IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 6, December 2025, pp. 4993~5007
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i6.pp4993-5007

Dynamic service-aware network selection framework for multi-objective optimization in 5G-advanced heterogeneous wireless networks

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Article Info

Article history:

Received Jan 3, 2025
Revised Aug 2, 2025
Accepted Sep 7, 2025

Keywords:

Deep learning
Dynamic service-aware network selector
Heterogeneous wireless networks
Machine learning
Quality of service

ABSTRACT

The increasing complexity of heterogeneous wireless networks (HWNs) and the diverse requirements of mobility patterns and service classes necessitate advanced solutions for network selection and resource optimization. Existing models often fall short in addressing dynamic mobility scenarios and service differentiation, leading to inefficiencies in resource allocation, suboptimal throughput, and increased latency. To overcome these limitations, this study proposes a dynamic service-aware network selector (DSANS) framework for 5G-advanced environments. The framework integrates an adaptive deep decision network (ADDN) for multi-objective optimization, addressing critical quality of service (QoS) metrics such as throughput, delay, and energy efficiency while enhancing quality of experience (QoE) for applications like enhanced mobile broadband (eMBB), ultra-reliable low latency communication (URLLC), and internet of things (IoT). The DSANS framework dynamically adapts to mobility patterns and varying network conditions, ensuring efficient resource estimation and optimal network selection. Simulation results highlight its superiority, achieving up to 25% improvement in throughput and a 15% reduction in latency compared to state-of-the-art algorithms. These findings validate DSANS as a robust solution for mitigating the limitations of existing models, optimizing network performance, and meeting the stringent demands of next-generation HWNs.

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1. INTRODUCTION

The exponential growth of the internet of things (IoT) and the increasing integration of connected devices into daily life have led to the proliferation of heterogeneous wireless networks (HWNs). These networks combine multiple radio access technologies (RATs) such as 4G/5G, Wi-Fi, and low-power wide area networks (LPWANs) to enable seamless communication. With the rapid evolution toward 5G-advanced and beyond, HWNs have emerged as a key enabler for future smart applications, including autonomous vehicles, smart cities, industrial automation, and critical IoT-driven infrastructures [1]. While HWNs provide flexibility and scalability, their heterogeneity also introduces significant challenges in managing network resources and ensuring seamless handover operations, particularly for IoT devices characterized by diverse mobility behaviors and service requirements. Devices ranging from static sensors to highly mobile nodes exhibit varying throughput, latency, and energy constraints, demanding adaptive solutions capable of addressing these dynamic scenarios. Traditional network selection and handover strategies, often reliant on signal strength-based metrics such as received signal strength indicator (RSSI) or signal-to-interference-plus-noise ratio (SINR), fail to optimize system performance under such heterogeneous and resource-constrained conditions [2], [3]. To meet the stringent quality of service (QoS) and quality of experience (QoE) requirements, next-generation HWNs must be accommodated.

Diverse mobility patterns (e.g., stationary, low-speed, and high-speed users) that significantly impact handover frequency, resource allocation, and signaling overhead. Multiple service classes such as real-time video, latency-sensitive virtual reality (VR), and low-power industrial internet of things (IIoT) applications, each imposing unique demands on network throughput, delay, and energy efficiency. Existing handover and network selection methodologies lack the necessary intelligence to dynamically adapt to these complexities. Many conventional approaches suffer from high signaling overhead, frequent handover failures, and inadequate resource optimization, particularly in environments with dense user traffic and limited bandwidth availability. Centralized algorithms, while effective in small-scale scenarios, become computationally prohibitive and impractical for large-scale HWNs due to scalability and privacy concerns. Meanwhile, heuristic-based methods fail to deliver optimal solutions in real-time for dynamic and multi-service environments [4]. Recent advancements in machine learning (ML) and distributed optimization techniques have unlocked new possibilities for addressing the complex challenges faced in HWNs. These networks, characterized by diverse connectivity options and an increasing number of IoT devices, must meet the stringent requirements of QoS and QoE under dynamic and resource-constrained conditions. The need for efficient resource management and adaptive decision-making is particularly critical, as HWNs serve devices exhibiting varying mobility behaviors and service demands. Traditional network selection and resource allocation methods, often reliant on static thresholds or centralized architectures, struggle to handle the rapidly changing network conditions [5]–[7]. Centralized approaches face challenges such as scalability issues, increased signaling overhead, and concerns over privacy when sharing raw data across nodes. In addition, the heterogeneity of HWNs introduces significant challenges in managing devices operating under different mobility patterns ranging from stationary nodes to high-speed mobile devices and catering to multiple service classes, including latency-sensitive, throughput-intensive, and energy-constrained applications.

While distributed learning techniques have emerged as promising solutions to improve scalability and adaptability, the integration of such methods for achieving multi-objective performance optimization remains limited. Existing approaches often fail to account for the combined impact of mobility behaviors and service-specific constraints on network performance, leading to frequent handover failures, inefficient resource utilization, and degraded user satisfaction. The absence of dynamic load balancing mechanisms further exacerbates these issues, particularly during congestion and high-load conditions [8].

The rapid proliferation of IoT devices in HWNs has introduced significant challenges in ensuring seamless connectivity and optimal performance. Devices with diverse mobility behaviors ranging from stationary to high-speed users experience frequent handovers, leading to signaling overhead and degraded performance. Additionally, catering to multiple service classes, such as latency-sensitive applications (e.g., VR) and energy-constrained IoT sensors, demands adaptive resource allocation to balance QoS and QoE. Existing methods lack the capability to dynamically optimize network selection and resource estimation while addressing these complexities [9], [10]. Therefore, there is a pressing need for intelligent, multi-objective optimization strategies that can adapt to varying mobility patterns and service-specific requirements, ensuring efficient resource utilization, reduced latency, and improved user satisfaction in HWNs. His study addresses the limitations of existing network selection and resource optimization models in 5G-advanced HWNs. The key contributions are as follows:

– Proposed framework: a novel dynamic service-aware network selector (DSANS) framework designed to optimize network performance by dynamically adapting to mobility patterns and service class variations.
– Multi-objective optimization: integration of an adaptive deep decision network (ADDN) to balance critical QoS metrics such as throughput, delay, and energy efficiency while enhancing QoE for diverse applications like enhanced mobile broadband (eMBB), ultra-reliable low latency communication (URLLC), and IoT.
– Scalability and efficiency: development of algorithms for efficient resource estimation and adaptive network selection, ensuring scalability across varying user demands and network conditions.
– Performance validation: demonstrated superiority of the proposed framework through simulations, achieving up to 25% improvement in throughput and a 15% reduction in latency compared to state-of-the-art algorithms.

2. RELATED WORK

QoS and intelligent flow control are key aspects in network optimization. According to Ba [11], a three-step QoS-forecasting scheme is proposed to enable user equipment (UE) to intelligently determine the data flow direction based on network characteristics and load distribution across nodes. This approach prioritizes load balancing and user fairness while assigning data to secondary nodes (SNs) based on QoS requirements and the average transmission capabilities of the UE. Such schemes aim to enhance network efficiency while catering to user-specific priorities. In the context of network selection strategies, Ma *et al.* [12] introduces a multi-agent Q-learning-based approach, referred to as the multiagent Q-learning network selection (MAQNS) algorithm. This method employs Nash Q-learning to achieve a joint optimal selection strategy that improves system throughput and reduces user blocking while meeting the stringent requirements of IoT services. The use of discrete-time Markov chains for modeling network selection, coupled with techniques like the analytic hierarchy process (AHP) and gray relational analysis (GRA), helps capture user preferences and enhance decision-making accuracy. The application of generative adversarial networks (GANs) in [13] for cell load estimation demonstrates significant progress in 5G communication networks. This approach estimates cell load based on terminal-measured wireless information, addressing critical challenges such as low data transmission rates, high signaling costs, and delays in traditional load estimation methods. By enabling real-time, terminal-side decision-making, this method improves overall network performance and enhances user experience.

Further advancing resource optimization, Cabrera *et al.* [14] presents SVORA, a novel approach integrating virtualized/open radio access network (V/O-RAN) concepts with a service-based architecture (SBA). The proposed delay-aware energy efficiency-based RAN selection algorithm (DEER) leverages utility functions to account for QoS metrics such as throughput, resource block utilization, delay, and energy consumption. DEER's flexibility allows it to adapt to varying priorities, including critical delay-sensitive services, energy efficiency, or a balanced optimization approach, making it highly applicable in dynamic network scenarios. In the same vein, Cabrera *et al* [14] emphasizes SVORA's utility in optimizing energy consumption and minimizing communication delays in heterogeneous networks. By integrating SBA with RAN selection mechanisms, this approach demonstrates the ability to address the demands of modern communication systems through robust and adaptable solutions. Zhu *et al.* [15] proposes REMNS, a novel access selection mechanism tailored for IoT services in 5G heterogeneous networks. This mechanism introduces a fuzzy logic-based pre-assessment framework to filter potential networks, ensuring that only the most suitable options are considered. Furthermore, it incorporates a dual-evaluation framework combining subjective-oriented AHP and objective-oriented entropy weight method (EWM) to assess preference degrees of IoT services for various network attributes. REMNS effectively balances user-centric QoE optimization with efficient network utilization. Efficient handover (HO) management and resource optimization in heterogeneous networks (Het-Nets) are critical for ensuring seamless connectivity and QoS.

According to Tashan *et al.* [16], a velocity-aware fuzzy logic controller with weighted function (VAW-FLC-WF) algorithm is proposed to enhance the HO self-optimization process. This algorithm incorporates a trigger timer to reduce handover ping-pong (HOPP) effects and aims to address issues like HOPP, radio link failure (RLF), and received signal reference power (RSRP). Additionally, categorizing speed scenarios is highlighted as a significant factor in mitigating mobility-related challenges, with comparative results demonstrating its effectiveness over non-categorized scenarios. Resource allocation in heterogeneous mobile edge computing (Het-MEC) networks is further explored in [17], where the energy-efficient resource allocation problem is formulated as a time-variant mixed-integer nonlinear programming (MINLP) problem. To address this, a multi-agent deep reinforcement learning (MADRL)-based algorithm is proposed, featuring the multi-actor shared-critic (MASC) architecture and the regional training distributed execution (RTDE) framework. This innovative approach stabilizes model training and reduces information exchange, ensuring efficient and scalable resource management. Building on the advantages of decentralized solutions, Xiao *et al.* [18] introduces a decentralized MADRL-based resource allocation algorithm. By employing a decentralized partially observable Markov decision process (dec-POMDP) and a mixed-centralized-decentralized (MCD) framework, this approach effectively addresses partial observability and scalability challenges. Furthermore, a reward function is designed with objective decomposition, baseline-guided scaling, and QoS violation penalties, enabling agents to operate in a coordinated manner. To enhance intelligent resource management, Yang *et al.* [19] proposes a multi-agent dueling deep-Q network-based algorithm that leverages distributed coordinated learning. This approach utilizes a dueling architecture to estimate both state-value and action advantage functions, enabling the algorithm to rapidly converge to an optimized policy. The distributed learning framework ensures efficient policy development for intelligent resource management.

Finally, Xu *et al.* [20] formulates the resource allocation problem as a combination of multi-armed bandit and optimization problems, introducing the network coordination selection algorithm (NCSA) and the network selection algorithm (NSA). Additionally, the multi-traffic network selection algorithm (MT-NSA) is developed to address the diverse traffic requirements of devices, offering a tailored approach to network selection that accounts for varying traffic types and device-specific needs. A distinguishing feature of 5G networks is their capability to meet diverse QoS requirements across different services while maintaining slice independence and enabling flexible resource sharing. Alsenwi *et al.* [21] propose a multi-service partitioning strategy designed to balance functional isolation with the optimal sharing of resources. This system leverages a POMDP to enhance network slice service level agreement (SLA) compliance, spectrum utilization efficiency, and fairness. Similarly, Papa *et al.* [22] introduces a two-level dynamic network slicing framework that incorporates tenants' priorities, baseband resources, interference, and throughput into its design. The framework operates with an upper level dedicated to admission control and user association, while the lower level ensures fair radio resource allocation among users. The solution is implemented using a gradient-based optimization approach, which considers historical resource allocations and users' average data rates. Moreover, works presented in [23], [24] emphasize network throughput optimization while maintaining fairness across network slices.

3. PROPOSED METHODOLOGY

The proposed study addresses the challenges involved in efficient selection of a network considering advanced 5G environment. Therefore, an intelligent and privacy aware resolution is proposed for the selection of network while allowing efficient and proper use of the network and improvising user experience. We consider that a network is used as a set of W user resource that is distributed at random expressed as $\mathbb{W}$ having sub-index $w\ belongs\ to\ \{1,2,\dots,W\}$. According to the SLAs of prior studies, the users could belong to either one of the three stages of priority $priority^{w} = \{1,2\}$. For $priority^{w} = \{1\}$, which implies that the priority is high resulting in high level clients that pay higher for best QoS level. On the contrary, $priority^{w} = \{2\}$ implies the priority is low involving normal users that do not pay much and are appeased with the quality of necessary services being minimum. We categorize the two types of users, sensors having fixed position and high priority as well as cellular user resource having fixed or random way point motion and one of the stages of priority that is possible.

Consider a sequence D base stations expressed as $\mathbb{D}$ having sub index $d\ belongs\ to\ \{1,2,\dots,D\}$, in which $\mathbb{D} = \mathbb{V} \cup \mathbb{Q}$. Here, the collective group of base stations is given as $\mathbb{V}$ for terrestrial network base stations. The set of P network selections is given as $\mathbb{P}$, having sub index $p\ belongs\ to\ \{1,2,\dots,P\}$ that could be obtainable or not for various base stations. The particular service that is requested is represented as $\mathcal{R}^{w}$. The sequence of network selections to adjust the user resource WG_{w} is expressed as $\mathbb{P}_{w}$, in which $\mathbb{P}_{w} \subseteq \mathbb{P}$. Every $baseStation_{d}$ has its capacity expressed considering resource blocks of a constant bandwidth $Bandwidth_{Resblock}$. There exists a fixed count of resources as well as changing variations for service requests, that prior define the resource blocks for every network selection process that could result in ineffective usage of resources having a bad effect of the QoS. Further, we take into account the slicing scheme while omitting the resources being fixed for every network selection. The resource blocks that are available represented as $ResBlock_{d}^{avail}$ for the base station $baseStation_{d}$ is allocated dynamically while looking at the count of requests, priority of the users, the challenges on the QoS and the mobility characteristics. The parameter $t_{p}^{d}\ belongs\ to\ \{0,1\}$ which expresses the resources that are available for the $NetSelection_{p}$ in the $baseStation_{d}$, implying that zero indicates the count of resources available are inadequate to be allocated for minimum throughput (TH) needed by the user for the $NetSelection_{p}(TH_{p}^{minimum})$. The $NetSelection_{p}$ that can be accessed through the $baseStation_{d}$ is expressed as $f_{p}^{d}\ belongs\ to\ \{0,1\}$, in this case zero could imply that the $NetSelection_{p}$ is not available from the $BaseStation_{d}$ because of the access being impossible for service or lack of functionality.

The set of services possible denoted as N defined as $\mathbb{N}$ having sub-index $n\ belongs\ to\ \{1,2,\dots,N\}$. For the proposed work, we take into account three different services, namely VR, video (vid), and IIoT Apps, this is characterized using various need considering the TH, delay (F), and consumption of energy ($EnCon$). Hence, every service is mapped onto various network selections. The significance of every service provides the parameters of 'QoS' expressed using weights $weight_{TH}, weight_{F}$ and $weight_{EnCon}$ with $weight_{TH} + weight_{F} + weight_{EnCon}\ equals\ one$. The TH that a user resource WG_{w} can gain considering the $baseStation_{d}(TH_{d,p}^{w})$ depending of the reception constraints of the user and the resource blocks $ResBlock_{d,p}^{w}$ from $ResBlock_{d}^{avail}$.

$$TH_{d,p}^{w} = g_{h\,h_{d}}^{w} \times ResBlock_{d,p}^{w} \times Bandwidth_{Resblock_{d}} \tag{1}$$

In this case, $ResBlock_{d,p}^{w}\ is\ lesser\ than\ or\ equal\ to\ ResBlock_{d}^{avail}$. The $g_{h\,h_{d}}^{w}$ is the efficiency relating to the modulation encoding mechanism gained by WG_{w} regarding $baseStation_{d}$. $F_{d,p}^{w}$ is represented in second, defines the delay of the user for accessing the service that is needed using the $baseStation_d$. For the (2), the delay in transmission is given as $F_{d,p}^{w,V\,z}$ and the delay in queuing is given as $F_{d,p}^{w,S}$. The consumption of energy, measured in joules is denoted as $EnCon_{d,p}^{w}$ is evaluated by the access of user to the service that is requested through the $baseStation_d$, this is formulated as (3).

$$F_{d,p}^{w} = F_{d,p}^{w,V\,z} + F_{d,p}^{w,S} \tag{2}$$

$$EnCon_{d,p}^{w} = F_{d,p}^{w} * R \tag{3}$$

Here, R is the consumed power that is given as watt representing the user resource for the reception of particular service. The TH value that is normalized given as $TH_{d,p}^{w,normal}$ is evaluated through the upward criteria $UFunc^{up}$ as in (4). However, to gather the delay and energy consumption values that are normalized being denoted as $F_{d,p}^{w,normal}$ and $EnCon_{d,p}^{w,normal}$, respectively. The downward criteria $UFunc^{down}$ equation is given as (5).

$$UFunc^{up} = \begin{cases} 0, if\ z\ is\ lesser\ than\ z_{min} \\ 1 - \left((z_{max} - z)\left(\rho' \times (z_{max} - z_{min})\right)^{-1}\right), if\ z_{min} is\ lesser\ or\ equal\ to\ z\ lesser\ than\ z_{max} \\ 1\ otherwise \end{cases} \tag{4}$$

$$UFunc^{down} = \begin{cases} 1, if\ z\ is\ lesser\ than\ z_{min} \\ 1 - \left((z - z_{min})\left(\rho' \times (z_{max} - z_{min})\right)^{-1}\right), if\ z_{min} is\ lesser\ or\ equal\ to\ z\ lesser\ than\ z_{max} \\ 0\ otherwise \end{cases} \tag{5}$$

In this case, $\rho'\ is\ greater\ than\ or\ equal\ to\ 2$ is the refined steepness variable and z_{max}, z_{max} are the max and minimum scores relating to every service challenge and the particular utility functions. For calculating the conditions of the network to be satisfied for every service request, the dimensionless value function is given as $ValFunc_{d,p}^{w}\ belongs\ to\ [0,1]$. This unit is a combination of various normalized features considering the accessibility of network selection, availability of resource, user as well as app profiles. When $ValFunc_{d,p}^{w}\ is\ equal\ to\ one$, it implies that $baseStation_d$ can satisfy requests that maximize the QoS. The $ValFunc_{d,p}^{w}$ is formulated as (6).

$$ValFunc_{d,p}^{w} = \begin{cases} U_{d,p}^{w}, if\ t_p^w is\ equal\ to\ 1 \\ E_{d,p}^{w}, x\ if\ t_p^w is\ equal\ to\ 0 \\ 0\ if\ R_{ResBlock_d}^{normal} = 0\ \vee\ F_{d,p}^{w,normal} = 0\ \vee\ EnCon_{d,p}^{w,normal} = 0 \end{cases} \tag{6}$$

The value to attend the request of the user by the $baseStation_d$ is denoted as $U_{d,p}^{w}$ when the network has sufficient resources and is expressed in (7). The value at an overload is given as $E_{d,p}^{w}$ which is also evaluated in the (7) given. For the (7), $\rho''\ is\ greater\ than\ one$ is a value factor that adapts to $E_{d,p}^{w}$ score to benefit the base stations omitting the overload.

$$\begin{aligned} U_{d,p}^{w} &= f_p^d \times \left(weight_{TH} \times TH_{d,p}^{w,normal} + weight_F \times F_{d,p}^{w,normal} + weight_{EnCon} \times EnCon_{d,p}^{w,normal}\right) \\ E_{d,p}^{w} &= \left(\left(f_p^d(\rho'')^{-1}\right) \times weight_{TH_{satisfcation}} \times TH_{satisfaction,d}^{average} + weight_{R_{ResBlock}} \times R_{ResBlock_d}^{normal}\right) \end{aligned} \tag{7}$$

$R_{ResBlock_d}$ represents the possible resource block that the $baseStation_d$ has until all these users have the least possible TH considering the restrictions on the service. The normalized power consumption denoted as $R_{ResBlock_d}^{normal}$ which is evaluated as given in (8). In this case, the maximum and minimum count of resource blocks to attain the $TH_p^{maximum}$ and $TH_p^{minimum}$ are expressed as $ResBlock_{d,p}^{w,max}$ and $ResBlock_{d,p}^{w,min}$, respectively. The satisfactory throughput $TH_{satisfaction,d}^{w}$ for the dimensionless score have a range between 0 and 1.

$$R_{ResBlock_d}^{normal} = \begin{cases} 0, R_{ResBlock_d}\ is\ lesser\ than\ ResBlock_{d,p}^{w,min} \\ \left(\left(R_{ResBlock_d}\right)\left(ResBlock_{d,p}^{w,min}\right)^{-1}\right), ResBlock_{d,p}^{w,min} \leq R_{ResBlock_d} \leq ResBlock_{d,p}^{w,max} \\ 1, otherwise \end{cases} \tag{8}$$

3.1. Dynamic service-aware network selector

The proposed study for the DSANS mainly includes the selection of network as well as resource estimation. At every transmission period v, every local evaluation model gathers the service requests from the users that are new, service updates from users that are existing, or the channel indication of the existing user considering the threshold. This is explained in the Figure 1. The events that are captured separately by the application are gathered by the general evaluation model for a totally G events. When every event g ends, the algorithms run for the next $g+1$ event from the count of event that are identified for the particular transmission period v. The event requests that are rejected are stored in the starting of the queue for $v+1$ being the next transmission period.

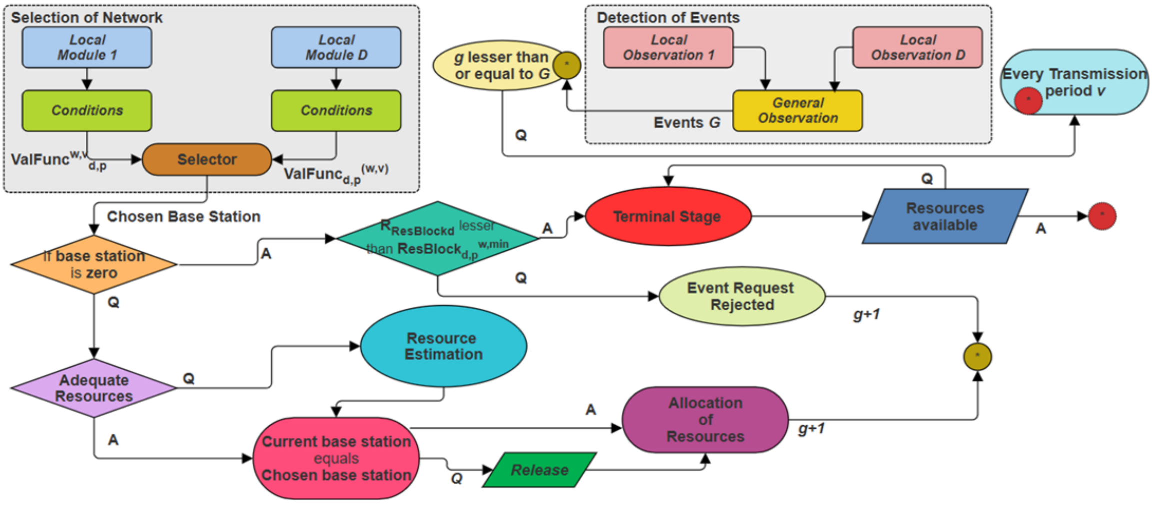

Figure 1. Dynamic service-aware network selector

After every local model makes a separate decision considering the particular information for the $baseStation_d$ for g, the selection model then chooses the base station having the highest $ValFunc_{d,p}^{w,v}$ among all the models that tend to the request. This selection model is unaware of the $baseStation_d$ local information, as it only grasps the $ValFunc_{d,p}^{w,v}$, upholding the privacy and decreasing overhead communication. The proposed improvised decentralized radio access network has a dynamic bitrate traffic for networks environment, priority of the user and service difficulties. When there is sufficient capacity of the network, the algorithm allocates the count of resource blocks for $TH_p^{maximum}$ while taking into account the service needs and neglects the priority of the user. On the contrary, if the base station lacks sufficient resource, the DSANS implements a resource estimation scheme considering the performance of service and the service level agreement proves to be advantageous to users and neglects the sudden degradation of the QoS. The resource estimation focuses on releasing resources as well as tending to new users considering the requirements. Although, if the request for service relates to the network having a new user, the chosen base station proceeds to the allocation of resources for the network selection process. Assume the no base station is chosen implying $baseStation = 0$, as there are inadequate possible resources for releasing as well as satisfying the least constraints. Then, the model gets to a terminal stage ($Flag_{ends} = 1$) and new events are not attended to. This condition prevails until release of the resources.

$$\begin{aligned}
&maximum \lim_{V\to\infty} \textstyle\sum_{v=1}^{V} \sum_{w=1}^{W} ValFunc_{d,p}^{w,v} \\
&s.t\ TH_p^{minimum}\ less\ than\ equal\ to\ TH_p^{w,v}\ less\ than\ or\ equal\ to\ TH_p^{maximum} \\
&F_{d,p}^{w,v}\ lesser\ than\ or\ equal\ to\ F_p^{maximum} \\
&EnCon_{d,p}^{w,v}\ lesser\ than\ or\ equal\ to\ EnCon_p^{maximum} \\
&f_p^d\ equals\ one \\
&R_{ResBlock_{d,v}}^{normal}\ greater\ than\ zero
\end{aligned} \tag{9}$$

The DSANS focuses on the best base station for satisfying the requests and optimization of slicing the usage of resources for every transmission period v. Hence, the algorithm is formulated as given. Here, V expresses the total count of transmission periods. The QoS and perception of the user is directly affected by $ValFunc_{d,p}^{w,v}$, while considering the diversity of network conditions, types of users, constraints on service as well as access to slicing.

3.2. Proposed adaptive deep decision network

The proposed DSANS for choosing the network is based on the ADDN implementing collaborative knowledge aggregation framework (CKAF) approach to develop a ML global module. Local agents cooperate to choose the policy ω^* that increases the QoS for every user of the network as well as maximizes the optimization of using resources that is exposed to diverse demands of the user as well as constraints on the service. Consider v'as a particular decision period, where $v' belongs\ to \{1,2,..,V'\}$ and $V' = J \times V \times G$. The count of events at transmission period v is given as $G.$ the count of transmission periods at period j is denoted as $V$and J is the count of episodes at the training phase. Initially, the global module initializes the global parameter θ^i at random and is shared with the local module. There is a local agent for every base station that executes the training phase for each g event in v, gathering new parameters θ^d. Further, to omit overhead communication, for each decision period h', local parameters are transferred to the global module aggregating them through a federated average scheme denoted as $FeDAverage$ resulting in the new global module.

$$\theta^{i,v'+1} = D^{-1} \times \sum_{d=1}^{D} \theta^{d,v'} \tag{10}$$

Here, the count of local agents that are involved in the training phase is represented as D. Furthermore, the weight of the model is transferred back to the local module. This iteration continues till the algorithm reaches the ideal optimized global module θ^{i^*}. These parameters $\theta^1 = \cdots = \theta^D = \theta^{i^*}$ are used by the local agents while preventing transfer of sensitive information within them. The interactions of the local module are formalized considering states, rewards (S, R, A) as well as actions that are described in detail as follows: i) State: is defined for every local module as $State_d$ and has user, network information and application relating to the base state=ion. The state is noticed by every local module related to the base station at the time of an event g during v; ii) Reward: every local module attains a reward denoted as $reward_{d,g}^{w,v}$ because of the action that contributes to the phase of learning. The combined reward is maximized by training the local agents given as $Reward = \sum_v \sum_g \beta \times reward_{d,g}^{w,v}$; and iii) Action: the possible set of actions that are to be performed by every local agent is denoted as $Action = \{0,1,2\}$. The action performed by local agent at the event g at v, relating to WG_w request is given as $action_{d,g}^{w,v}$. When $action_{d,g}^{w,v} = 1$, it implies that the base station can tend to the request with ample resources, if $action_{d,g}^{w,v} = 2$, the base station can also tend to the request but has to undergo the process of resource estimation because of overloading. Whereas, if $action_{d,g}^{w,v} = 0$, the base station is unable to tend to the request and $ValFunc_{d,p}^{w} = 0$. At this stage, the base state is not suitable for the selector model. However, if the base station satisfies the demands but every action is zero, then the request of the user is rejected which therefore affects the QoS.

The ADDN enhances the learning ability of the model and evades the too optimistic reward evaluation using approximating function via two neural networks for value function. The initial Q-value function $S(state, \theta, action)$, where the vector for the neural network weights is given as θ, this is used is selecting the action. The second Q-value function $\hat{S}(state, \theta^-, action)$ for evaluation of the reward. We assume that $\theta^-\ equals\ \theta$. Further, the parameters of $\hat{S}$ are updated considering the rate of updating denoted as τ of the destined network. The agents use a greedy mechanism based on epsilon ε for choosing actions and avoiding stalling. Every agent considers the best action $(argumaximum_c, S_c(state, \theta, action))$ based on prior experiences having $1 - \varepsilon$ as a probability. Every agent utilizes the experience to enhance efficiency, the experiences $\beth_{d,g}^{v} = state_{d,g}^{v}, action_{d,g}^{w,v}, reward_{d,g}^{w,v}, state_{d,g}^{v+1}$ is stored in the replay buffer denoted as Buf. When the experiences that are stored $|Buf|$ is adequate to be sampled at random at a smaller batch dimension $|\mathcal{M}|$, this action is performed by the agents. The destined score of every local module at the phase of training is formulated as (11).

$$a_{d,g}^{v} = reward_{d,g}^{w,v} + \beta \times \hat{S}_d\left(state_{d,g}^{v+1}, argumaximumS_d\left(state_{d,g}^{v+1}, action_{d,g}^{v}; \theta^d\right); \theta^{d-}\right)\right) \tag{11}$$

In this case, if the model attains the terminal state, the destination score is equivalent to $reward_{d,g}^{w,v}$. The Q-score that is updated is given as (12). For the (12), $\mu\ belongs\ to\ [0,1]$ which defines the rate of learning controlling the speed at which the algorithm learns. Every local module evaluates the loss function and utilizes it to minimize the error that occurs during training. This is relating to the mean squared error and if given as (13). Here, the sub index for iteration for all the elements in the small batch is given as m. In conclusion, the loss function globally is formulated as given as (14). The entire process of optimized ADDN described in Algorithm 1.

$$S_d\left(state_{d,g}^{v+1}, action_{d,g}^{v+1}; \theta^d\right) = (1-\gamma) \times S_d\left(state_{d,g}^{v}, action_{d,g}^{v}; \theta^d\right) + \mu \times a_{d,g}^{v} \tag{12}$$

$$LossFunc_d(\theta^d) = (|\mathcal{M}_d|)^{-1} \sum_{\mathcal{M}} (a_m - S_d(state_m, action_m, \theta^d))^2 \quad (13)$$

$$LossFunc_{Global}(\theta^f) = (\sum_{d=1}^{D} |\mathcal{M}_d|_{d=1})^{-1} \sum_{d=1}^{D} |\mathcal{M}_d| \times LossFunc_d(\theta^d) \quad (14)$$

Algorithm 1. Optimized DDN at the training phase

Input: $state_d, Action, Reward, J, h', |\mathcal{M}_d|, \varepsilon, \mu, \tau, \beta$
Initialization: $v' equals\ zero, H' equals\ zero, Machine\ Learning\ Global\ Module: \theta^{Gobal},$
$Machine\ Learning\ local\ Module: \theta^d = \theta^{d-} = \theta^{Gobal}, |Buf| \leftarrow \emptyset$
Output: θ^{Global^*}
Step 1: For every episode $j = 1, \dots, J$ do
Initialization $state_d$, $Flag_{end} = 0$
Step 2: While $Flag_{end} = 0$ do
For every transmission period v do
Step 3: For every event $g\ belongs\ G$ do
$v' + +$
Local Modules
Step 4: For every ML model $d\ belongs\ to\ D$ do
On observing the present state $state_{d,g}^{v}$
The agent takes action $action_{d,g}^{w,v}$ relating to ε
Step 5: Agent receives $reward_{d,g}^{w,v}$
Situation varies to $state_{d,g}^{v+1}$ and Buf stores $\beth_{d,g}^{v}$
Step 6: If $|Buf| is\ greater\ than\ |\mathcal{M}_d|$ then
Small batch of $|\mathcal{M}_d|$ is sampled from Buf
Step 7: $a_{d,g}^{v}$ and $LossFunc_d$ are evaluated using (10) and (12)
$LossFunc_d$ is used to update θ^d
Updating after back propagation; $\theta^{d-} \leftarrow \tau\theta^d + (1-\tau)\theta^{d-}$
Step 8: End
End
Step 9: If $mod(v', h') equals\ 0$ then
$H' + +$; Global Module
Gather $\theta^{d,v'}\ and\ \theta^{d,v'-}$ to every machine learning model d
Step 10: End
End
End
End
Step 11: If $\varepsilon\ is\ greater\ than\ 0,1$ then
Apply $\varepsilon - decay$ scheme
Step 12: End
End

3.3. Adaptive resource management module

The adaptive resource management module (ARMM) has to be implemented when the chosen base station is overloaded. It enhances the experience of the user by decreasing latency and reduces throughput by preventing congestion of network. It also ensures all the network contributes to the complete performance, leading to efficient usage of resources. ARMM plays an essential role in enabling a seamless and efficient network operations by dynamic distribution of traffic and optimization of resource usage via CKAF. The process of ARMM is explained in detail using the Algorithm 2.

Algorithm 2. ARMM

Input: $\mathbb{R}, r^w, ResBlock_{require}, ResBlock_d^{avail}, Service\ restrictions$
Initialization: $\mathbb{E}_{success} = \{\}$, $E_{minimum} = 0$, $x^{max}(E) = 0$
Output: $E_{minimum}, W_{affusers}, \vartheta, ResBlock_{release}^{E_{minimum}}$
Step 1: Priority base scheduling is used $\mathbb{E} \rightarrow \mathbb{E}^*$
Step 2: For each $E \subset \mathbb{E}^*$ *do*
If $\sum_{k=1}^{|E|} ResBlock_d^{avail} + ResBlock_{release}^{k}\ is\ greater\ or\ equal\ to\ ResBlock_{require}$ then
Evaluate affected users $W_{affusers}, \vartheta_E$
Step 3: Append (E) to $\mathbb{E}_{success}$
End
Step 4: For $b\ belongs\ to\ \mathbb{E}_{success}$ do
Evaluate $x(E_b)$
Step 5: If $x(E_b)\ is\ greater\ than\ x^{max}(E)$ then $x^{max}(E) = x(E_b)$
$E_{minimum} = E_b$
End
Step 6: $ResBlock_{release}^{E_{minimum}} = \sum_{k=1}^{|E_{minimum}|} ResBlock_{release}^{k} + ResBlock_d^{avail}$

4. RESULTS AND DISCUSSION

We compare our proposed algorithm against four state-of-the-art algorithms. That implement intra-slice scheduling mechanisms. These include the user-oriented quality of service (UQoS) algorithm [23], the max bit rate throughput multi-connectivity (TMC) greedy algorithm [24]. The priority-based proportional fairness (PPF) algorithm [25], [26].

4.1. Results

The cumulative distribution function (CDF) plot illustrates the distribution of average service throughput across four network slices, highlighting their performance variability and QoS differentiation. Network slice 1 achieves the highest throughput, catering to bandwidth-intensive services, while slice 4 demonstrates lower performance, likely allocated for low-throughput applications such as IoT. This distribution reflects the impact of mobility patterns and service classes on heterogeneous network performance, aligning with the objective of analyzing their influence. Additionally, the range of throughput across slices underscores the relevance of developing multi-objective resource allocation strategies to optimize fairness, throughput, and QoS, ensuring efficient resource utilization across diverse service demands. Figure 2 shows the CDF of average service throughput for network slices.

The CDF plot demonstrates the radio resource allocation distribution for four network slices, showcasing the system's ability to handle differentiated resource demands. Network slice 1 achieves the highest allocation, suggesting prioritization for high-demand applications, while slice 4 exhibits the lowest allocation, likely reserved for low-resource services such as IoT. The gradual and uniform rise in each curve indicates fairness within slices, though inter-slice gaps highlight opportunities for optimizing resource sharing. This analysis aligns with the objective of designing resource estimation algorithms to balance QoS and ensure efficient resource utilization across heterogeneous network slices. Figure 3 shows the radio resource allocation.

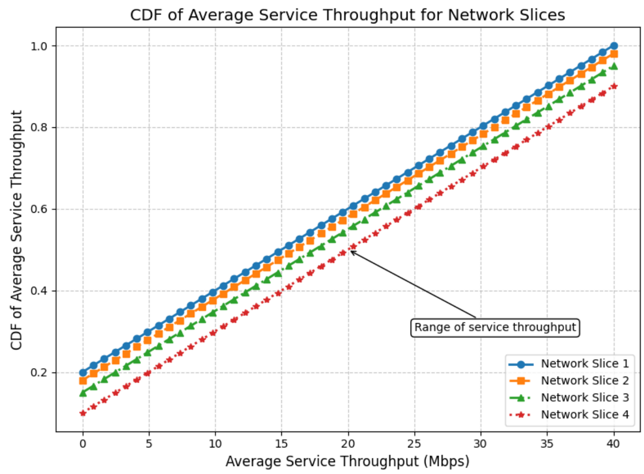

Figure 2. CDF of average service throughput for network slices

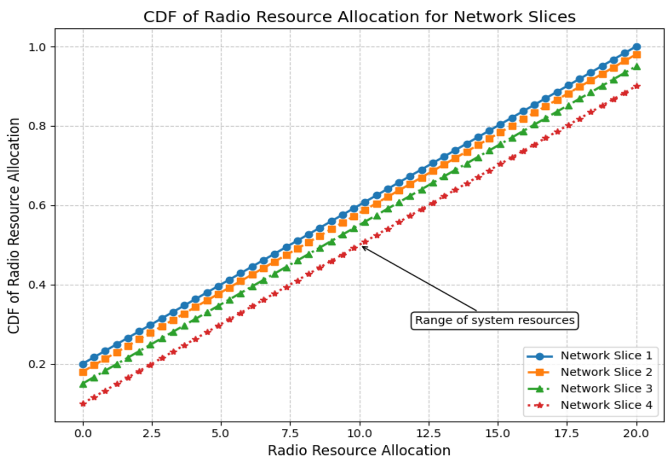

Figure 3. Radio resource allocation

Figure 4 demonstrates the performance of the pattern search (PS) algorithm across three configurations (N1, N2, and N3) in terms of slice throughput as the number of eMBB network services increases. N1 exhibits limited throughput (capped at 80 Mbps), while N2 achieves up to 140 Mbps, and N3 outperforms both with a peak of 165 Mbps, showcasing significant scalability and resource efficiency. The transition from N1 to N3 highlights a substantial improvement in resource utilization, with throughput gains of 75 and 17.8% for N2 and N3, respectively. This reflects the algorithm's adaptability to diverse service demands, aligning with the objectives of optimizing resource allocation and addressing mobility patterns in heterogeneous networks.

Figure 5 illustrates the serving probability of the PS algorithm across three configurations (N1, N2, and N3) as the number of eMBB network services increases. N1 shows steady growth but stabilizes at 0.8, indicating lower reliability under heavy loads. In contrast, N2 and N3 outperform N1, with N3 achieving near-optimal serving probability (~0.95), demonstrating superior scalability and resource allocation. The progression highlights the efficiency of the PS algorithm in meeting QoS requirements and its adaptability to increased service demands, aligning with the objectives of optimizing resource allocation and enhancing user satisfaction in heterogeneous networks.

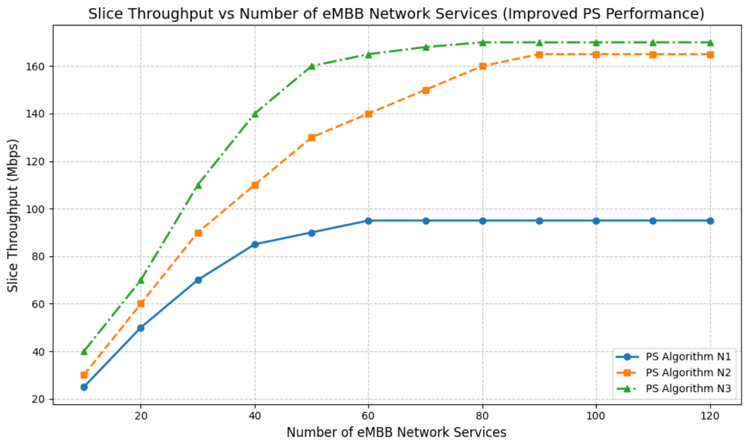

Figure 4. Performance of the PS algorithm across three configurations

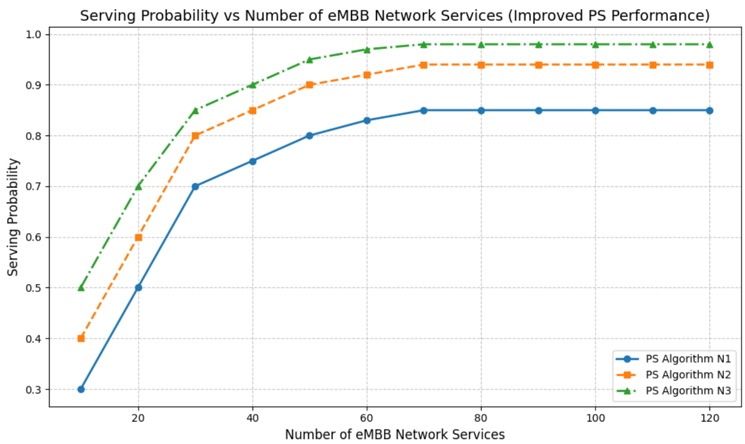

Figure 5. Serving probability of the PS algorithm across three configurations

Figure 6 compares the pseudo randomized search strategy (PRSS), TMC, and the proposed PS algorithm against the total number of eMBB network services. The PS algorithm consistently outperforms the others, achieving a peak throughput of approximately 165 Mbps, showcasing superior resource allocation and scalability. The TMC algorithm exhibits moderate performance, stabilizing near 140 Mbps, while the PRSS algorithm lags behind, peaking at around 120 Mbps. The results highlight the efficiency of the PS algorithm in optimizing throughput, especially under high service demands, aligning with objectives related to enhancing QoS and efficient resource utilization in heterogeneous networks.

Figure 7 compares the number of served eMBB network services for the PRSS, TMC, and proposed PS algorithms against the total number of eMBB network services. The PS algorithm demonstrates superior performance, consistently serving a higher number of services and reaching approximately 130 at peak, reflecting its efficiency in resource allocation. The TMC algorithm shows moderate performance, stabilizing near 100, while the PRSS algorithm lags with a maximum of 80 services. These results underscore the adaptability and scalability of the PS algorithm, aligning with the objectives of improving service capacity and optimizing resource utilization in heterogeneous network environments.

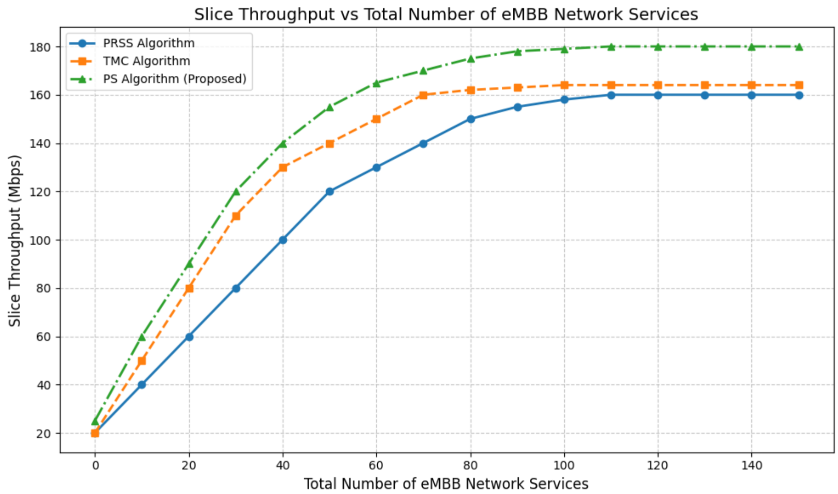

Figure 6. Slice throughput performance of three algorithms

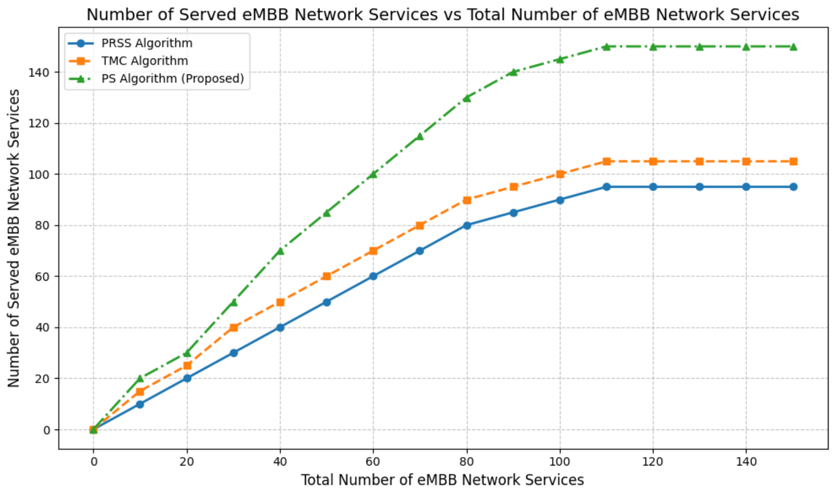

Figure 7. Compares the number of served eMBB network services

Figure 8 showcases the slice throughput performance against the total number of eMBB network services for the achieved slice throughput, minimum guaranteed throughput, and the PS algorithm (proposed). The PS algorithm demonstrates superior performance, achieving consistent throughput around 175 Mbps, surpassing the achieved slice throughput, which stabilizes near 160 Mbps. The minimum guaranteed throughput remains capped at 100 Mbps, highlighting the PS algorithm's ability to exceed baseline guarantees and efficiently allocate resources. This result emphasizes the PS algorithm's scalability and ability to maintain high QoS under increased service demands, aligning with the objectives of optimizing resource utilization and ensuring service quality in heterogeneous networks.

Figure 9 compares the number of served eMBB network services for the PRSS algorithm and the proposed PS algorithm as the total number of network services increases. The PS algorithm demonstrates superior scalability, serving nearly 120 network services at its peak, while the PRSS algorithm stabilizes at around 70 services, indicating limited capacity. This improvement aligns with the objective of optimizing resource allocation and network selection in heterogeneous networks, as the PS algorithm ensures higher service capacity and better utilization of network resources. Furthermore, it reflects the impact of mobility patterns and service classes, showcasing the PS algorithm’s ability to handle diverse service demands more effectively than PRSS.

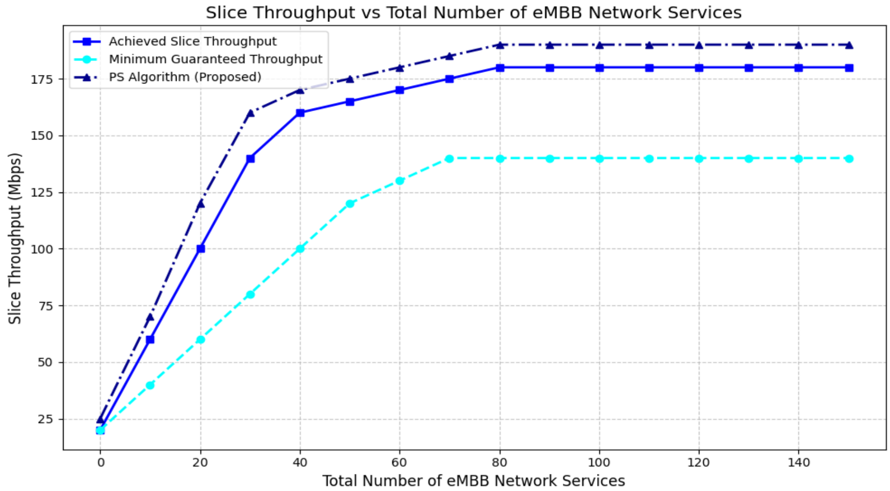

Figure 8. Slice throughput performance against the total number of eMBB network services

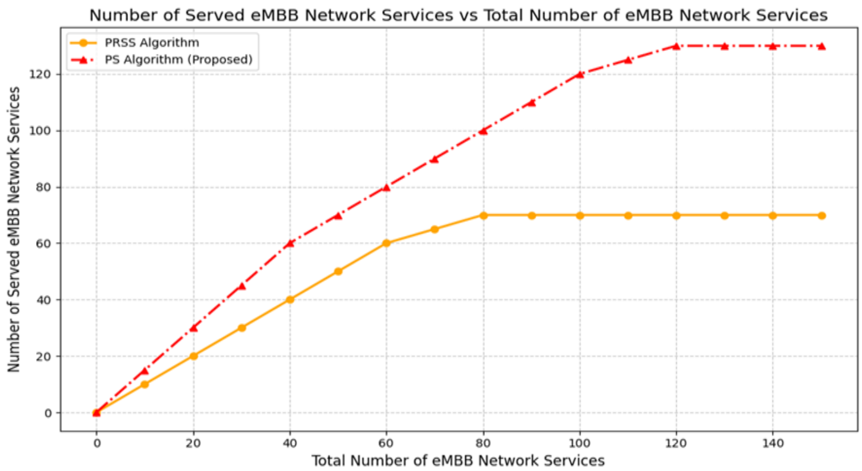

Figure 9. Compares the number of served eMBB network services

Figure 10 compares the number of served eMBB network services across the proportional fairness–based bandwidth estimation technique (PF-BET), PRSS, and proposed PS algorithms. The proposed PS algorithm significantly outperforms both PF-BET and PRSS, serving nearly 130 services at its peak, while PRSS stabilizes at approximately 90 and PF-BET at 60 services. This highlights the PS algorithm's superior scalability and efficiency in resource allocation. The results align with the objectives of designing algorithms for resource estimation and multi-objective optimization, ensuring better QoS and user satisfaction. Additionally, the PS algorithm’s ability to handle diverse and increasing service demands emphasizes its adaptability to varying mobility patterns and service classes in heterogeneous networks.

Figure 11 compares the minimum and maximum slice throughput for the PRSS, PPF, and proposed PS algorithms. The proposed PS algorithm demonstrates superior performance with a maximum throughput of 165 Mbps, slightly exceeding PRSS (161.88 Mbps) and PPF (161.15 Mbps). Additionally, the PS algorithm achieves a higher minimum throughput of 1.50 Mbps, compared to 1.03 Mbps for PRSS and 0.70 Mbps for PPF, indicating improved consistency and reliability. These results align with the objectives of ensuring efficient resource utilization and maintaining higher QoS, highlighting the PS algorithm's advantage in achieving both optimal and stable throughput across heterogeneous network slices.

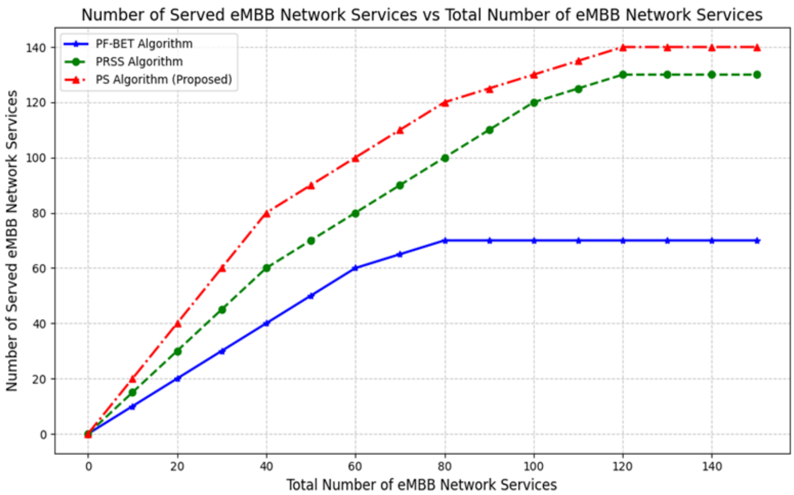

Figure 10. Compares the number of served eMBB network services

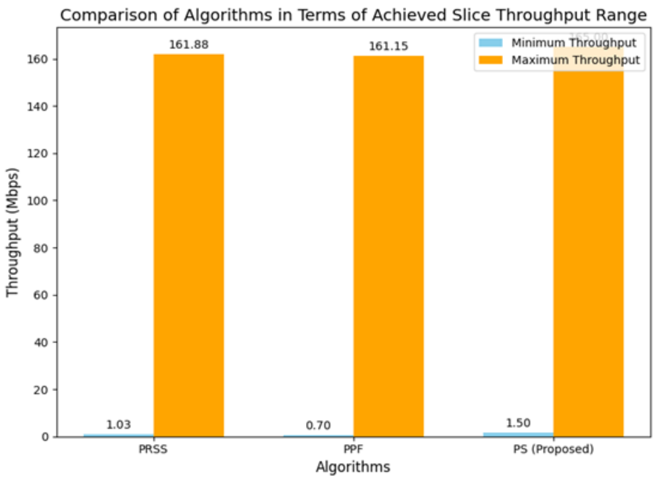

Figure 11. Minimum and maximum slice throughput for the PRSS, PPF, and proposed PS algorithms

4.1.1. Comparative analysis

The comparison between the PRSS and PS algorithms highlights the significant advancements offered by the PS algorithm in addressing the challenges of HWNs. The PS algorithm consistently outperforms PRSS across all key metrics. In terms of slice throughput, the PS algorithm achieves a peak throughput of 165 Mbps, representing a 37.5% improvement over PRSS's 120 Mbps. Similarly, the PS algorithm supports up to 120 eMBB services, a 50% increase compared to PRSS's maximum capacity of 70-80 services, demonstrating superior scalability and resource management. The serving probability of the PS algorithm stabilizes at 0.95, significantly higher than PRSS's 0.8, reflecting enhanced reliability and QoS. Furthermore, the PS algorithm achieves a minimum throughput of 1.50 Mbps, compared to 1.03 Mbps for PRSS, indicating better fairness and consistent resource allocation, while also improving the maximum throughput. These improvements are driven by the PS algorithm's adaptability to varying mobility patterns and diverse service classes, addressing the limitations of PRSS. Overall, the PS algorithm excels in optimizing resource allocation and network selection, ensuring superior performance and directly aligning with the objectives of enhancing mobility-aware service differentiation and multi-objective optimization in next-generation HWNs.

5. CONCLUSION

The proposed DSANS framework addresses the critical challenges of resource optimization and network selection in 5G-advanced HWNs. By integrating the ADDN, the framework achieves multi-objective optimization, effectively balancing QoS metrics such as throughput, delay, and energy efficiency while enhancing QoE for diverse service classes. Unlike existing models, which struggle to adapt to dynamic mobility patterns and service demands, DSANS demonstrates superior adaptability and efficiency. The simulation results validate the effectiveness of DSANS, showing significant improvements in throughput and latency compared to state-of-the-art algorithms. The framework's ability to dynamically allocate resources and adapt to network conditions ensures scalability and robust performance in real-world scenarios. These advancements highlight the potential of DSANS to meet the stringent requirements of next-generation HWNs, offering a foundation for future research in dynamic and adaptive network management systems.

ACKNOWLEDGMENTS
We would like to express our heartfelt thanks to our guide for his unwavering guidance, invaluable insights, and encouragement throughout the research process.

FUNDING INFORMATION
No funding is raised for this research.

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

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

CONFLICT OF INTEREST STATEMENT
Author declares no conflict of interest.

DATA AVAILABILITY
No dataset is utilized in this research.

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