the classification of cell users, this component next assigns sub-channels to the users in order to account for the complexity of the allocation [19].

Many-to-Many Sub-channel–User Matching Algorithm (MSUMA) [20]: [J]:

The following is a rundown of the model's phases for execution:

(1) We divide the different BSs into groups and extend the classic many-to-many two-side matching problem into a number of related non-cooperative sub-channel-user many-to-many matching problem groups. This allows us to solve the problem of matching more than two sides.

(2) In order to generate an associated CoMP set, the sub-channel for each group's CoMP user community has to be a perfect match. This indicates that the sub-channel for each group has to take into account not just matching with the user in that group but also matching with CoMP users from other groups.

(3) A need with a low rate and non-CoMP status Users of CoMP just need to send their curriculum vitae (CVs) to the sub-channel in their cell that provides the best degree of satisfaction; high-rate requirements are not essential. Users of the CoMP protocol send their CVs to sub-channels inside the CoMP cluster that have the same specified range as each other, in addition to sending them to the sub-channel that provides the highest level of satisfaction within their own cell.

(4) It is the responsibility of the subchannels to assess whether or not the user who has been matched is a CoMP user with a high-rate demand. For a CoMP user who has a high rate requirement, it is necessary to determine whether or not the joint CoMP cell selects the CoMP user who is on the same RB. The high-rate requirement CoMP user won't be scheduled until the BS of the shared CoMP cell decides which CoMP user should be assigned to the same RB. In the event that this is not the case, this user will not be booked on the RB, for instance at step 8.B. In addition to this, it is essential to determine whether or not just one cell choose a CoMP user with a low rate need.

Discrete Power Allocation Algorithm Based on Group Search in NOMA-CoMP Systems: K. Discrete Power Allocation Algorithm Using this method, the total power may be segmented into a number of power levels that are all the same, and the initial optimization issue can then be addressed using the group search method. [16].

(a) **DPS-CoMP Intra-Sub-Channel Power Allocation:** In the initial step of this model's implementation, the MSUMA algorithm is used to couple users. After pairing, you may generate a variety of different paired user combinations by rearranging the paired users in decreasing order based on the identical channel gain. After users are paired, the base station will broadcast a range of different total power levels for each sub-channel. The power level that the BS has assigned to each user in the user pair for their particular connection. Achieve the greatest possible throughput at the current power level for a variety of user pairs by constantly achieving the highest possible throughput for the users that are paired together. The throughput of user pairs on sub-channels is decided to be equal to the maximum possible overall rate. In the last step, the level of the sub-power channel is altered so that the system can attain its maximum total rate.

(b) Power Distribution Within the JT-CoMP Intra-Sub-Channel:

After pairing, the users are ranked in decreasing order by equivalent channel gain to determine the order in which they were matched. It is possible to generate two sets of paired users for a single edge user with a high-rate requirement. Then, BS will supply a different amount of overall power for each individual sub-channel. The power level that the base station designates for each user in a user pair when they join together. Iterate until you have achieved the maximum rate of the edge users in the paired user pair group, and then repeat the procedures above to acquire the maximum rate of the edge users that can be accommodated by the present power level on the sub-Channel for the remaining user pair groups. Choose the maximum rate that can be achieved by the edge user as your maximum rate. Last but not least, adjust the amount of power that is sent on the sub-channel in order to get the highest possible sum-rate for the edge users in the JT-CoMP system.

(c) Power Distribution Across Inter-Sub-Channels:

It is necessary to repeat the methods described above for each of the distinct JT-CoMP and DPS-CoMP subchannels in order to achieve the required maximum rate, which is achieved by a variety of paired users (groups) operating at varying power levels. According to the idea of group search, the maximum user sum-rate in the DPS-CoMP cluster and the maximum edge user sum rate in the JT-CoMP clusters may be attained when the sum of the power levels on all subchannels is less than the total power delivered by the base station. This can be the case when the DPS-CoMP cluster and the JT-CoMP cluster are both combined. Determine the power that is allotted by the JT-CoMP sub-channel after taking into consideration the minimum rate requirement of the centre user and the maximum sum-rate of the edge users in the JT-CoMP clusters. This should be done after determining the power that is allocated by the JT-CoMP sub-channel. It is necessary to allocate the remaining total power to the DPS-CoMP channel in order to achieve the greatest possible sum-rate in the DPS-CoMP clusters.

Table 1: Limitations of various power allocation algorithms in NOMA:

Power allocation algorithms	**Limitations**
Water filling	Although this system outperforms equal power distribution, it has a variable outage probability and a poor fairness index.
Fixed power allocation	This technique reduces signalling cost and is straightforward, but it requires a specific formula to determine power distribution based on channel gain. The user's multiple QOS requirements cannot be fulfilled by this technique.
Fractional Transmit Power Allocation	More complicated than FPA and largely dependent on channel conditions
Improved FTPA	This method outperforms orthogonal frequency division multiple access (OFDMA), non-orthogonal multiple

	access (NOMA-FPA), and non-orthogonal multiple access (NOMA FTPA) in terms of the bit error rate (BER). Although it has a superior capacity to adapt to the conditions of the channel, it is still essential to make intelligent decisions about the numerous decay variables. The individual decay factors of each user have an impact on the detection accuracy.
Generalised Power Allocation	With various modulation strategies, GPA performs consistently.
Optimal Power Allocation	OPA conducts an extensive analysis to determine the best possible outcome under the fairness constraint.
Target SNR-based PA	OPA does a thorough search to deliver the greatest performance while adhering to a fairness requirement.
Eigenvalue-based power allocation	When combined code-power domain NOMA and other MIMO-NOMA channel model types are taken into account, it becomes difficult.
Particle Swarm Optimisation (PSO) based PA	It is an iterative process, so it takes time but produces wonderful results.
User	This model is not appropriate

Classification and Preference Ranking Algorithm	for ultra-dense networks in 5G scenarios, since this is where the number of sub-channels and users of CoMP cells might potentially be quite high.
Many-to-Many Sub-channel–User Matching Algorithm (MSUMA)	If the value for paired users is continuous, then it is difficult to split the power allocation values of paired users based on an exhaustive search in order to reach the greatest sum rate of high-speed demanding users.
Discrete Power Allocation algorithm Based on Group Search in NOMA-CoMP Systems	Less Efficiency.

4. Machine learning based power allocation in NOMA:

This section focuses mostly on the distribution of power in NOMA according to AI. We examine and evaluate a number of different approaches to power distribution that are based on machine learning and deep learning.

A. Power distribution determined by AI: The application of artificial intelligence models in downlink NOMA is an alternative to computationally costly optimum power allocation strategies. AI models are able to attain cumulative capacity that is practically ideal while also giving significant increases in the speed of processing. A few examples of AI-based power allocation strategies are DNN, exhaustive search, and normal equation methods [17].

B. Power distribution determined by supervised learning: DNN-based algorithms provide cutting-edge solutions for deep learning (DL)-based 5G and future scenarios. Create a power allocation plan with the objective of achieving the highest possible system total rate for a downlink NOMA scenario while taking into account the fact that SIC will likely be imperfect [12].

C. Semi-supervised power allocation: This approach proposes a DL framework to manage user association, sub-channel allocation, and power allocation while maximizing the system's energy efficiency (EE) within the constraint of a power limit [6]. [Citation needed] [Citation needed] [Citation needed] [Citation needed] [Citation needed] [Citation needed] [Citation needed

D. Unsupervised power allocation: This approach analyzes the problem of sum-rate maximization with restricted total transmission power [27]. It does this by satisfying the Qos limitations that the users have imposed on themselves. K-means clustering is by far the most used kind of clustering method. This technique to unsupervised learning is the one with the fewest moving parts and is centered on centroids. It is a method for unsupervised learning that can solve clustering problems and is an algorithm. Data sets are partitioned into a predetermined number of clusters, which we will refer to as K, in such a manner that the data points included within each cluster are consistent with one another and easily distinguishable from the data points contained within the other clusters.

E. Power distribution based on reinforcement learning: If all of the alternative actions are repeatedly chosen across all of the phases in the Markov decision process, then reinforcement learning methods such as Q-learning may determine the best action to perform with a probability of one. We therefore propose a power allocation technique based on Q-learning that selects the transmit power in accordance with the observed state of the radio environment, the jamming power, and a quality function, or Q-function, that describes the potential long-term reward for each state-action combination. This technique chooses the transmit power in accordance with the observed state of the radio environment, the jamming power, and a quality function, or Q-function. The BS uses this approach to identify the best action to take for multiple users in the dynamic anti-jamming MIMO NOMA game without being aware of the jamming and channel models. This method is utilized to discover the best action to do for numerous users. In the presence of an intelligent jammer, power distribution is handled by the Q learning base station (BS). The process is intended to be carried out in the manner of a game with no winner and no losers. [24]. In order to effectively distribute transmission resources, you should provide a strategy to perform channel assignment utilizing an attention-based neural network (ANN).

F. Power distribution on the basis of federated learning:

A well-known technique to artificial intelligence known as federated learning (FL) allows for a model to be trained centrally while yet keeping decentralized data. Because FL utilizes dispersed processing, it is well suited for use in situations when the available bandwidth is limited, in particular in wireless communications. It is possible for a large number of dispersed edge devices to be connected to a single parameter server (PS), and these devices will be able to repeatedly get data from and send data to the PS. Due to the limitations imposed by bandwidth, only a subset of the connected devices may be scheduled throughout each cycle. When it comes to modern machine learning models, such as deep learning, the normal number of parameters is in the millions. This not only makes the process of gathering and distributing training data more computationally complicated, but it also makes it more difficult to communicate with others [4]. in order to enhance the effectiveness of communication and get the training model closer to completion more quickly. This approach presents a novel scheduling strategy in addition to a cutting-edge technology for power allocation [32]. The goal of this method is to maximize the weighted total data rate while taking into consideration the limits that are imposed by the real environment.

Table 2: Various machine learning model and research challenges:

Machine learning algorithms	**State of Art**
AI based power allocation	All algorithms are applicable for few users only. Complex calculations needed for interference cancellation processes at the receiver and time-consuming computations for power allocation coefficients at the transmitter are the main obstacles to the deployment of NOMA thus far. The computational challenges are even further compounded by

	the mobility nature of the provided user base.
Supervised learning based power allocation	The requirement for the method to function properly not just on the training data, but also on model unobserved inputs, is a significant challenge in supervised learning. Another major problem in non-stationary contexts is dataset shift, when the linear combination of inputs and outputs shifts between the training and testing phases.
Unsupervised power allocation	For unsupervised power allocation, we need to use a different performance measure, one that can give the model a score that ranges from 0 to 100 and is continuous-valued. An example of this would be density estimation.
Semi-supervised power allocation	Trade-Off Between Accuracy And Interpretability
Reinforcement learning based power allocation	• In ML applications, high-quality data is a critical component. • The No Free Lunch Theorem in machine learning states that if we take the mean of

	all conceivable data-generated distributions, then any machine learning algorithm will have the same performance when it comes to inferring unobserved data. • Selection of hyper parameters.
Federated learning based power allocation	Privacy and security

5. RESEARCH CHALLENGES AND FUTURE DIRECTIONS:

The following section highlights numerous research challenges for power allocation using NOMA.

(a) Acquisition of a Data Set:

The quantity and quality of the training and test sets have a significant impact on how well a framework that is based on deep learning can perform its tasks. In the discipline of computer science, natural language processing (NLP), computer vision (CV), and autonomous driving have all seen rapid advancements in recent years. As a result, numerous well-known and highly effective data sets, such as ImageNet and the MNIST, have been readily accessible. Although there are certain data sets, such as RML2016, that may be utilized in particular areas of deep learning-based wireless communication, there aren't a lot of common data sets that cover issues that are connected to those fields. In order to facilitate research, it would be helpful to have a data collection that is both consistent and accurate across a range of concerns [3].

(b) Choosing the Model That Best Suits Your Needs: Developing neural networks is the primary obstacle faced while attempting to develop communication frameworks that are based on deep learning. Several different technologies based on deep learning have been created recently, and these technologies follow general model conventions. For example, the CNN is always used for CV, whereas the LSTM is usually used for natural language processing. Similarly, the CNN is always used for image classification. Despite the fact that we believe that generic models would make it simpler to bring such frameworks into the real world, we are interested in knowing whether or if there are models for deep learning-based wireless communication. When it comes to engineering projects, using universal models might cut down on the cost and amount of time spent on model selection, as well as make it simpler to optimize the communication frameworks. It is necessary to do extensive research on this topic [2-3] before it may be possible to construct models that are not only useful but also somewhat generic.

(c) Performance Evaluation and Learning Mechanisms: It has been shown that the communication architecture that is based on deep learning operates well when it comes to channel estimation and encoding. Massive MIMO, encoding, and decoding, amongst a great deal of other circumstances, are examples. Nevertheless, in order to conduct a more in-depth analysis of the usefulness of the framework, we have not yet developed accurate mathematical proofs and sound theorems. The creation of sound theories would also be of assistance to us in gaining a better knowledge of the communications system, which is the foundation for the modification of networks and the implementation of more efficient communication frameworks. Because the original input signals are frequently transformed into binary signals, one hot vectors, modulated integers, and other styles of data representation for the purpose of improving network performance in the deep learning area, it is not exactly clear whether cutting-edge performance can be achieved in the deep learning-based wireless communication frameworks while changing the styles of data representation. We are aware that the optimum results of deep learning-based communication frameworks have not yet been discovered, and that the rules of learning schemes in the area of wireless physical layer deep learning have not yet been clarified. In addition, we do not yet have a strategy for picking training examples based on such systems [3], and this is something that we are working on.

(d) Broadening of Assistance Learning Appropriate Physical Layer of Wireless: Deep Reinforcement Learning has Been Proposed as an Alternative Approach to Address Resource Allocation Problems In recent years Deep reinforcement learning has been proposed as an alternative approach to address resource allocation problems. For 5G to be successful, several problems relating to resource allocation and energy management need to be overcome; yet, existing solutions struggle with the enormous data processing concerns that must be addressed. As a result, in order to address the issues described above, the exceptional deep reinforcement learning that is available is able to improve the performance of the equipment in areas such as

CSI, latency, and bandwidth management. Due to the fact that it is able to deal with communication systems that have complex features, this approach is a good competitor for the management of radio resources. Therefore, in order to successfully increase the essential value responsibilities, additional research into a deep reinforcement learning-based wireless physical layer should be conducted in the future [4].

(e) Deep Learning-based model approximation for fifth-generation wireless networks:
Because of the high computational complexity involved in some deep learning algorithms designed to handle communication difficulties, it might be challenging to implement these kinds of algorithms on tiny terminals such as mobile phones. Existing frameworks that are based on deep learning have this limitation, which is one of its drawbacks. Up to this point, LSTM and CNN have provided the foundation for a large branch of these frameworks by serving as their respective backbones. On the other hand, these models provide extraordinarily high parameter values in addition to a huge increase in the complexity of both time and memory. As a consequence of this, it suggests that we may be able to create super-efficient deep compression schemes to improve deep learning-based networks and lessen their complexity. Additionally, it suggests that model compression techniques such as prone, quantization, and Huffman coding may be taken into consideration when developing new frameworks [3-5].

(f) Constrained model-based ML for Next Generation Multiple Access: Non-convex and associated mixed-integer constraints, such as SIC decoding restrictions and users' QOS needs, are frequently included in the communication architecture for NGMA. This is due to the fact that NGMA is designed to support multiple users simultaneously. The vast majority of machine learning algorithms either convert violations of constraints into loss functions or use projection to find workable solutions. Neither of these approaches is particularly effective at strictly guaranteeing linked mixed-integer constraints due to their inherent limitations. In order to accomplish model-based machine learning, the Lagrangian multiple methodology and the interior point approach were proposed. These methods demonstrated the potential of constrained optimization theory in guiding machine learning. Because of this, there is a heightened level of interest in the research of model-based limited machine learning for the NGMA communication design [10].

(g) Dynamic multi-objective optimization for NGMA achieved through ML:

The communication design will meet into such a number of competing optimization objectives or constraints involving the system rate, energy consumption, traffic delay, outage likelihood, and other factors since next-generation wireless networks are time-variant and heterogeneous. Furthermore, as wireless settings alter, these competing goals and constraints could also alter over time, making it difficult to forecast how the Pareto optimum front would change. This requires for the investigation of effective multitasking machine learning methods to enable dynamic multi-objective evaluation for NGMA [9-10].

(h) Optimizing Auto ML performance for NGMA:

While machine learning may predict desirable solutions using low-complexity forward propagation, back-propagation learning algorithm often requires large data samples and involves significant computational overhead. The training process would take longer and need more computing power, especially when implementing Auto ML approaches (such meta-learning and NAS). How to build high-performance lightweight models and accelerate Auto ML to support NGMA communication design while eliminating training costs is still a crucial but challenging research area [10].

(i) Millimeter wave Dynamic NOMA: Most of the previously reported optimum power allocation methods don't account for stronger reinforcement and online learning processes that update the partitioning in accordance with a dynamic mm Wave NOMA scenario. For the sake of science, this is a promising field for the future.

(j) In the case of smart jamming, whereby a programmable jammer makes use of radio equipment to choose jamming policies in a flexible way, it is possible to improve upon some of the works that have previously been reviewed to include more beneficial applications for NOMA broadcasts.

(k) Power Allocation and Beam Selection in Real Time for Multiple Antennas and Mobile Users: Some of the evaluated works may be relevant to users with multiple antennas and take into consideration mobile users in scenarios where the power allocation and beam selection must be altered.

6. CONCLUSION

This article addresses power domain NOMA. In this article, we examine the limitations of non-overlapping multiple access (NOMA) power distribution techniques in emerging wireless networks. Later phases explore various machine learning techniques. Each algorithm has significant challenges. As we've shown, machine learning has enough potential that we may envisage and experiment with a future in which it is becoming a core aspect of wireless communications. Future research directions are eventually highlighted.

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