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Enabling quality of service guarantees through an optimal resource allocation model in 5G network slicing

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***Abstract*—In 5G, network slicing alludes to the dividing of an actual organization foundation into different virtual organizations, known as slices. Each slice works as a free organization with its own committed assets and tweaked functionalities. Network slicing takes into account the effective assignment and the executives of organization assets in light of the particular requirements of each slicing. By using network slicing, specialist co-ops can enhance the portion of organization assets, further develop administration quality, and convey a more productive and financially savvy network framework. It takes into consideration the conjunction of various administrations and applications on shared network framework while guaranteeing that each slicing works autonomously and meets its quality of service (QoS) targets. In this paper, we present a methodology for enhancing asset distribution in the 5G organization slicing to guarantee excellent help conveyance which centers on accomplishing proficient traffic the executives all through the organization slicing. To accomplish this, we present the Markov jump neural network (MJNN) for grouping of exact traffic stream, empowering the arrangement of traffic into various need classes in view of seriousness levels. Furthermore, we plan an enhanced proportional topology optimization (EPTO) calculation for network slicing asset designation and client task. It plans to parcel network assets ideally among various slicing while considering client prerequisites and keeping up with asset utilization inside predefined limits. To get the ideal asset allotment that amplifies QoS for each organization slicing demand, we utilize the modified momentum search (MMS) calculation. Through broad assessments and execution evaluations, we show that our model beats existing methodologies with regards to QoS and asset use productivity. The outcomes demonstrate the efficacy of our strategy in facilitating high-quality, dependable service delivery in the network slicing environment.**

***Index Terms*—Asset portion, network slicing, nature of administration, traffic stream class, force search**

I. Introduction

Coming of 5G cell networks alluded to comprehensively as worldwide portable broadcast communications 2020 (IMT-2020), has introduced an extraordinary time, reshaping the collaborations among people and machines [1]. This quick advancement is moved by the heightening interest for high information rates, the multiplication of associated gadgets, and the worldwide extension of different applications. 5G cell networks expect to furnish clients with a flexible cluster of administrations while quality of service (QoS) requirements innate in conventional cell networks [2]. Standard associations have distinguished two urgent 5G use cases: upgraded versatile broadband (eMBB), which centers around conveying extraordinarily high information rates and limit with quick connection arrangement, and enormous machine type correspondence (mMTC), intended to help applications with rigid inertness necessities [37]. The device-to-device (D2D) correspondence in 5G cell networks has acquired conspicuousness because of its various benefits, including diminished transmission delay, framework load, energy effectiveness, and further developed generally framework execution and throughput [4]. By dividing the available network resources into logical slices that are tailored to meet specific service-based demands of users, the emerging technology of 5G network slicing improves the adaptability of future networks [5] [38]. Simultaneously, versatile edge-based calculation utilizes worldview where edge gadgets expect a significant piece of control and the executives inside the framework. Looking ahead, these technological advancements are poised to provide users with real-time experiences across various applications such as smart online gaming, autonomous vehicles, latency-sensitive medical emergency services, and remote intelligent applications [6]. It is noteworthy that the spectrum, a crucial resource in network slicing for 6G-WCS, has been extensively explored in existing literature primarily within the context of licensed spectrum [7]. However, with the rapid proliferation of 6G-WCS services, the scarcity of spectrum resources becomes an increasingly significant consideration[39], shaping the future trajectory. User demands, categorized based on latency, reliability, and bandwidth, necessitate a nuanced approach in addressing diverse service requirements. The advent of 5G network slicing has introduced a paradigm where the original network is partitioned into multiple logical and independent networks, each tailored to efficiently meet specific application demands [3] and [8]. Each of these segmented networks, known as network slices, operates as an isolated end-to-end network designed to fulfill the unique requirements of a particular application. In the different 5G and past application situations, guaranteeing QoS for a large number of organization slicing becomes pivotal, requesting the execution of powerful asset distribution procedures [10]. Moreover, investigating viable figuring engineering becomes principal to work with consistent exchanges among assorted elements, including client hardware (UE), edge gadgets, base stations (BSs), and cloud servers [11]-[13]. Even though network slicing has many advantages, it is difficult to allocate resources effectively for multiple network slices over a shared physical infrastructure [40]. This highlights how important it is to address this problem if network slicing is to be successful [15]. The essential objective in asset distribution for network slicing is deciding how to allocate virtual assets to each organize slicing and client inside that slicing in light of individual assistance prerequisites and the unique condition of the organization [16]. Existing works zeroing in on asset assignment in network slicing frequently expect the presence of an elite substrate network with static, constant assets after some time [41]. In multi-tenant scenarios, however, this assumption becomes invalid, rendering these strategies useless. Thusly, there is a critical need to devise asset designation techniques reasonable for situations where accessible assets go through unique changes over the long run [18]. Planning powerful asset portion approaches even with network elements, originating from both fluctuating organization assets and shifting client traffic, presents a few difficulties [9]. The need to constantly adjust resource allocation solutions in response to changing network dynamics and unidentified future information is one of these difficulties [19]. Forming this issue as a successive stochastic improvement issue adds further intricacy. The test lies in the huge activity space of the issue, frequently alluded to as the ”scourge of dimensionality,” combined with the way that choices made in the present may not be guaranteed to yield ideal results in the long haul [20]. To adjust to the consistently changing organization elements, constant re-design choices are basic, introducing a difficult errand in the domain of organization asset the board. A focus on effective traffic management throughout the network slice is essential in order to further enhance the 5G network slicing for improved service delivery. The proposed work acquaints key commitments with address those difficulties.

- We use the Markov jump neural network (MJNN) to create a precise method for classifying traffic flow [21][17]. This considers the exact arrangement of traffic into unmistakable need classes in view of seriousness levels, empowering successful administration and prioritization of organization assets [14].
- We present the enhanced proportional topology optimization (EPTO) calculation for asset portion and client task inside network slicing. It guarantees ideal apportioning of organization assets among various slicing while considering client necessities and keeping up with asset utilization inside predefined limits.
- We use the modified momentum search (MMS) algorithm to find the best resource allocation with the highest possible QoS for each network slice request. It is intended to tweak the distribution cycle, guaranteeing that each slicing gets assets in a way that ideally fulfills its particular QoS prerequisites.

The remainder of this paper is coordinated as follows: Section 2 investigated the different asset portion models for 5G organization slicing. Section 3 gives the issue portrayal and framework plan of our proposed work. The definite working course of proposed ideal asset allotment model for 5G organization slicing is given in Section 4 with the point by point numerical models. Section 5 inspects the viability of the proposed and existing ideal asset allotment model for 5G organization slicing utilizing results and similar examination. At last, the paper finishes up in Section 6

II. Literature Review

In this part, we give a far reaching survey of late works zeroed in on different asset distribution models inside the setting of 5G organization slicing. There are a variety of approaches outlined in the reviewed literature that are aimed at resolving the intricate issues associated with effectively allocating resources for multiple network slices across shared physical infrastructures. The paper [42] investigated 5G wireless organizations with network slicing are fundamental for portable correspondence because of the developing interest for administrations from additional gadgets. This study emphasizes efficient resource allocation within this framework to meet users' different QoS priorities. The study examines a QoS-based resource allocation strategy for two 5G slices: eMBB slice, which prioritizes high data rates, and the mMTC slice, which prioritizes little dormancy. They use D2D 5G wireless network ideal through network slicers and distributed algorithm (DA) that optimizes resource allocation using edge computation. Using the augmented Lagrange method[42-43], edge routers handle the problem locally, reducing central load and time for computation. Simulation investigation shows that this approach may allocate resources depending on QoS needs while lowering central server load and computing time. The researcher [22] offer evolving virtual allocation of resources strategy for uplink communication that uses RAN slicing to achieve QoS. To simplify calculation, the asset control issue is framed as horizon infinity constrained Markov decision process (CMDP) with act network distribution Q-factor equivalent Bellman reckoning. A distributed online stochastic learning approach improves assessment purposes and logical marks and the sub channel distribution Q-factor is roughly equal to the sum of per-slice Q-factors to simplify computations. Simulations show the suggested technique converges and improves user performance over baselines. Analyzing many base stations in RAN slicing networks, eliminating user interference, and exploring optimum policies under limited or erroneous state data utilizing CMDP formulations are future research objectives. The paper [23] describes the network slicing helps adapt services in fast-changing 5G cell phone network. Network slices virtualized network entities are designed for individual usage scenarios to assure end-to-end capabilities, QoS, and SLAs. The method prioritizes traffic flows by severity for mobile then IP-based schemes. ML processes evaluate QoS outline features to prioritize traffic. Network slices reserve splitting and operator distribution uses a connected simulated mainstay and priority class-based packet routing. The method integrates QoS, energy efficiency, and lively control reserves. Simulations show the developing control structure algorithm slicing node usage by 23The author [24] offer a novel online evolutionary slicing strategy optimizer for Slice as a Service that optimizes long-term network utility. Numerical simulations show that the suggested approach approximates the global optimum, converges quickly, adapts to environmental changes, and scales well. Unlike prior techniques, this strategy optimizer stores slicing strategies as binary sequences, allowing natural optimization for inter-slice administration of resources built on occupant needs and MNO dual choices. It adapts to changing network conditions because it doesn't require traffic or utility model expertise. The evaluation shows that this new approach optimizes slicing algorithms for SlaaS network usefulness. The researcher [25] propose a dynamic virtual resource allocation method for NOMA downlinks. Built on approximation dynamic programming (ADP) theory, the technique addresses average delay and likelihood of outages restrictions. The CMDP theory is used to create a dynamic resource allocation model by analyzing network slice rate and queue length. Power granularity and subcarrier number are adjusted to adapt virtual resources while overall rate is rewarded. The research introduces post-decision states and allocation action basis functions to avoid the curse of multiplicity. Simulation results show the PGU-ADP algorithm improves system performance and meets QoS requirements. The author [26] discusses the rising demand for high-speed internet, exacerbated by the COVID-19 pandemic lockdown, which drives telecommuting and the need for reliable mobile connectivity. To address these connectivity needs, 5G mobile communication technology with extremely low latency and high bandwidth is essential. The study discusses 5G network slicing, which divides the network into virtual networks for certain industries. They provide a paradigm that tailors network segments to industry vertical QoS requirements to maintain QoS. Software simulation shows that QoS-enabled network slicer improves throughput and loss, especially in highly unpredictable network settings. The paper [27] address the difficulty of network operators providing good customer experiences in resource-constrained situations where different application needs require beyond best-effort resource allocation strategies. The exploration presents QoS Streams and organization slicing for QoS-mindful allotment of assets in 5G versatile organizations. Slicing are particular internet based networks with amassed QoS affirmations and powerful segregation, while QoS Streams permit per-stream QoS profiles. The examination shows that asset confinement brought about by slicing might bring down application quality and framework usage in a multi-application setting utilizing the OMNeT++ recreation climate. To meet the high throughput requirements, the eMBB slices need more bandwidth, the uRLLC slices need shorter time slots to guarantee lower latency, and the mMTC slices need better frequency management to support a large number of connected devices. The Researcher [28] examine the complicated 5G system environment, intended for varied usage situations and requirements. The network slicing divides a network infrastructure into numerous logical networks with appropriate isolation and QoS. This radio access network work configures several RAN behaviors across an identical pool of radio resources using slices. A Markov model for RAN slicing offers several RRM techniques for multi-tenant and multi-service 5G, including proven and un-assured bit rate services. The model incorporates diverse radio link spectral efficiency from diverse users to reflect resource requirements' randomization. this paper [29] integrated 5G mobile networks with the end-to-end network slicing, maximize profits, and optimize resources. In order to provide consumers with a variety of services, slice providers construct network slices. Network slice sizing is necessary for effectiveness of resources. The optimization framework for network slices includes the slice customer's problem for slice customer's profit and the slice provider's problem for net social benefit. While the study found that slice provider's profitability and net societal welfare are in sync when resources are few, they are in conflict under other conditions. The proposed scheme [30] addresses the pressing need to optimize 5G slicing utilization and performance for software-defined networking/NFV-enabled mobile networks. As data traffic from apps and smart mobile devices with varying QoS needs increases, network operators face congestion and overload issues that slow radio access network performance. SSR and DSR operation modes maximize resource utilization and 5G slice isolation in the packet-based planning method. The SSR method fairly shifts shared assets to maximize bandwidth and avoid 5G slices from overwhelming others. Simulations show that DSR outperforms SSR in delay and throughput. The study emphasizes the flexibility of choosing token bucket parameters and capacity weights for each slice in accordance with desired QoS to estimate theoretically delay bounds for the slices' maximum delay bounds.

III. Problem methodology and System design of proposed methodology

A. Research Gaps

Ref.	Methodology	Technique	Findings	Research gaps
[21]	QoS based resource allocation in D2D	Distributed algorithm (DA)	Central load and computational time	Failed to get acceptance ratio and resource efficiency
[22]	Dynamic virtual resource allocation for 5G	Constrained Markov decision process (CMDP)	Delay and user transmission rate	The network resources were not considered which limits the QoS
[23]	Joint QoS and energy efficient resource	Gradient boosting and random forest regression	Accuracy, root mean square deviation	Failed to guarantee the QoS satisfaction of the various slices
[24]	Inter-slice resource management for 5G	Long-term strategy optimization	Delay and user transmission rate	The slices with high data rate traffic requests large number of resources.
[25]	Adaptive virtual resource allocation in 5G network slicing	Adaptive resource allocation approximate dynamic programming	Outage probability and user data rate	They focused mainly on maximizing the tradeoff between the energy and latency
[26]	QoS enabled network slicing model in 5G	Long short term memory (LSTM)	Throughput and loss	Requires large amounts of training data to validate the results
[27]	Achieve QoE-aware resource allocation	Fuzzy inference model with PSO	Delay and user transmission rate	Affected by multiservice resource allocation problem in the inter-slice
[28]	Radio access network slicing scenarios with 5G	Markov model for RAN slicing	Resource efficiency and delay	QoS requirement for each 5G slice was not addressed
[29]	Resource allocation for network slices in 5G	Maximizing the profit of SP and social-welfare aware pricing (SWAP)	Number of slices and user transmission rate	They not consider QoS parameters such as average response time and resource utilization.
[30]	Resource allocation in 5G slicing networks	General processor sharing-based scheduling	Delay and user transmission rate	User traffic passed through the central administration which leads to latency

Fig. 1. Research Gaps

The Fig. 1 shows the research gaps.In the context of 5G network slicing, the imperative for an optimal resource allocation model arises from the diverse and evolving nature of service requirements. With 5G designed to support a spectrum of applications, each with distinct demands for latency, reliability, and bandwidth, an optimal allocation model becomes essential to tailor network slices effectively. This ensures that the unique needs of different applications are met, enhancing the overall QoS across the network. Besides, the proficient usage of assets is a basic thought, requiring a model that sensibly distributes assets to stay away from wastage and further develop by and large organization effectiveness. In multi-occupant situations, where asset accessibility powerfully changes over the long run, the model should be versatile, acclimating to ongoing vacillations to guarantee slicing get assets lined up with their developing prerequisites. The help for super low inertness applications, worked with by edge figuring inside slicing, further highlights the significance of an ideal allotment model. Past specialized contemplations, the monetary angle is additionally huge, as proficient asset distribution to the expense viability by limiting pointless asset use and improving generally speaking organization tasks. The paper [31] acquainted a methodology with network plan for hub assignment and connection development with regards to 5G organizations. For these purposes, the PROMETHEE-II and SLE algorithms were utilized in the study. PROMETHEE-II calculation worked with the development of a hub significance rank cluster, taking into account different hub qualities like hub limit, data transmission of adjoining associations, hub degree, and nearness centrality. Then again, the SLE strategy was utilized to inventory all conceivable connection setups for the network slice request (NSR) hubs, ensuring a high acceptance rate for the shortest path array of the NSR. A methodology's viability was assessed utilizing execution measurements, including administration income and acknowledgment proportion. The concentrate methodically analyzed the effect of organization slicing under various framework models to survey whether little world organization would be worthwhile for 5G organizations. Asset allotment in 5G organization slicing experiences a few unpredictable difficulties, coming from the different idea of administration necessities, dynamic organization conditions, and the basic to enhance asset usage. One significant issue lies in tending to the wide range of administrations provided food by 5G organizations, like eMBB, mMTC, and URLLC. Dispensing assets to meet the unmistakable and dynamic requirements of each organization slicing turns into an intricate enhancement task. Problems are made even more complicated by the dynamic nature of resource demands, which necessitate real-time adjustments to resource allocation in response to shifting service requirements, shifting traffic patterns, and shifting user demands. Guaranteeing the tough QoS prerequisites for various slicing, enveloping low inactivity, high dependability, and explicit transfer speed needs, adds an extra layer of intricacy. In multi-occupant situations, where different clients share the framework, keeping up with asset segregation and decency among inhabitants represents a significant test. The reconciliation of edge registering acquaints intricacies related with planning the assignment of both correspondence and calculation assets. Additionally, resource allocation mechanisms that are capable of effectively managing these dynamic slicing operations are necessary for the dynamic creation, modification, and deletion of network slices in response to shifting requirements. Addressing the algorithmic complexity of NP-hard optimization problems and balancing optimization with energy efficiency further contribute to the multifaceted challenges of resource allocation in 5G network slicing, especially in light of the uncertain future conditions. To address the above assembled research holes, we present a methodology for upgrading asset assignment in 5G organization slicing to guarantee top notch administration conveyance.

- Develop an adaptive resource allocation algorithm that can dynamically adjust to the changing demands of diverse network slices and services in real-time.
- An optimization framework that prioritizes QoS assurance for network slices, incorporating mechanisms to balance low latency, high reliability, and specific bandwidth requirements.
- Devise mechanisms to address resource allocation challenges in multi-tenant scenarios, ensuring fair and isolated resource allocation among multiple users or entities sharing the same physical infrastructure.
- Design optimization algorithm to optimizes the network

slice request to maximizes QoS for each network slice request

B. System design of proposed methodology

The proposed framework shows in Fig. 2 that ideal asset distribution in 5G organization slicing follows a distinct framework plan. At its center are the User Equipment (UE) and the organization model. The organization model consolidates Kaggle dataset, serving as the foundation for subsequent processes. Resource allocation and user alignment are carried out using the enhanced proportional topology optimization (EPTO) algorithm.

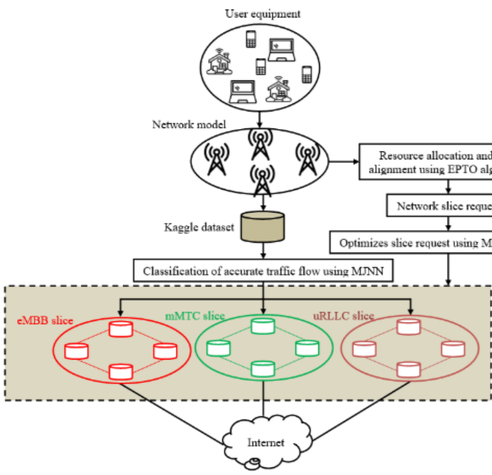

Fig. 2. Proposed Model

This algorithm, leveraging insights from the Kaggle dataset, ensures the efficient allocation of resources and optimal user alignment within the network. It considers different factors, for example, client requests, network conditions, and administration elements to upgrade asset usage. A basic part of the framework includes the grouping of precise traffic stream and undertaking achieved utilizing the Markov jump neural network (MJNN) on the Kaggle dataset. To precisely classify traffic into distinct classes, MJNN makes use of a number of features from the dataset, such as the eMBB slice, the mMTC slice, and the uRLLC slice. This arrangement is fundamental for understanding and overseeing various sorts of organization traffic really. Following asset designation and client arrangement, the framework gathers network slicing demands. The modified momentum search (MMS) algorithm is used to optimize these requests. It is instrumental in handling and improving slicing demands, taking into account the powerful idea of organization conditions, developing client requests, and the changing scene of administrations. Its goal is to make the network's overall responsiveness and efficiency in responding to different slice requests better, making the proposed method more effective.

IV. Proposed Methodology

In this segment, we depict the functioning system of ideal asset portion in the 5G organization slicing which comprises of cycle, for example, order of traffic stream, asset assignment and advancement of organization slicing demand.

A. Traffic flow classification

In the domain of traffic stream order, the Markov jump neural network (MJNN) assumes a critical part in guaranteeing the accuracy and precision of classifying traffic into unmistakable need classes. The MJNN is the standards of both Markov bounce frameworks and brain organizations. This combination permits the organization to successfully catch and dissect the dynamic and stochastic nature of traffic designs inside the framework. The MJNN works by considering different elements and properties got from the traffic information. These elements could incorporate qualities, for example, traffic volume, parcel misfortune rates, and dormancy, among others. The brain network part is capable at learning perplexing examples and conditions inside the information, while the Markov hop frameworks system empowers the model to represent unexpected changes or bounces in the rush hour gridlock elements. Utilizing the MJNN's ultimate objective is to establish a reliable and accurate classification of traffic flows. The network will be able to classify traffic according to severity into various priority classes. This characterization is instrumental in relegating fitting degrees of significance and asset assignment to various kinds of traffic. For example, it can recognize customary information traffic, dormancy touchy correspondences, or high-need crisis administrations. The MJNN's capacity to adjust to changing traffic conditions and gain from verifiable examples makes it an incredible asset with regards to traffic stream order. It improves the organization's ability to answer powerfully to differing requests, guaranteeing that assets are apportioned proficiently founded on the seriousness and not entirely set in stone by the rush hour gridlock arrangement. Basically, the MJNN presents a refined and clever layer to the traffic stream grouping process, adding to the general viability and versatility of the organization. The limited time roundedness for Markovian jump neural networks (MJNNs) with time-fluctuating postponements. It can jump from one mode to another using a Markovian process with known transition probabilities because it has a limited number of jumping modes.

$$\begin{cases} a(i+1) = K(R,x(i)) + C(R)F(x(i)) + e(R)F(x \\ (j-a(i))) + Y(R,x(i)) \\ a(k) = \phi(k), \quad k = -cP, -cP+1, \ldots, -1, 0 \end{cases} \tag{1}$$

where is the neuron state vector, is the neuron authorization ability and $z(j) \in R^n$ is the disrupting impact input. Rj is a homogenous confined state Markov process taking qualities in a limited state space Q = 1, 2,...,Q $Q\mathbb{W}+$. The probabilities of Rj's progress are given by.

$$MR\{R_{j+1} = n \mid R_j = m\} = \pi_{mn} \tag{2}$$

where $\pi mn > 0$and $\pi mn = 1$ for all $m \in N$. For each Rj = $m \in Q$, the structure organizations of the m-th mode are implied by Xm, Cm, em, and Ym which are known real consistent grids with fitting viewpoints. c(j) is the delay that changes over time and satisfies cm c(j) cP, where cm and cPare are positive integers that are well-known.$\phi()$ is the secret condition and is accepted to be zero all through this paper, i.e., $\phi() = 0$. The disturbing effect z(s) is set to be mean-square confined fulfilling the going with edge condition.

$$\mathbb{E}\left[z^s(j)z(j)\right] \leq \omega, \quad \forall j \in W \tag{3}$$

where an allowance for a positive scalar is made. We acknowledge each commencement ability FI(•)is unsurprising and limited, and there exist constants and with the ultimate objective that

$$\rho_t^- \leq \frac{F_t(x_1) - F_t(x_2)}{x_1 - x_2} \leq \rho_t^+, \quad t = 1, 2, \ldots, q \tag{4}$$

In the previous works, we extended the possibility of reachable set assessment to Markovian leap NNs as shown in (1). The conclusion of an ellipsoid-like set that restricts the reachable set Rx of Markovian jump NNs will serve as the foundation for our endeavors.

$$\gamma_a = \{a(j) \in \mathbb{R}^q \mid \gamma^q \mid a(j), z(j)\} \tag{5}$$

Like the turn out in for the erratic case, the ellipsoid like set is portrayed as follows:

$$\varepsilon(M, \gamma) = \{a \in \mathbb{R}^q : \mathbb{E}[a^s M a \mid f_0] \leq \gamma, M > 0\} \tag{6}$$

where F0 = (σ) x0,r0 is described as the (σ)-polynomial math delivered by (a0,R0) and M is a symmetric positive clear grid and (γ) is a positive consistent. The neuron commencement capacity g fulfills the condition as follows

$$0 \leq \frac{h_0(\delta)}{\delta} \leq t_0, \quad h_0(0) = 0 \quad \forall \delta \neq 0, \quad 0 = 1, 2, 3, \ldots, q \tag{7}$$

When s = sj , the state of (1) is sampled, where sj satisfies

$$0 = s_0 < s_1 < s_2 < \cdots < s_j < \cdots < s_j^+ \in \mathbb{R}^+, \quad \forall j \in P \tag{8}$$

The sampled-data control input is given as follows.

$$U(s) = J_{R(\varepsilon),\xi}(s_j), \quad \forall s \in [s_j, s_{j+1}] \tag{9}$$

where Kr(tk) is inspected information regulator gain. The example c information period gj is meant by gj = sj+1-sj and fulfills $0 < gp \leq gj \leq gP$. The determined and restricted nonlinear sanctioning capacity FI(•), I $\in \psi$n 1, 2,..., n with FI(0) = 0 satisfies the uniqueness (2) χ1 = χ2

$$L_I \leq \frac{F_I(\chi_1) - F_I(\chi_2)}{\chi_1 - \chi_2} \tag{10}$$

where the scalars are known. The heterogeneous boundaries are communicated as follows for the slave MJNNs, what share a similar construction as the expert MJNNs (1).

$$\delta(j+1) = X_{w,j}\delta(j) + X_{w,j}F(\delta(j)) + \varepsilon_{w,j}F(\delta(j - \zeta(j))) + U(j) \tag{11}$$

$$b(j) = \varphi_\lambda(j), \quad \forall - c_2 \leq j \leq 0 \tag{12}$$

Algorithm 1 is given as the operational traffic stream grouping system for MJNN.

Algorithm 1 Traffic flow classification using MJNN

Input: Network slicing, traffic traces, and maximum iteration
Output: Traffic flow - eMBB slice, mMTC slice, and uRLLC slice
Initialize parameters of MJNN
Compute transition probabilities:
$MR\{R_{j+1} = n | R_j = m\} = \pi_{mm}$
if $I = 0$ **then**
  $J = 1$
end if
Define disturbance $z(s)$ as mean-square limited fulfilling:
$\mathbb{E}[z^S(j)z(j)] \leq \omega, \forall j \in W$
while true **do**
  Fix sampled-data control input:
  $U(s) = J_{R(\epsilon),\xi}(s_j), \forall s \in [s_j, s_{j+1}]$
  Compute heterogeneous parameters:
  $b(j+1) = X_{w,j}b(j) + X_{w,j}F(b(j)) + \varepsilon_{w,j}F(b(j - \tau(j))) + U(j)$
  Find the best output solution
  if condition met **then**
    Break
  end if
end while

B. Resource allocation and user assignment

The enhanced proportional topology optimization (EPTO) algorithm is a carefully designed methodology that addresses the critical tasks of resource allocation and user assignment within a network slicing framework. Its essential goal is to advance the parceling of organization assets among various slicing, considering different client prerequisites and guaranteeing that asset utilization stays inside predefined limits. The EPTO calculation works by utilizing a relative way to deal with the geography of the organization. Geography, in this specific situation, alludes to the plan of different organization components and their interconnections. The calculation decisively assesses the ongoing geography and powerfully changes it to accomplish an ideal dispersion of assets. This incorporates contemplations for elements like transfer speed, inertness, and limit, among others. Asset designation includes the wise appropriation of accessible organization assets, for example, recurrence groups, figuring limit, and transmission power, among the various slicing. The calculation expects to guarantee that each organization slicing gets a designation of assets that lines up with its particular prerequisites. This is significant for fulfilling assorted client needs and supporting different applications, each with its novel arrangement of requirements. Client task, inside the setting of the EPTO calculation, includes the wise relationship of clients with explicit slicing in light of their prerequisites and the qualities of the slicing. Clients might have changing requests for information rates, inertness, and dependability, and the calculation thinks about these variables while making client tasks. The algorithm improves the network's overall quality of service by matching users with slices that best meet their requirements. The objective of primary geography advancement is to track down the ideal conveyance of articles that fulfills the limitations and streamlines the goal capability of the numerical model. Prior to taking care of the streamlining issue, the primary assignment is to foster its numerical model. In any case, in the event that the originator can't precisely develop a numerical model as per the necessities of the issue, the ideal outcomes will be extraordinarily impacted.

$$\min D = u^S ku = \sum_{h\in B} e(p_h) u_h^S K_0 u_h$$
$$\text{s.t.} \quad \begin{cases} ku = f \\ \sum_h p_h v_h - v_{SA} = 0 \\ 0 \le p_{Min} \le p_h \le p_{Max} \le 1 \end{cases} \tag{13}$$

where D is the structural conformation, u and f are the global displacement and external force vectors of the construction, individually, k is the worldwide solidness network and the same Youthful's modulus , h is the component dislodging vector, which is the unit size of component firmness . The unit Youthful's modulus is the component size , VTM is the objective material volume in the plan space , B is the quantity of components obtained by removing the design domain, Individual element i, and its worth decides the maintenance and expulsion of components and addresses the upper and lower limits of the element concentration variable, respectively. In general, p_{Min}, and p_h, and p_{Max} should be given a lower bound slightly greater than zero to avoid the stiffness singularity; however, it is the performance that determines the value.

$$e(p_h) = e_{Min} + p_h^*(e_0 - e_{Min}), \quad p_h \in [0, 1] \tag{14}$$

For the minimization optimization problem, an improved density filter is used and presented here:

$$\tilde{p}_h = \frac{1}{\sum\limits_{g\in B_h} I_{h,g}} \sum_{g\in B_h} I_{h,g} p_g \tag{15}$$

All g elements at an h element distance are filtered densities measured B_h from their respective centers R_{Min}. The $e(p_h)$ derivative is the weighting $I_{h,g}$ factor between the elements h and g.

$$I_{h,g} = \max(0, R_{Min} - c(h, g)) \tag{16}$$

where h and g are the geometric centre $c(h, g)$ distance between the elements and the radius R_{Min} of the filter.

$$\Delta p_h^{out} = v_{ra} \cdot \tilde{p}_g \cdot \Delta\tilde{D}_h \tag{17}$$

For the consistence coefficients to assume a bigger part in refreshing the thickness variable in the inward circle, the consistence coefficient channels.

$$\Delta\tilde{D}_h = \frac{1}{\sum\limits_{g\in B_h} I_{h,g}} \sum_{g\in B_h} I_{h,g} \Delta D'_g \tag{18}$$

Correspondence coefficient is computed by Bickley checking validity for solving optimization tasks.

$$\Delta D_h = \frac{D_h^\lambda}{\sum\limits_{g=1}^{B} D_g^\lambda v_g} \tag{19}$$

The lingering volume of the material VRM is a significant middle variable for refreshing the thickness variable in the inward circle, which is composed as follows.

$$v_{ra} = v_{Sa} - \sum_{h\in B} p_h^{pro} \cdot v_h \tag{20}$$

The thickness variable obtained at every iteration of the internal cycle, h, is the variable expansion in component thickness, and λ is the conformational impact coefficient. h and g represent the item relevance. Δp_h^{out}, D_h and D_g. represent the relevance ratio and filtered relevance ratio, respectively. ΔD_h and $\Delta\tilde{D}_h$,y is the influence ratio of the relevance ratio.

Here, we consider the same density variable optimization scheme as written.

$$p_h^{out} = p_h^{pro} + \Delta p_h^{out} \tag{21}$$

The variable density gain of element h is calculated as the weighted average of its neighboring elements' variable density gains using the weighting factor

$$p_h^{out} = p_h^{pro} + \Delta\tilde{p}_h^{out} \tag{22}$$

where $\Delta\tilde{p}_h^{out}$ is the elemental clean density adjustable increment, which is assumed as follows.

$$\Delta\tilde{p}_h^{out} = \frac{1}{\sum\limits_{g\in B_h} I_{h,g}} \sum_{g\in B_h} I_{h,g} \Delta p_g^{out} \tag{23}$$

where $\Delta\tilde{p}_g^{out}$ is the variable thickness augmentation of component g adjoining component h.

$$p_h^{pro} = \begin{cases} p_{Min}, & p_h^{out} \le p_{Min} \\ p_h^{out}, & p_{Min} < p_h^{out} < p_{Max} \\ p_{Max}, & p_h^{out} \ge p_{Max} \end{cases} \tag{24}$$

where p_{Min} and p_{Max} are the density variable's respective upper and lower limits. The algorithm 2 describes the working process of resource allocation and user assignment using EPTO.

Algorithm 2 Algorithm 2 Resource allocation and user assignment using EPTO

Input: Number of user equipments, Network model, and termination condition
Output: Resource allocation and user assignment
Initialize the random population
Compute the material interpolation

$$e(p_h) = e_{Min} + p_h^x(e_0 - e_{Min}), \quad p_h \in [0, 1]$$

if $i = 0$ **then**
    $j = 1$
end if
while true **do**
    Define the density filter

$$\tilde{P}_h = \frac{1}{\sum\limits_{g \in B_h} I_{h,g}} \sum_{g \in B_h} I_{h,g} P_g$$

    Compute correspondence coefficient

$$\Delta D_h = \frac{D_h^{\lambda}}{\sum\limits_{g=1}^{B} D_g^{\lambda} v_g}$$

    Find the density variable optimization

$$p_h^{out} = p_h^{pro} + \Delta p_h^{out}$$

    Define clean density adjustable increment

$$\Delta \tilde{p}_h^{out} = \frac{1}{\sum\limits_{g \in B_h} I_{h,g}} \sum_{g \in B_h} I_{h,g} \Delta p_g^{out}$$

end while
Update the final value

C. Optimization of network slice request

The enhancement cycle is finished in a fake and time-discrete utilizing energy and movement regulations. The utilized system is made up of a collection of solution bodies, and the possible solutions are represented by their positions in a space with n dimensions. The mass of bodies is relating to their wellbeing capacity which is regarding what is happening. Energy is an idea for a thing with mass n and speed B. It is shown by O and depicted as follows.

$$O = NB \tag{25}$$

We describe the controllable energy in relation to mass m and speed B. The fundamental laws of actual science are Newton's development guidelines. G Is second rule conveys that the net power on an anticipated mass is tantamount to its power speed of progress. Since Newton's following rule is legitimate for bodies with steady mass, the new kind of Newton's subsequent rule can be introduced as complies with.

$$d = N\beta = N\frac{FB}{FR} = \frac{F(NB)}{R} = \frac{FO}{FR} \tag{26}$$

where d is the increased speed of the body. Besides, trustworthy with Newton's by and large significant rule, which imparts that the net power on body with a dependable speed is tantamount to nothing, the energy of a body won't change when the net power on it is zero.

$$N_1B_1 + N_2B_2 = N_1B_1 + N_2B_2 \tag{27}$$

The area of the *u-th* body in time *r* should be visible to, and the body's position is in accordance with the f -th perspective is shown by.

$$S_U(R) = \left(S_U^{(1)}(R), \ldots, S_U^{I}(R), \ldots, S_U^{(N)}(R)\right) \tag{28}$$

$$S_{Nr}^{(I)} \leq S_U^{(I)}(R) \leq S_{Max}^{(I)}, \quad U = 1, \ldots, N, \quad I = 1, \ldots, N \tag{29}$$

Plans that are more advanced have more mass, whereas plans that are less good have less mass, which causes them to gravitate toward the plans that are better.

$$N_U(R) = \frac{\text{Fit}(R) - \text{worst}(R)}{\text{best}(R) - \text{worst}(R)} \tag{30}$$

For $Z_u(r)$ where is the value of objective capacity? The bodies with high appropriateness receive more mass to reach the ideal point. The following figure depicts the value of and.

$$Best(R) = \min_{U=1,\ldots,N} Fit_u(R) \tag{31}$$

$$\text{wors}(R) = \max_{U=1,\ldots,N} Fit_u(R) \tag{32}$$

The better game-plans will move more postponed than the more appalling ones. To accomplish this undertaking, the mass and speed of outside body decline in time with the best mass of strength for outer body.

$$n(R) = 1 - \frac{R-1}{r-1} \tag{33}$$

where is the most silly number of cycles obtained by the assessment. The mass of outside body is tantamount to 1 at the fundamental complement and a brief time frame later is decreased in a reliable rate till appears at zero at the last cycle. The external body's speed is a vector of the same size as the structure's viewpoint (W)

$$I_u^{(s)}(R) = T_1\left(1 - \frac{R-1}{r-1}\right) \cdot I_{\max} \cdot \text{SIGN}\left(S_{\text{BEST}}^{(F)}(R) - S_u^{(F)}(R)\right) \tag{34}$$

where is an irregular number with a uniform dissipating in the degree of [0, 1] which gives the issue an unusual show for looking for unquestionably the ideal depicted by the prerequisites of the issue control factors is the most unbelievable speed of outside body.

$$O_u^{(s)}(R) = n(R) i_u^{(F)}(r) \tag{35}$$

It indicates that the sum of each body's previous positions and a level of its crash speed determines its current position.

$$S_U^{(F)}(R+1) = S_u^{(F)}(R) + T_2 v_U^{(F)}(R) \tag{36}$$

Where $v_U^{(F)}(R)$ is a sporadic number with a uniform flow in the compass of [0, 1] and is the speed of the Ith body in the direction of the th viewpoint at time . Computation 3 gives the working arrangement of headway of association slicing request using MMS.

V. Results and Discussion

In this part, we present the outcomes and near examination of proposed and existing asset allotment for 5G organization slicing methodologies. To approve the exhibition of proposed MJNN+EPTO+MMS approach through the different reenactment situations, for example, number of organizations slicing demands and slicing traffic load. The consequences of our methodology is contrasted and the current condition of-workmanship approaches, for example, network slicing demand (NSR-NR) [32], reenacted tempering and Boltzmann (SAB) [33], layered V-FiNE algorithm (LAVA) [34], greedy least loaded (GLL) [35], heuristic 5G core network slice provisioning (VIKOR-CNSP) [36] and PROMETHEE-II+SLE [37]. The performance can be validated through the different measure such as resource efficiency, acceptance ratio, average coverage ratio, average occupied resource, average blocking ratio and average handover ratio.

A. Dataset description

In the evaluation of our approach, we conducted simulations using the Python programming language, defining service as combination of one or more functions. The simulation parameters were carefully chosen to capture the dynamic nature of the network environment. The arrival rate of services was set at one every 5 time units, and each service occupied the resources of a designated node until its processing was completed. The simulation parameters, unless specified otherwise, were selected randomly from uniform distributions with specified minimum and maximum values.

Parameter	Value
Number of nodes	100-300
Node buffer capacity	75-100
Distribution of CPU for each node	30-40
Function processing times	15-30
Function buffer demand	7.5-10
Number of functions per service	5-10
Service processing deadline	5000-10000
Distribution of length of the links	1-5
Network slice requests arrived in the time frame	5-35
Nodes for each network slice requests	10-30
Time duration of each network slice request	10-40

Fig. 3. Simulation parameter

Fig. 3 shows that the infrastructure model involved a variable number of nodes, ranging from 100 to 300, each with a buffer capacity fluctuating between 75 and 100 units. The distribution of CPU for each node followed a uniform pattern with values ranging from 30 to 40. Function processing times varied between 15 and 30 time units, and function buffer demand was uniformly distributed with values ranging from 7.5 to 10. Each service comprised a variable number of functions, ranging from 5 to 10, and was assigned processing deadlines spanning from 5000 to 10000 time units. The network characteristics included the distribution of link lengths following a uniform pattern with values ranging from 1 to 5. Network slice requests arrived at varying rates, between 5 and 35, each associated with a variable number of nodes (10 to 30) and lasting for time durations ranging from 10 to 40 time units. Furthermore, the framework upheld a limit of 17,554 central processors and at least 2921 computer chips inside the scope of 100 to 300 hubs. Data transmission utilization went from a limit of 16,676 to at least 2775 under a similar working state. These simulation parameters collectively formed a diverse and dynamic environment, enabling via assessment of the proposed approach's performance under various conditions and scenarios.

B. Comparative analysis

Resource allocation for 5G network slicing approaches	Number of network slicing request														
	10	20	30	40	50	10	20	30	40	50	10	20	30	40	50
	Resource efficiency					Acceptance ratio					Average coverage ratio				
NSR-NR	0.674	0.642	0.609	0.598	0.583	0.815	0.782	0.770	0.758	0.744	0.651	0.622	0.608	0.597	0.564
SAB	0.726	0.694	0.661	0.650	0.635	0.839	0.806	0.793	0.782	0.768	0.703	0.674	0.660	0.649	0.616
LAVA	0.778	0.746	0.713	0.702	0.687	0.862	0.829	0.817	0.805	0.791	0.756	0.727	0.713	0.702	0.669
GLL	0.830	0.798	0.765	0.754	0.739	0.886	0.853	0.840	0.829	0.815	0.808	0.779	0.765	0.754	0.721
VIKOR-CNSP	0.882	0.850	0.817	0.806	0.791	0.909	0.876	0.864	0.852	0.838	0.860	0.831	0.817	0.806	0.773
PROMETHEE-II+SLE	0.934	0.902	0.869	0.858	0.843	0.933	0.900	0.887	0.876	0.862	0.912	0.883	0.869	0.858	0.825
MJNN+EPTO+MMS	0.986	0.954	0.921	0.910	0.895	0.956	0.923	0.911	0.899	0.885	0.964	0.935	0.921	0.910	0.877
	Average occupied resource (Gbps)					Average blocking ratio					Average handover ratio				
NSR-NR	15.158	16.188	16.485	16.605	16.713	0.460	0.483	0.493	0.505	0.514	0.309	0.325	0.339	0.349	0.366
SAB	16.393	17.423	17.72	17.84	17.948	0.404	0.427	0.437	0.449	0.458	0.275	0.291	0.305	0.315	0.332
LAVA	17.628	18.658	18.955	19.075	19.183	0.348	0.371	0.381	0.393	0.402	0.241	0.257	0.271	0.281	0.298
GLL	18.863	19.893	20.19	20.31	20.418	0.292	0.315	0.325	0.337	0.346	0.207	0.223	0.237	0.247	0.264
VIKOR-CNSP	20.098	21.128	21.425	21.545	21.653	0.235	0.258	0.268	0.280	0.289	0.173	0.189	0.203	0.213	0.23
PROMETHEE-II+SLE	21.333	22.363	22.66	22.78	22.888	0.179	0.202	0.212	0.224	0.233	0.139	0.155	0.169	0.179	0.196
MJNN+EPTO+MMS	22.568	23.598	23.895	24.015	24.123	0.123	0.146	0.156	0.168	0.177	0.105	0.121	0.135	0.145	0.162

Fig. 4. Comparative Analysis with existing scheme

1) Results analysis with respect to varying network slicing ratio: The comparative analysis in Fig. 4 explores the impact of varying network slicing ratios on key performance metrics.

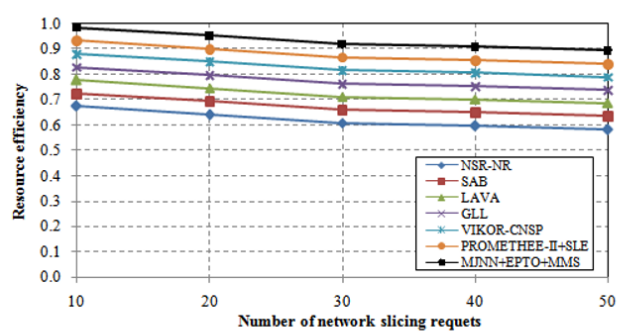

Fig. 5. The resource efficiency of various 5G network slicing approaches under different numbers of network slicing requests

Fig. 5 illustrates the resource efficiency of various 5G network slicing approaches under different numbers of network slicing requests. Examining the results, we observe a noticeable trend across the approaches. All methods generally experience a decrease in resource efficiency as the number of requests for network slicing increases. NSR-NR, SAB, LAVA, GLL, VIKOR-CNSP, and PROMETHEE-II+SLE exhibit decrease in resource allocation from 0.674 to 0.583, 0.726 to 0.635, 0.778 to 0.687, 0.830 to 0.739, 0.882 to 0.791, and 0.934 to 0.843, respectively. Notably, MJNN+EPTO+MMS approach consistently outperforms the other methods, showcasing higher resource efficiency percentages ranging from 0.986 to 0.895. Our approach exhibits an increase in resource efficiency compared to other methods, ranging from approximately 3.44 to 5.41 percent across the varying number of network slicing requests. These results suggest that as the network experiences an increase in slicing requests, the proposed approach maintains superior resource efficiency compared to existing methods

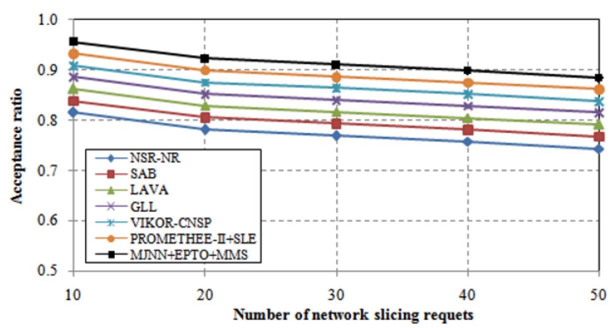

Fig. 6. The acceptance ratio of different 5G network slicing approaches under varying numbers of network slicing requests.

Fig. 6 presents the acceptance ratio of different 5G network slicing approaches under varying numbers of network slicing requests. Analyzing the results reveals a consistent pattern across the approaches. With an increase in the number of network slicing requests, there is a general decrease in the acceptance ratio for all methods. NSR-NR, SAB, LAVA, GLL, VIKOR-CNSP, and PROMETHEE-II+SLE exhibit a decline in acceptance ratio from 0.815 to 0.744, 0.839 to 0.768, 0.862 to 0.791, 0.886 to 0.815, 0.909 to 0.838, and 0.933 to 0.862, respectively. Our MJNN+EPTO+MMS approach consistently outperforms other methods, demonstrating higher acceptance ratio ranging from 0.956 to 0.885. Our approach exhibits an increase in acceptance ratio compared to other methods, ranging from 2.35 to 3.49 percent across the varying number of network slicing requests. These outcomes underline the adequacy of MJNN+EPTO+MMS in accomplishing higher acknowledgment proportions, even as the organization battles with a raising number of slicing solicitations.

Fig. 7 shows the typical inclusion proportion of different 5G organization slicing methodologies as the quantity of organization slicing solicitations fluctuates. As the quantity of organization slicing solicitations builds, there is general decrease in the normal inclusion proportion for all techniques. NSR-NR, SAB, LAVA, GLL, VIKOR-CNSP, and PROMETHEE-

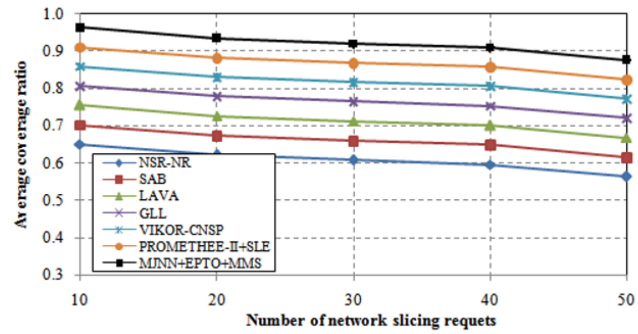

Fig. 7. Average coverage ratio with varying number of network slicing request

II+SLE exhibit a decline in coverage ratio from 0.651 to 0.564, 0.703 to 0.616, 0.756 to 0.669, 0.808 to 0.721, 0.860 to 0.773, and 0.912 to 0.825, respectively. MJNN+EPTO+MMS approach outperforms other methods, demonstrating higher average coverage ratio ranging from 0.964 to 0.877. Our methodology displays an expansion in normal inclusion proportion contrasted with different strategies, going from around 3.39 to 5.09 percent across the changing number of organization slicing solicitations. The discoveries highlight the adequacy of MJNN+EPTO+MMS in keeping up with higher normal inclusion proportions in the midst of a heightening number of organization slicing solicitations.

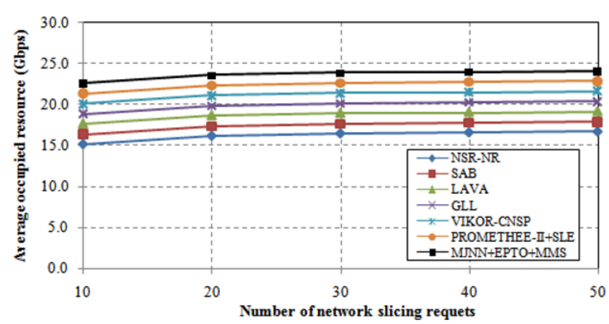

Fig. 8. Average occupied resource with varying number of network slicing reuqest

Fig. 8 gives understanding into the typical involved asset values for different 5G organization slicing methodologies across various quantities of organization slicing solicitations. With an expansion in the quantity of organization slicing solicitations, there is a general ascent in the normal involved asset for all strategies. NSR-NR, SAB, Magma, GLL, VIKOR-CNSP, and PROMETHEE-II+SLE show an increase in average occupied resource from 15.158 to 16.713, 16.393 to 17.948, 17.628 to 19.183, 18.863 to 20.418, 20.098 to 21.653, and 21.333 to 22.888, respectively. Remarkably, the proposed MJNN+EPTO+MMS approach outperforms other methods, shows higher average occupied resource values ranging from 22.568 to 24.123. Our approach exhibits an increase in average occupied resource compared to other methods, ranging from approximately 5.40 to 6.20 percent across the varying number of network slicing requests. These outcomes accentuate the capacity of MJNN+EPTO+MMS to effectively designate assets, even as the organization fights with a raising number of slicing solicitations.

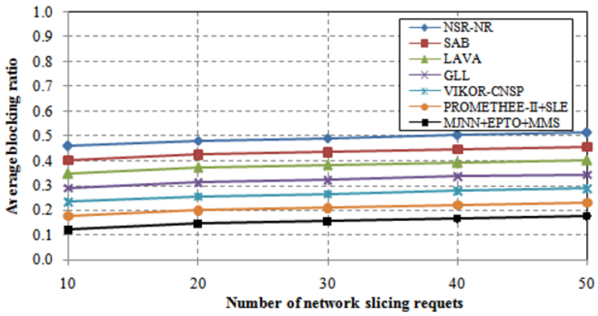

Fig. 9. Average blocking ratio with varying number of networking slicing request

Fig. 9 shows the typical hindering proportion for various 5G organization slicing methodologies across fluctuating quantities of organization slicing solicitations. Upon assessment, a clear trend emerges across the approaches. As the number of network slicing requests increases, there is a general decrease in the average blocking ratio for all methods. NSR-NR, SAB, LAVA, GLL, VIKOR-CNSP, and PROMETHEE-II+SLE exhibit a decline in blocking ratio from 0.460 to 0.514, 0.404 to 0.458, 0.348 to 0.402, 0.292 to 0.346, 0.235 to 0.289, and 0.179 to 0.233, respectively. Our proposed MJNN+EPTO+MMS approach outperforms others, demonstrating lower average blocking ratio percentages ranging from 0.123 to 0.177. Our approach exhibits a decrease in the average blocking ratio compared to other methods, ranging from 50.29 to 38.59 percent. The findings highlight the effectiveness of MJNN+EPTO+MMS in minimizing blocking ratios, even as the network experiences an increasing number of slicing requests Fig. 10 displays the average handover ratio for various

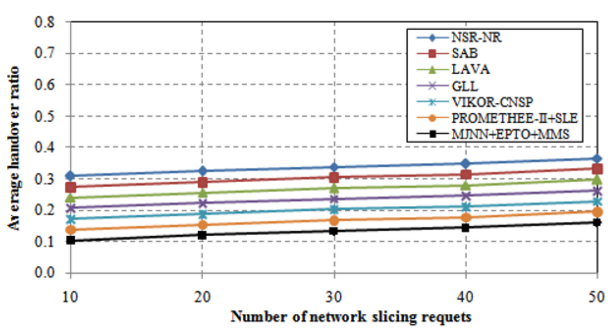

Fig. 10. average handover ratio with varying number of network slicing request

5G network slicing approaches across different numbers of network slicing requests. With an increase in the number of network slicing requests, there is a general rise in the average handover ratio for all methods. NSR-NR, SAB, LAVA, GLL, VIKOR-CNSP, and PROMETHEE-II+SLE show an increase in average handover ratio percentages from 0.309 to 0.366, 0.275 to 0.332, 0.241 to 0.298, 0.207 to 0.264, 0.173 to 0.23, and 0.139 to 0.196, respectively. Our MJNN+EPTO+MMS approach outperforms other methods, shows lower average handover ratio values ranging from 0.105 to 0.162. Our approach exhibits a decrease in the average handover ratio compared to other methods, ranging from 55.95 to 36.73 Percent across the varying number of network slicing requests. These results highlight the efficiency of MJNN+EPTO+MMS in minimizing handover ratios, even as the network contends with an escalating number of slicing requests

2) Results analysis with respect to varying slice traffic load: The comparative analysis in Fig. 11 explores the impact of varying slice traffic load on key performance metrics.

Resource allocation for 5G network slicing approaches	Slice traffic load (Erlang)														
	10	20	30	40	50	10	20	30	40	50	10	20	30	40	50
	Resource efficiency					Acceptance ratio					Average coverage ratio				
NSR-NR	0.669	0.637	0.604	0.593	0.578	0.838	0.805	0.793	0.781	0.767	0.626	0.597	0.583	0.572	0.539
SAB	0.721	0.689	0.656	0.645	0.630	0.862	0.829	0.816	0.805	0.791	0.678	0.649	0.635	0.624	0.591
LAVA	0.773	0.741	0.708	0.697	0.682	0.885	0.852	0.840	0.828	0.814	0.731	0.702	0.688	0.677	0.644
GLL	0.825	0.793	0.760	0.749	0.734	0.909	0.876	0.863	0.852	0.838	0.783	0.754	0.740	0.729	0.696
VIKOR-CNSP	0.877	0.845	0.812	0.801	0.786	0.932	0.899	0.887	0.875	0.861	0.835	0.806	0.792	0.781	0.748
PROMETHEE-II+SLE	0.929	0.897	0.864	0.853	0.838	0.956	0.923	0.910	0.899	0.885	0.887	0.858	0.844	0.833	0.800
MJNN+EPTO+MMS	0.981	0.949	0.916	0.905	0.890	0.979	0.946	0.934	0.922	0.908	0.939	0.910	0.896	0.885	0.852
	Average occupied resource (Gbps)														
NSR-NR	12.595	13.625	13.922	14.042	14.150	0.484	0.507	0.517	0.529	0.538	0.305	0.321	0.335	0.345	0.362
SAB	13.830	14.860	15.157	15.277	15.385	0.428	0.451	0.461	0.473	0.482	0.271	0.287	0.301	0.311	0.328
LAVA	15.065	16.095	16.392	16.512	16.620	0.371	0.394	0.404	0.416	0.425	0.237	0.253	0.267	0.277	0.294
GLL	16.300	17.330	17.627	17.747	17.855	0.315	0.338	0.348	0.360	0.369	0.203	0.219	0.233	0.243	0.260
VIKOR-CNSP	17.535	18.565	18.862	18.982	19.090	0.259	0.282	0.292	0.304	0.313	0.169	0.185	0.199	0.209	0.226
PROMETHEE-II+SLE	18.770	19.800	20.097	20.217	20.325	0.203	0.226	0.236	0.248	0.257	0.135	0.151	0.165	0.175	0.192
MJNN+EPTO+MMS	20.005	21.035	21.332	21.452	21.560	0.147	0.170	0.180	0.192	0.201	0.101	0.117	0.131	0.141	0.158

Fig. 11. Comparative Analysis

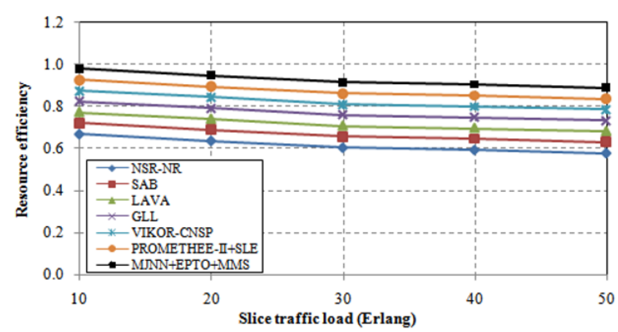

Fig. 12. Resource efficiency with varying slice traffic load

Fig. 12 illustrates the resource efficiency of various 5G network slicing approaches under different slice traffic loads, with the number of network slicing requests ranging from 10 to 50. As the slice traffic load increases, there is a general decline in resource efficiency for all methods. NSR-NR, SAB, LAVA, GLL, VIKOR-CNSP, and PROMETHEE-II+SLE demonstrate a decrease in resource efficiency from 0.669 to 0.578, 0.721 to 0.630, 0.773 to 0.682, 0.825 to 0.734, 0.877 to 0.786, and 0.929 to 0.838, respectively. MJNN+EPTO+MMS approach consistently surpasses other methods, exhibiting higher resource efficiency values ranging from 0.981 to 0.890. Our approach shows an increase in resource efficiency compared to other methods, ranging from approximately 46.77 percent to 32.98 percent across the varying slice traffic loads. These findings underscore the superior resource efficiency of MJNN+EPTO+MMS, even under increased slice traffic loads.

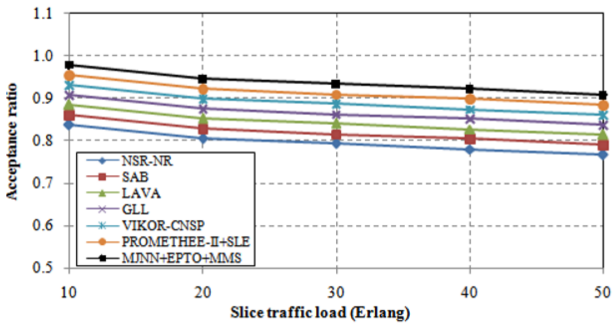

Fig. 13. acceptance ratio with varying slice traffic loads

Fig. 13 presents the acceptance ratio for various 5G network slicing approaches, considering varying slice traffic loads with the number of network slicing requests ranges. NSR-NR, SAB, LAVA, GLL, VIKOR-CNSP, and PROMETHEE-II+SLE shows decrease in acceptance ratio percentages from 0.838 to 0.767, 0.862 to 0.791, 0.885 to 0.814, 0.909 to 0.838, 0.932 to 0.861, and 0.956 to 0.885, respectively. MJNN+EPTO+MMS outperform other methods, exhibiting higher acceptance ratio values ranging from 0.979 to 0.908. Our approach demonstrates an increase in acceptance ratio compared to other methods, ranging from approximately 16.27 to 2.82 percent across the varying slice traffic loads.

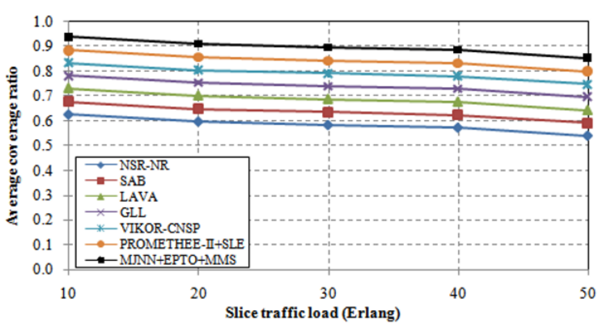

Fig. 14. average coverage ratio with varying slice traffic loads

Fig. 14 illustrates the average coverage ratio for different 5G network slicing approaches, considering varying slice traffic loads with the number of network slicing requests. Upon analysis, it is observed that the average coverage ratio with the increase in slice traffic load across methods. NSR-NR, SAB, LAVA, GLL, VIKOR-CNSP, and PROMETHEE-II+SLE exhibit a reduction in average coverage ratio from 0.626 to 0.539, 0.678 to 0.591, 0.731 to 0.644, 0.783 to 0.696, 0.835 to 0.748, and 0.887 to 0.800, respectively. Our MJNN+EPTO+MMS approach consistently outperforms other methods, demonstrating higher average coverage ratio values ranging from 0.939 to 0.852. Our approach shows an increase in average coverage ratio compared to other methods, ranging from approximately 15.31 to 6.02 percent across varying slice traffic loads. These findings emphasize the superior average coverage ratio achieved by MJNN+EPTO+MMS which shows efficacy in providing coverage of network slicing demands even under elevated slice traffic loads

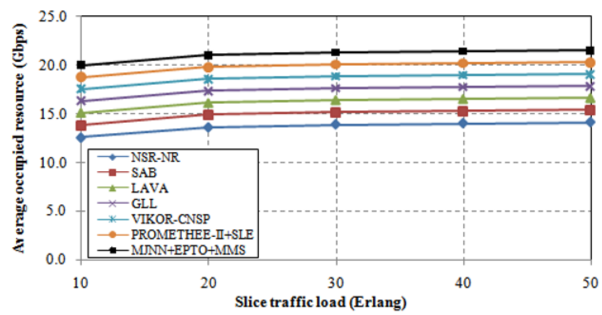

Fig. 15. the average occupied resource with varying slice traffic loads

Fig. 15 presents the average occupied resource for different 5G network slicing approaches, considering varying slice traffic loads with the number of network slicing requests ranging from 10 to 50. Upon examination, it is evident that the average occupied resource generally increases with the rise in slice traffic load across all methods. NSR-NR, SAB, LAVA, GLL, VIKOR-CNSP, and PROMETHEE-II+SLE show an increment in average occupied resource from 12.595 to 14.150, 13.830 to 15.385, 15.065 to 16.620, 16.300 to 17.855, 17.535 to 19.090, and 18.770 to 20.325, respectively. Our MJNN+EPTO+MMS approach outperforms other methods, shows lower average occupied resource values ranging from 20.005 to 21.560. Our approach shows a decrease in average occupied resource compared to other methods, ranging from approximately 10.94 percent to 5.89 percent across varying slice traffic loads. These findings highlight the effectiveness of the proposed approach in optimizing resource allocation and minimizing average occupied resource, even under elevated slice traffic loads. Fig. 16 shows the average blocking ratio for different 5G network slicing approach with varying slice traffic loads with the number of network slicing requests. Upon analysis, it is observed that the average blocking ratio generally increases with the growth in slice traffic load across all methods. NSR-NR, SAB, LAVA, GLL, VIKOR-CNSP, and PROMETHEE-II+SLE show an increment in average blocking ratio from 0.484 to 0.538, 0.428 to 0.482, 0.371 to 0.425, 0.315 to 0.369, 0.259 to 0.313, and 0.203 to 0.257, respectively. Our MJNN+EPTO+MMS approach consistently outperforms other methods, shown lower average blocking ratio values ranging from 0.147 to 0.201. Our approach shows a decrease in average blocking ratio compared to other methods, ranging from approximately 69.21 to 62.67 percent across varying

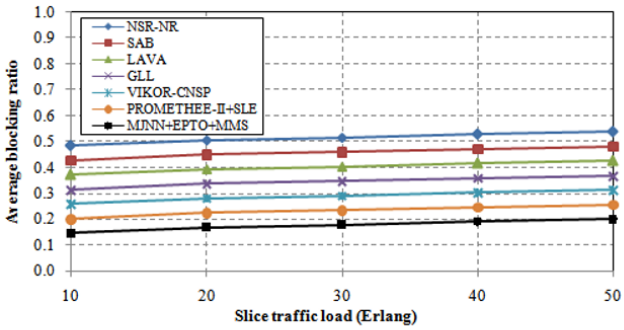

Fig. 16. the average blocking ratio with varying slice traffic loads

slice traffic loads. These results emphasize the effectiveness of the proposed approach in minimizing average blocking ratios, even under increasing slice traffic loads.

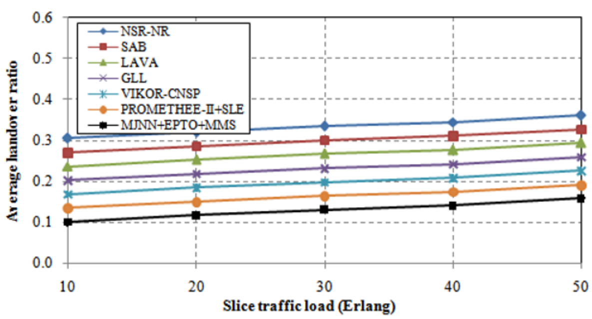

Fig. 17. Average handover ratio with varying slice traffic load

Fig. 17 presents the average handover ratio for different 5G network slicing approaches with varying slice traffic loads with the number of network slicing requests. Upon assessment, it is obvious that the normal handover proportion for the most part increments with the development in slicing rush hour gridlock load across all strategies. NSR-NR, SAB, LAVA, GLL, VIKOR-CNSP, and PROMETHEE-II+SLE show an increment in average handover ratio from 0.305 to 0.362, 0.271 to 0.328, 0.237 to 0.294, 0.203 to 0.260, 0.169 to 0.226, and 0.135 to 0.192, respectively. MJNN+EPTO+MMS approach reliably outflanks different techniques, showing below handover proportion values going from 0.101 to 0.158. Our methodology shows a decline in the normal handover proportion contrasted with different strategies, going from roughly 66.23 to 54.17 percent across changing slicing traffic loads. These outcomes feature the unrivaled presentation of the proposed approach in limiting normal handover proportions, considerably under expanding slicing traffic loads.

VI. CONCLUSION

We have presented an exhaustive methodology pointed toward streamlining asset designation inside the 5G organization slicing worldview, guaranteeing the conveyance of top notch administrations with effective traffic the executives all through the organization slicing. Our procedure consolidates the Markov jump neural network (MJNN) to precisely order traffic stream, characterize it into unmistakable need classes in light of seriousness levels. For network slicing asset portion and client task, we have planned an enhanced proportional topology optimization (EPTO) calculation. It ideally conveys network assets among various slicing, with client prerequisites and keeping up with asset utilization inside predefined limits. To accomplish ideal asset designation and augment QoS for each organization slicing demand, we use the modified momentum search (MMS) calculation. The aftereffects of our methodology show viability in guaranteeing solid and excellent help conveyance inside the organization slicing climate. The proposed MJNN+EPTO+MMS method consistently outperformed other approaches when analyzing a variety of network slicing requests. It displayed a normal increment of 1.7 percent in asset productivity, 2.3 percent in the acknowledgment proportion, and 4.8 percent in inclusion proportion. Additionally, it demonstrates significant decreases in the blocking ratio of 37.2 percent and the handover ratio of 31.2 percent, respectively. Also, in the examination of fluctuating slicing traffic stacks, our methodology kept up with its greatness, shows a typical increment of around 3.4 percent in asset effectiveness, 2.5 percent in the acknowledgment proportion, and 5.3 percent in inclusion proportion. It likewise accomplished critical declines of around 27.6 percent in the impeding proportion and 33.7 percent in the handover proportion. These outcomes highlight the vigor and productivity of our proposed approach, laying out its prevalence in advancing asset distribution for 5G organization slicing under different functional situations.

REFERENCES

[1] Sharma, S., Deivakani, M., Reddy, K. S., Gnanasekar, A. K., and Aparna, G. (2021, March). Key enabling technologies of 5G wireless mobile communication. In Journal of Physics: Conference Series (Vol. 1817, No. 1, p. 012003). IOP Publishing.

[2] Zhang, S. (2019). An overview of network slicing for 5G. IEEE Wireless Communications, 26(3), 111-117.

[3] Gaurav, C., Jiyoon, K., and Vishal, S. (2018). Security of 5G-Mobile Backhaul Networks: A Survey. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 9(4), 41-70.

[4] Bairagi, A. K., Munir, M. S., Alsenwi, M., Tran, N. H., Alshamrani, S. S., Masud, M., ...and Hong, C. S. (2020). Coexistence mechanism between eMBB and uRLLC in 5G wireless networks.IEEE transactions on communications, 69(3), 1736-1749.

[5] Kim, H. (2020). 5G core network security issues and attack classification from network protocol perspective. Journal of Internet Services and Information Security, 10(2), 1-15

[6] Jiang, M., Condoluci, M., and Mahmoodi, T. (2016, May). Network slicing management and prioritization in 5G mobile systems. In European wireless 2016; 22th european wireless conference (pp. 1-6). VDE.

[7] Dogra, A., Jha, R. K., and Jain, S. (2020). A survey on beyond 5G network with the advent of 6G: Architecture and emerging technologies. IEEE Access, 9, 67512-67547.

[8] Ahmad, H. F., Rafique, W., Rasool, R. U., Alhumam, A., Anwar, Z., and Qadir, J. (2023). Leveraging 6G, extended reality, and IoT big data analytics for healthcare: A review. Computer Science Review, 48, 100558.

[9] Balaji, R., Deepakkumar, A., Prabhu, G., Thinakaran, P., and Gowtham, S. (2023). Enhancing Network Security by using SDN Algorithm in

Cloud Computing. International Academic Journal of Science and Engineering, 10(1), 14–19. https://doi.org/10.9756/IAJSE/V10I1/IAJSE1003

[10] Wijethilaka, S., and Liyanage, M. (2021). Survey on network slicing for Internet of Things realization in 5G networks. IEEE Communications Surveys and Tutorials, 23(2), 957-994.

[11] Kao, H. W., and Wu, E. H. K. (2023). QoE Sustainability on 5G and Beyond 5G Networks. IEEE Wireless Communications, 30(1), 118-125.

[12] Kapassa, E., Touloupou, M., Stavrianos, P., Xylouris, G., and Kyriazis, D. (2019). Managing and optimizing quality of service in 5G environments across the complete SLA lifecycle. Advances in Science, Technology and Engineering Systems Journal, 4(1), 329-342.

[13] Akpakwu, G. A., Silva, B. J., Hancke, G. P., and Abu-Mahfouz, A. M. (2017). A survey on 5G networks for the Internet of Things: Communication technologies and challenges. IEEE access, 6, 3619-3647.

[14] Atiyah, A. G. (2023). Power Distance and Strategic Decision Implementation: Exploring the Moderative Influence of Organizational Context. International Academic Journal of Business Management, 10(1), 71–80. https://doi.org/10.9756/IAJBM/V10I1/IAJBM1007

[15] Afolabi, I., Bagaa, M., Taleb, T., and Flinck, H. (2017, September). End-to-end network slicing enabled through network function virtualization. In 2017 IEEE Conference on Standards for Communications and Networking (CSCN) (pp. 30-35).IEEE.

[16] Mohammed, N. A., Mansoor, A. M., and Ahmad, R. B. (2019). Mission-critical machine-type communication: An overview and perspectives towards 5G. IEEE Access, 7, 127198-127216.

[17] Mousavi, A., and Karshenasan, A. (2017). Forecasting Stock prices of banks using artificial neural networks (GMDH). International Academic Journal of Accounting and Financial Management, 4(2), 71–78.

[18] Papavassiliou, S., Tsiropoulou, E. E., Promponas, P., and Vamvakas, P. (2020). A paradigm shift toward satisfaction, realism and efficiency in wireless networks resource sharing. IEEE Network, 35(1), 348-355.

[19] Wijethilaka, S., and Liyanage, M. (2021). Survey on network slicing for Internet of Things realization in 5G networks. IEEE Communications Surveys and Tutorials, 23(2), 957-994.

[20] Shen, X., Gao, J., Wu, W., Lyu, K., Li, M., Zhuang, W., ...and Rao, J. (2020). AI-assisted network-slicing based next-generation wireless networks. IEEE Open Journal of Vehicular Technology, 1, 45-66.

[21] Jelena, T., and Sran, K. (2023). Smart Mining: Joint Model for Parametrization of Coal Excavation Process Based on Artificial Neural Networks. Archives for Technical Sciences, 2(29), 11-22. https://doi.org/10.59456/afts.2023.1529.011T

[22] Song, F., Li, J., Ma, C., Zhang, Y., Shi, L., and Jayakody, D. N. K. (2020). Dynamic virtual resource allocation for 5G and beyond network slicing. IEEE Open Journal of Vehicular Technology, 1, 215-226.

[23] Saibharath, S., Mishra, S., and Hota, C. (2023). Joint QoS and energy-efficient resource allocation and scheduling in 5G Network Slicing. Computer Communications, 202, 110-123.

[24] Han, B., Lianghai, J., and Schotten, H. D. (2018). Slice as an evolutionary service: Genetic optimization for inter-slice resource management in 5G networks. ieee access, 6, 33137-33147.

[25] Tang, L., Tan, Q. I., Shi, Y., Wang, C., and Chen, Q. (2018). Adaptive virtual resource allocation in 5G network slicing using constrained Markov decision process. IEEE Access, 6, 61184-61195.

[26] Govender, P., Ogudo, K. A., and Chabalala, C. (2021, September). Quality of Service Enabled Network Slicing Model in 5G and the Next Generation Virtualized Networks. In 2021 IEEE AFRICON (pp. 1-5).IEEE.

[27] Bosk, M., Gajić, M., Schwarzmann, S., Lange, S., Trivisonno, R., Marquezan, C., and Zinner, T. (2021, October). Using 5G QoS mechanisms to achieve QoE-aware resource allocation.In 2021 17th International Conference on Network and Service Management (CNSM) (pp. 283-291).IEEE.

[28] Vila, I., Pérez-Romero, J., Sallent, O., and Umbert, A. (2020). Characterization of radio access network slicing scenarios with 5G QoS provisioning.IEEE access, 8, 51414-51430.

[29] Wang, G., Feng, G., Tan, W., Qin, S., Wen, R., and Sun, S. (2017, December). Resource allocation for network slices in 5G with network resource pricing. In GLOBECOM 2017-2017 IEEE Global Communications Conference (pp. 1-6).IEEE.

[30] AlQahtani, S. A. (2020). An efficient resource allocation to improve QoS of 5G slicing networks using general processor sharing-based scheduling algorithm. International Journal of Communication Systems, 33(4), e4250.

[31] Venkatapathy, S., Srinivasan, T., Jo, H.G. and Ra, I.H., 2023. Optimal Resource Allocation for 5G Network Slice Requests Based on Combined PROMETHEE-II and SLE Strategy. Sensors, 23(3), p.1556.

[32] Guan, W., Wen, X., Wang, L., Lu, Z. and Shen, Y., 2018. A service-oriented deployment policy of end-to-end network slicing based on complex network theory. IEEE access, 6, pp.19691-19701.

[33] Yu, C., Hou, W., Guan, Y., Zong, Y. and Guo, P., 2016. Virtual 5G network embedding in a heterogeneous and multi-domain network infrastructure. China Communications, 13(10), pp.29-43.

[34] Mijumbi, R., Serrat, J., Gorricho, J.L., Bouten, N., De Turck, F. and Davy, S., 2015, April. Design and evaluation of algorithms for mapping and scheduling of virtual network functions. In Proceedings of the 2015 1st IEEE conference on network softwarization (NetSoft) (pp. 1-9). IEEE.

[35] Li, X., Guo, C., Gupta, L. and Jain, R., 2019. Efficient and secure 5G core network slice provisioning based on VIKOR approach. IEEE Access, 7, pp.150517-150529

[36] Rost, P., Mannweiler, C., Michalopoulos, D. S., Sartori, C., Sciancalepore, V., Sastry, N., ...and Bakker, H. (2017). Network slicing to enable scalability and flexibility in 5G mobile networks.IEEE Communications magazine, 55(5), 72-79.

[37] Salhab, N., Langar, R., and Rahim, R. (2021). 5G network slices resource orchestration using Machine Learning techniques. Computer Networks, 188, 107829.

[38] Coelho, A., Rodrigues, J., Fontes, H., Campos, R., and Ricardo, M. (2022). An Algorithm for Placing and Allocating Communications Resources Based on Slicing-Aware Flying Access and Backhaul Networks. IEEE Access, 10, 128923-128942.

[39] Barakabitze, A. A., Ahmad, A., Mijumbi, R., and Hines, A. (2020). 5G network slicing using SDN and NFV: A survey of taxonomy, architectures and future challenges. Computer Networks, 167, 106984.

[40] Manvi, S. S., and Shyam, G. K. (2014). Resource management for Infrastructure as a Service (IaaS) in cloud computing: A survey. Journal of network and computer applications, 41, 424-440.

[41] Nadeem, L., Amin, Y., Loo, J., Azam, M. A., and Chai, K. K. (2022). Quality of service based resource allocation in D2D enabled 5G-CNs with network slicing. Physical Communication, 52, 101703.

[42] Nayyar A., Gadhavi L., Zaman N., ”Machine learning in healthcare: Review, opportunities and challenges”, *Machine Learning and the Internet of Medical Things in Healthcare*, pp. 23 - 45, 2021. DOI: 10.1016/B978-0-12-821229-5.00011-2

[43] Zaman N., Tang Jung L., Yasin M.M., ”Enhancing Energy Efficiency of Wireless Sensor Network through the Design of Energy Efficient Routing Protocol”, *Journal of Sensors*, 2016, art. no. 9278701, DOI: 10.1155/2016/9278701