Resource Allocation and Service Provisioning for Softwarized Network Slicing using Game Theory: A Techno-economic Approach

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***Abstract*—Softwarized Network Slicing (SNS) is a forthcoming technological advancement that is going to transform conventional resource allocation techniques. Optimizing the flow of slice resources among the key network players, namely MVNOs (Mobile Virtual Network Operators), MIPs (Mobile Infrastructure Providers), and UEs (User Entities), is a complex and challenging task due to its complicated combinatorial nature. Moreover, maintaining the concurrent quality of service of end-users based on UE fairness is also difficult. Considering these factors, in this work, we have proposed a novel resource allocation strategy using a two-tier matching game between MIPs, MVNOs, and UEs, which not only minimizes the resource allocation cost but also maintains a decent UE satisfaction by providing desired UE SINR. An MILP (Mixed Integer Linear Programming) is formed for cost minimization, and the same is solved using a modified differed acceptance stable algorithm. We have compared our improvement with existing and latest state-of-the-art techniques.**

***Index Terms*—SNS, Resource Allocation, Modified Matching Game, MVNO, MIP, Cost Model**

I. Introduction

THE notion of virtualization and softwarization are gaining popularity and are being utilized in several fields, including virtual machines, virtual memory, and virtual data centers. Additionally, such new advancements immensely influence the next-generation communication networks like 5G and 6G. Virtualization of network functions is a technique that involves the creation of several virtual networks, each of which is a subset or combination of the underlying physical network [1]. It encompasses the process of abstracting, isolating, and distributing resources across various organizations. This allows for the support of diverse applications without the need to alter the underlying architecture. Network virtualization provides significant network flexibility, optimizes network use, and fosters innovation in goods and services. Network virtualization, along with softwarization, enables the notion of network slicing technique, which is widely used in next-generation communication networks [2].

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This research utilizes the benefits of matching theory to include the interactions among the three components of abstraction in wireless network virtualization, in contrast to prior studies that mostly focused on service providers (SPs) and infrastructure providers (InPs) [3]. Therefore, this work provides a resource allocation paradigm for network virtualization that uses a matching game to pair three network components: resources, infrastructure, and end users, all at the same time. The benefits of our two-step matching architecture and its associated matching-based solution are as follows: (a) The traditional centralized resource allocation separates the process of generating virtual services by the MVNOs from the process of managing user services by the UEs. This can lead to sub-optimal outcomes compared to our integrated two-step matching framework, where MVNO, MIP, and UE are considered together (Fig. 1). (b) The dynamic user demands vary the spectrum requirements for end users, which further needs frequent adjustments in resource allocation. A suitable matching algorithm can satisfy such network conditions.

Motivation and Contributions: The preliminary research works, as stated in Table I, it has been observed that satisfying the UE fairness by maintaining a decent SINR (Signal to Interference Noise Ratio) along with low-cost resource flow is a complex task. Even though game theoretic approaches are used in some of the works, no work has considered both upper-tier (MIP and MVNO) and lower-tier (MVNO and UE) resource flow together, which significantly can improve the system model performance. Following this, the contributions given below are made.

- Initially, a system model is considered, as shown in Fig. 2, where MIPs are selling the slice resources (spectrum resource) to the MVNOs. The MVNOs then virtualize those resources and distribute them to the end-users.
- Next, we formulate the cost-optimization MILP based on UE fairness and QoS, which is NP-hard and solve it using a strictly non-cooperative two-stage matching game.
- Finally, we propose two separate algorithms addressing

the UE fairness and QoS quota fulfillment through a many-to-one matching game between UEs and MVNOs and an MVNO-optimal revenue generation model through a restricted many-to-many matching game between MIPs and MVNOs, respectively.

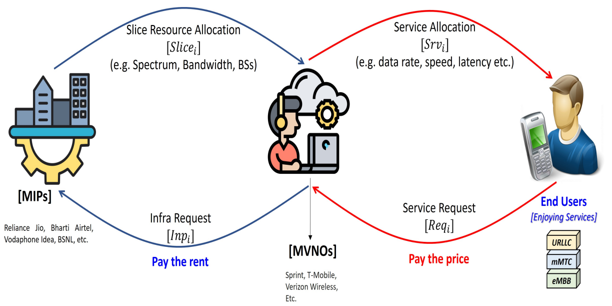

Fig. 1: Flow of network resources and pricing model of MIPs, MVNOs, and UEs

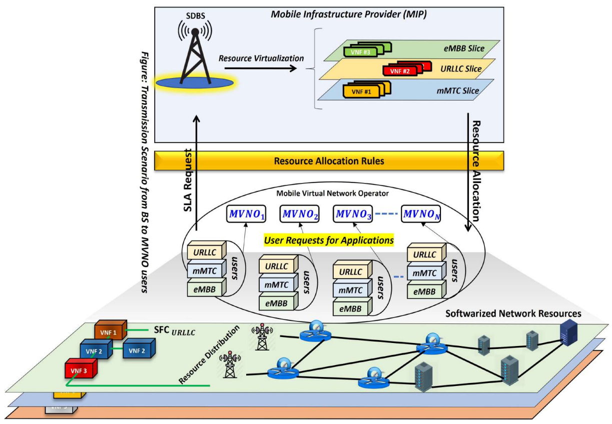

Fig. 2: Service Transmission Scenario between UEs of an MVNO and MIP-BS.

II. Literature Survey

Utilizing physical resources via network slicing (NS) may effectively decrease operational expenditures (OPEX) by enabling more adaptable network operations. In addition, a stringent SLA (service level agreement) is followed by the UEs for resource assignment. An infrastructure provider base station (MIP-BS) performs wireless network slice resource allocation (RA) to allocate resources to users or by a mobile infrastructure provider (MIP) to provide resources to mobile virtual network operators (MVNOs), who then decide the resource allocation for their clients. The primary issue to be addressed in this work is the efficient allocation of resources to UEs from MIP via MVNOs. SNS allows the separation of virtual resources, enabling the sharing efficiency and utilizing the enhanced data rate of UEs in wireless networks. Many researchers have recently suggested novel ways to address this optimisation challenge, such as heuristics, admission control, AI/ML methods, random allocation, and auction models.

[4] defined the challenge of associating user equipment as a matching game with one-to-many association. The environment includes an ultradense heterogeneous 5G architecture as their system model. They have introduced the NS scheme for better isolation between macro and micro-cells. An algorithm based on UE slice association is used to realize a stable matching game between the UEs and network operators. The objectives were to enhance user QoS, energy efficiency and network performance. The letter [5] proposes a new approach towards spectrum fragility in 5G wireless networks. The approach facilitates access to both unlicensed and licensed bands. The authors categorized the issue as a vulnerable shared pool of resources, necessitating a pricing mechanism for the Nash equilibrium. A pricing function is established to measure both static and dynamic RA schemas using decision metrics for UEs and network resources. Kazmi et al. [6] formulated the service provisioning and resource allocation problem in a multi-cell virtualized wireless network as a two-stage combinatorial optimization problem. The authors propose a hierarchical matching game that fulfils the need for tight isolation and also meets the criteria for effective resource allocation.

Furthermore, some researchers have explored the use of machine learning and artificial intelligence techniques, including deep reinforcement learning (DRL), Q-learning, federated learning, and double deep reinforcement learning (double DRL), to address the optimization of decision-making in the dynamic context of next-generation networks. Within this particular framework, Du et al. [12] presented various methodologies that utilize artificial intelligence and machine learning to facilitate ultra-reliable, ultra-massive access, low-latency, and ultra-broadband services. The method uses fog, edge, and cloud computing to cache valuable information extracted using ML for prediction mechanisms. Authors in [8] address the centralized RA problem using a distributed ML-based UE-centric framework. In order to enhance the efficiency of URLLC & eMBB services, the authors [9] suggested a strategy that utilizes an SDN controller to allocate radio resources to gNodeBs over an extended duration according to the requirements of service demands. Moreover, a deep Q-learning technique is established that distributes the resources to cater to the UEs for a short-term RA. The study [16] offers a comprehensive description of algorithms based on AI for resource management for NS in next-generation networks, providing an in-depth understanding of AI/ML approaches. In order to conduct a thorough analysis of the past studies, Table I presents a detailed comparison using several criteria linked to whether they were treated or not.

Our study utilizes game theory as an appropriate method for addressing RA issues. The primary objective of our proposed theory is its distinct capacity to achieve a balance among the many participants involved, namely MIP, MVNO, and UE. The matching algorithm offers a sub-optimal and consistent solution.

III. System Model and Problem Formulation

Each MIP has a collection of channels (Ch_n^{slice}) for each slice which are mutually orthogonal in nature. Each channel

Comparison With State-of-the-art Techniques

Approach	RA for Upper-tier	Market Model	Service Types	Pricing Technique	Down-link Transmission	Network Slicing	Game Theory	Upper & Lower tier RA
Proposed Approach	✔	✔	✔	✔	✔	✔	✔	✔
2023 [7]	✔	✔	✔	✔	✔	✔	✔	–
2022 [8]	✔	–	–	–	–	✔	–	–
2022 [9]	✔	–	✔		✔	✔	–	–
2022 [10]	–	–	–	–	–	–	✔	–
2021 [11]	–	–	–	✔	–	✔	✔	–
2020 [12]	–	–	✔	–	–	✔	–	–
2020 [13]	–	–	✔	–	✔	–	–	–
2020 [14]	–	✔	–	–	–	–	–	–
2020 [4]	✔	–	–	–	–	✔	✔	–
2019 [5]	–	–	–	✔	–	–	–	–
2019 [15]	✔	–	–	–	–	✔	–	–
2018 [6]	–	–	–	–	✔	–	✔	–

TABLE I: Comparative analysis with the state-of-the-art techniques

has a bandwidth of $\mathcal{W}$. MIPs procure administrative licensing from different vendors for those frequency channels. We make the assumption of static inter-MIP interference, meaning that the interference caused by other MIPs is considered to be part of the background noise, denoted as δ^2. Furthermore, we make the assumption that the power is evenly distributed across all channels of an MIP n, denoted as $\mathbb{P}_n = \mathbb{P}_n^{max} / |Ch_n^{slice}|$. Moreover, a MIP n offers separate services via a collection of $\mathbb{R}_n$ slices, where each slice r_n, assigned by MIP n to MVNOs m, will have a varying number of channels depending on the need of MVNO m. Next, the data rate for a User Equipment (UE) u on a slice r_n of an MIP is:

$$\mathbb{D}_{n,u}^{\mathbb{R}_n} = \sum_{Ch \in r_n} \mathcal{W} \log\left(1 + \gamma_{n,u}^{Ch}\right)$$

where $\gamma_{n,u}^{ch} = \frac{\mathbb{P}_n g_{n,u}^{ch}}{\delta^2}, g_{n,u}^{Ch}$ represents the channel gain between channel Ch of slice r_n of MIP-BS n and UE u.

A. The MILP Problem Formulation

SNS architecture (Fig. 1) always targets to fulfil the objectives of MIPs, MVNOs, and UEs. The MIP aims to satisfy MVNOs' demands such that the contract agreements are not violated, which results in the following MILP formulation:

$$\textbf{MIP:} \max_{y_{m,n}^{r_n} \in \{0,1\}} \sum_{m \in O} \sum_{r_n \in \mathbb{R}_n} y_{m,n}^{r_n} \left({}^{\mathcal{D}_{m,n}}\Psi_{r_n,m}^{\mathbb{I}} \, |r_n|\right) \tag{1}$$

$$\textbf{MVNO :} \max_{\tilde{x}_{u,m}, \tilde{y}_{u,n}^{r_n} \in \{0,1\}} \sum_{u \in U} \tilde{x}_{u,m} \Psi_m^{\mathcal{O}} d_u - \sum_{n \in \mathcal{N}} \sum_{r_n \in \mathbb{R}_n} \tilde{y}_{u,n}^{r_n} \, {}^{\mathcal{D}_{m,n}}\Psi_{r_n,m}^{\mathbb{I}} \, |r_n| \tag{2}$$

Finally, Each UE $u \in \mathcal{U}$ chooses its service by:

$$\textbf{UE} : \min_{x_{u,m} \in \{0,1\}} \sum_{m \in \mathcal{O}} x_{u,m} \Psi_m^{\mathcal{O}} d_u, \tag{3}$$

Equation (1) targets n^{th} MIP's revenue maximization, where, $y_{m,n}^{r_n} \in \boldsymbol{Y}$. If n^{th} MIP agrees upon the proposal of m^{th} MVNO for buying the r_n slice resource, then $y_{m,n}^{r_n} = 1$, it remains 0 otherwise. ${}^{\mathcal{D}_{m,n}}\Psi_{r_n,m}$ is the price per unit infrastructure resource offered by m^{th} MVNO to n^{th} MIP for r_n resource with associated maintenance demand of $\mathcal{D}_{m,n}$. Here, the demand of m^{th} MVNO is given by d_m (i.e., $d_m = \sum_{u \in U_m} d_u$). The objective function in equation (2) depicts the equitable distribution of resources among MVNOs. d_u and $\|U_m\|$ are assumed by an MVNO based on the previous market forecasts. $\tilde{d}_{m,n}^{r_n}$ is the resource demand fulfilled by the n^{th} MIP with r_n resource type for m^{th} MVNO.

Equation (3) shows, if the u^{th} UE's proposal is accepted by the m^{th} MVNO, then $\tilde{x}_{u,m} = 1$ or if the proposal is rejected, then $\tilde{x}_{u,m} = 0$. Similarly, $\tilde{y}_{k,n}^{r_n} = 1$, if m^{th} MVNO chooses to buy r_n slice resources from n^{th} MIP. Otherwise, $\tilde{y}_{k,n}^{r_n} = 0$. $\Psi_m^{\mathcal{O}}$ is the per unit selling price of m^{th} MVNO. The m^{th} MVNO defines the required number of channels to satisfy d_u as $c_{u,m}$ [17].

Where, $x_{u,m} = 1$, it u^{th} UE chooses the m^{th} MVNO for suitable service selection and $x_{u,m} = 0$ otherwise. The demand of u^{th} UE is given by d_u. The act of minimizing (11) allows the UE to fulfil its objective of paying the lowest possible amount.

The MILP is restricted by the resource constraints that include:

- Each UE must be served by a single MVNO at a time.
- Each MVNO may buy resources from multiple MIPs until their resource quota gets filled.
- Each MVNO and UE follow the cost boundary as per the SLAs.

B. The Cost Model as per Market Condition

MIP offers the virtual resource slice to MVNOs at a price that is appropriate for each unit. The correct price refers to the lowest price that the MIP is willing to pay for each unit or channel, which is indicated by the lower price threshold limit. The price amount encompasses profit margin, OPEX (operating expenditure) and CAPEX (capital expenditure). Therefore, the income of MIP is as follows:

$$\mathcal{REV}_n^{\mathcal{N}}(p, y) = \sum_{m=1}^{O} p_{m,n}^{r_n} * y_{m,n}^{r_n} \tag{4}$$

Where, $y_{m,n}^{r_n}$ is the binary decision variable which becomes 1 if the m^{th} MVNO buys the slice resource r_n from the n^{th} MIP, it is 0 otherwise. $p_{m,n}^{r_n}$ is the price paid by the m^{th} MVNO to the n^{th} MIP for using the r_n slice resources. In addition, every MVNO strives to provide optimal service to its consumers by adhering to the minimal data rate necessary to minimize payments to the MIP.

IV. Proposed Algorithmic Solution

The two-tier matching game is formed in two stages. The matching between MIP and MVNO is framed as tier-one matching, and similarly, the matching between UE and MVNO is framed as tier-two matching. It is assumed that MVNOs predict the resource qouta based on previous market analysis. All the players (UEs, MIPs, and MVNOs) act independently in the gaming scenario. As a result, each entity inside a domain only considers optimizing its respective targets. Hence, strict non-cooperation is observed in the gaming model. For the first case, where MVNO and MIP form the gaming module as a bipartite graph where MIPs are at the left cluster, and MVNOs are at the right, the MIPs act as vendors and the MVNOs act as Buyers. A single MVNO may buy resources from multiple MIPs until its resource quota ($RQ_m^{\mathcal{O}}$) gets fulfilled.

Algorithm 1: Tier-I Matching Game: MIP & MVNO

Input: $f_m^{(0)} = f_m^i, \mathbb{F}_m^{(0)} = \mathbb{F}_m^{(t1)}$, $\mathbb{F}_n^{(0)} = \mathbb{F}_n$, $\forall n \notin \mathcal{G}_{n,m}^i$; $i = 0$

initialize: $i = 0$, $\mathcal{G}'^{i}_n = 0 \, \forall n.$
while $\mathcal{G}'^{i}_n \neq \mathcal{G}'^{i+1}_n$ **do**
  $i = i + 1;$
  $\alpha(m) \rightarrow$ MVNO-optimal matching
  $P \rightarrow$ Multi-partner stable marriage problem set
  $P \rightarrow \tilde{P} \Rightarrow$ initial pruning
  while $\rho \in \tilde{P}$ **do**
    remove $\rho \rightarrow$ meta-rotation set,
  end
  Building weighted meta-rotation poset;
  if $A \in$ *weighted poset* **then**
    $A \rightarrow$ Maximum-weitgted poset;
    Drop A from poset.
  else
    Continue searching;
  end
  Get $\alpha^*(m)$
  Update $\mathcal{G}'^{i}_n$, $\forall n$
end
Search space reduction for MIP and MVNO
Output: *Stable matching group* $\mathcal{G}'_n$
END

A. Tier-one Matching Game Between MIP and MVNO

As we strictly follow the SLAs between MVNOs and MIPs, a non-cooperative matching game is formed where all players from the same sets do not cooperate with each other. Each MVNO may buy resources from multiple MIPs depending on their requirements. As per our initial assumption, each MVNO has a predefined quota of resources $RQ_m \rightarrow m^{th}$ MVNO. Each MIP also has a $RQ_n \rightarrow n^{th}$ MIP. An MIP may serve multiple MVNOs until its raw resource is exhausted or it satisfies the SLA. The matching between MIPs and MVNOs is performed on the basis of the preference profiles of MIP and MVNO, respectively. $\mathbb{F}_n^{t1}$ is MIP's preference profile that ranks the MVNOs, and $\mathbb{F}_m^{t1}$ is the MVNO's preference profile that ranks the MIPs based on their selection criterion.

Algorithm 2: Tier-II Matching Game: UE & MVNO

Input: $f_{m_n}^{(0)} = f_{m_n}^i$, $\mathbb{F}_{m_n}^{(0)} = \mathbb{F}_{m_n}^{(t2)}$, & $\mathbb{F}_u^{(0)} = \mathbb{F}_u$, $\forall u \notin \mathcal{G}_{u,m}^i$; $i = 0$.

initialize: $i = 0$, $\mathcal{G}''^{i}_n = 0 \, \forall n.$
while $\mathcal{G}''^{i}_n \neq \mathcal{G}''^{i+1}_n$ **do**
  $i = i + 1;$
  while $u \notin \alpha(m_n)^{(i)}$ *and* $\mathbb{F}_u^{(i)} \neq \emptyset$ **do**
    if $f_{m_n}^{(i)} \leq c_{u,n}$ **then**
      $\mathbb{F}'^{(i)}_{m_n} = \{u' \in \alpha(m_n)^{(i)} | u \succ_{m_n} u'\} \cup u.$
      $u'_{lp} \leftarrow$ the least preferred $u' \in \mathbb{F}'^{(i)}_{m_n}$.
      while $(\mathbb{F}'^{(i)}_{m_n} \neq \emptyset) \cup (f_{m_n} \geq c_{u,n})$ **do**
        $\alpha(m_n)^{(i)} \leftarrow \alpha(m_n)^{(i)} \backslash u'_{lp}$,
        $\mathbb{F}'^{(i)}_{m_n} \leftarrow \mathbb{F}'^{(t)}_{m_n} \backslash u'_{lp}$.
        $f_{m_n}^{(i)} \leftarrow f_{m_n}^{(i)} + c_{u'_{lp},n}$,
        $u'_{lp} \leftarrow u' \in \mathbb{F}_{m_n}^{(i)}$.
      end
      Rejected players are removed from $\mathbb{F}_{m_n}^{(i)}$ & $\mathbb{F}_u^{(i)}$
    else
      $\alpha(m_n)^{(i)} \leftarrow \alpha(m_n)^{(i)} \cup \{u\}$, $f_{m_n}^{(i)} \leftarrow f_{m_n}^{(i)} - c_{u,n}$.
    end
    $\tilde{\mathbf{X}} \leftarrow \alpha^*$
  end
  Update $\mathcal{G}''^{i}_n$, $\forall n$
end
Output: *Stable matching group* $\mathcal{G}''_n$
END

B. Tier-two Matching Game Between UE and MVNO

Once the upper-tier matching is completed, a set of MIP-MVNO pairs is formed. Suppose an m^{th} MVNO buys resources from $\mathcal{N}_n$ MIPs with $n = 1, n = 2, n = 3$. Each m_n of m^{th} MVNO makes the UE profiles separately. All the UEs matched under the m_n clusters are grouped together and mapped to the m^{th} MVNO. A non-cooperative matching game is formed here as well. A UE can be mapped to a single MVNO at a time. Depending on the resource threshold, an MVNO allows a limited number of UEs to be associated with it. $\mathbb{F}_u^{t2}$ and $\mathbb{F}_m^{t2}$ are the preference profiles of UE and associated MVNOs at tier-two. UE u selects MVNO m based on the offered price in an increasing sequence. All the modeling parameters are taken from Table II.

V. Result Analysis and Discussion

Set/Parameter	***Value***
$\lvert UE\rvert \rightarrow \mathcal{U}$	Random Distribution 1 - 100
$\lvert MVNO\rvert \rightarrow \mathcal{O}$	5
$\lvert MIP\rvert \rightarrow \mathcal{N}$	5 [each with 5 BSs]
$\lvert MIP - BS\rvert \rightarrow \mathbb{N}$	25 at node locations
Grid size	1000 x 1000 area
$r_n \in \mathbb{R}_n$	6 - 100 Channels
$PUB_m^{\mathcal{O}}$	{ 6 to 10 } \$/bps/hz
$PLB_{r_n}^{\mathbb{I}}$	{ 1 to 4 } \$/bps/hz
d_u	{ 1 to 20 } bps/hz
Slice Resource Type	Three types
Max. UEs per MVNO	30
SLA speed eMBB UEs	[1 - 20] bps/hz
SLA speed mMTC UEs	[1 - 10] bps/hz
SLA speed URLLC UEs	[1 - 8] bps/hz
BS Transmit Power - $\mathbb{P}$	45 dB
Path loss - δ	3 dB
Channel gain - $g_{n,u}^{Ch}$	[17]

TABLE II: Evaluation settings for *two-tier matching game*

A. *Resource Allocation using Proposed Approach*

In the two-step matching game, our goal is to achieve stable matching at each stage. We have used a *modified multi-partner many-to-many stable marriage game approach* following [18]. This approach is in polynomial time as well. The second-tier matching is done using a *modified deferred-acceptance algorithm* rather than the traditional one due to the heterogeneous demands of the buyers. Due to such demand, a vendor can serve various buyer units, and its quota is not violated. A many-to-one matching is framed, which is stable in polynomial time as per the standard *Gale and Shapley many-to-one matching game* [19].

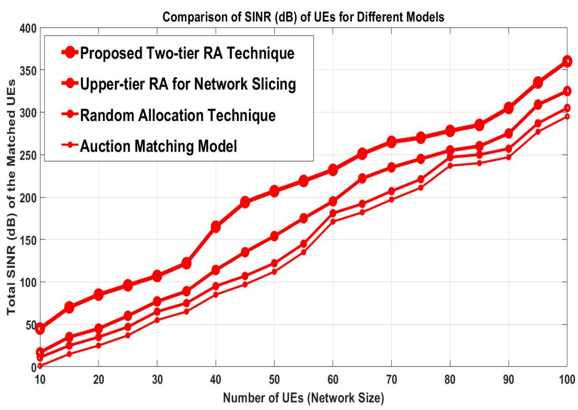

Fig. 3: The UE SINR for different models

Initially, the MVNOs locked their required resources following a well-defined market forecasting and user prediction model. The MVNOs first play the upper-tier game with the MIP to buy the required resources. Once the upper-tier resource allocation is done, MVNOs start selling the resources to their preferred UEs and follow each other's preference profiles. The lower-tier resource allocation gets completed once all UEs are covered or all resources are exhausted. Fig. 3 shows the comparative analysis of the UEs SINR. It can be seen that our proposed approach helps UEs to get associated with the best MIP-BSs covered by the paired MVNOs. Fig. 3 shows the allocated MVNOs with increasing no. of users. All MVNOs are getting some users as no unallocated MVNOs are there.

B. *Maximized MVNO Allocations*

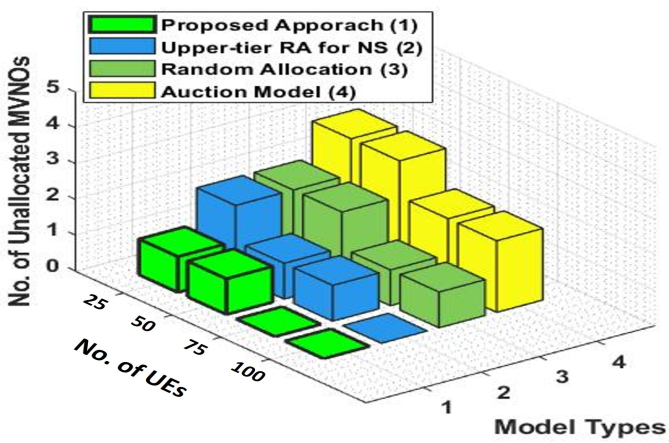

Fig. 4: MVNO allocations based on the no. of active UEs

Fig. 5 shows the comparison between avg. datarate for mMTC, eMBB, and URLLC users for various existing state-of-the-art approaches.

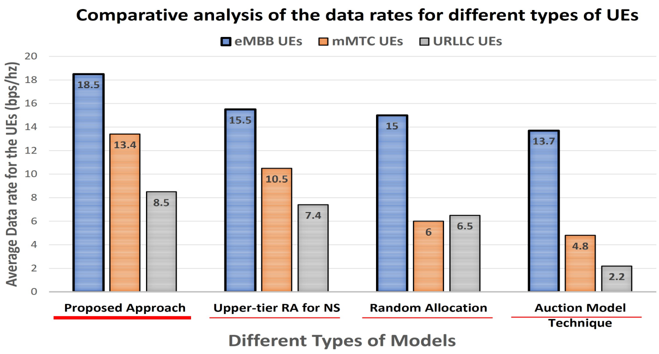

Fig. 5: Avg. data-rate for different UEs for diff. services

C. *Complexity Analysis of the Proposed Algorithm*

Fig. 6 shows the comparative complexity analysis of the proposed algorithm, which shows better performance.

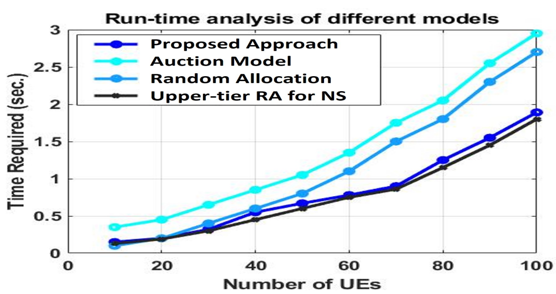

Fig. 6: Comparison of cumulative run-time analysis

VI. Conclusion and Future Direction

We have developed a multi-step (two-step) matching method for the purpose of selecting services and buying resources in the context of softwairzed network slicing. The results indicate that the suggested multi-step (two-step) matching algorithm achieves convergence within an acceptable timeframe and surpasses the auction method, random allocation model, and fixed allocation model in MIPs revenue maximization and user service availability. As part of our future plans, we want to include dynamic pricing and analyze its influence on the system's functioning.

Appendix A
Stability & Convergence of Tier-one Matching Game

Pruning Technique: The initial pruning for a single MVNO-optimality includes (a) erasing MIP $n \notin \alpha_m^{\mathcal{O}}$ from the list of MVNO, $\mathbb{F}_m^{t1}$ for which $R_m(n) < R_m\left(\min\left(\alpha_m^{\mathcal{O}}\right)\right)$, (b) erasing the MVNOs m from a MIP list for which $R_n(m) > R_m\left(\min\left(\alpha_n^{\mathcal{O}}\right)\right)$, (c) removing n from m 's list if the (so far) reduced list of n does not contain m, and (d) removing m from n 's list if the (so far) reduced list of m does not contain n. $R_m(n) \rightarrow$ preference rank of n^{th} MIP in m^{th} MVNOs list.

Meta-rotation:. A meta-rotation ρ is the feasible MIP-MVNO pairs $\{(m_0, n_0), \ldots, (m_i, n_i), \ldots, (m_{r-1}, n_{r-1})\}, r \geq 2$ such that $n_{(i+1) \text{ modulo } r} = \text{smin}\left(\alpha_{m_i}^{\mathcal{O}}\right)$ and $m_i = \min\left(\alpha_{n_1}^{\mathcal{O}}\right)$.

Elimination of meta-rotation: The exposed meta-rotation is eliminated for each $(m_i, n_i) \in \rho, m_i$ gets matched to $n_{(i+1) \text{ modulo } r}$ in place of n_i.

Reduced instance: A problem instance $\hat{P} = \left(\mathcal{O}, \mathcal{N}, \hat{\mathbb{F}^{t1}}_{\mathcal{O}}, \hat{\mathbb{F}^{t1}}_{\mathcal{N}}, RQ_{\mathcal{O}}, RQ_{\mathcal{N}}\right)$ is defined to be a reduced instance (or R-instance) of the problem instance $P = \left(\mathcal{O}, \mathcal{F}, \mathbb{F}_{\mathcal{O}}^{t1}, \mathbb{F}_{\mathcal{N}}^{t1}, RQ_{\mathcal{O}}, RQ_{\mathcal{N}}\right)$ if it is obtained either by applying initial pruning on P or by the elimination of a meta-rotation from another R-instance $\hat{P}^*$ of P.

Appendix B
Proof of Stability of Tier-Two Matching Game

In the game $\mathcal{G}'$, a matching α is said to be stable if there exists no blocking pair (S', B'), where $S' \neq \emptyset$, $S \succ_{B'} \alpha(b), \forall b \in S'$ and $(S \cup S') \succ_{B'} \alpha(B'), S \subseteq \alpha(B')$, where $\alpha(b)$ and $\alpha(S')$ represent, respectively, the current matched partners of sellers and buyers.

Consider UEs as buyers B and MVNOs as sellers S. Now, $\mathcal{P}_1$ as a buyer $\in B$ and $\mathcal{P}_2$ as a seller $\in S$ would not like to change their preference list even if they are not matched because: (i) If $\mathrm{p}_1 \in \mathcal{P}_1$ prefers p_2 over its current match, it would have rejected p_2. (ii) $\mathrm{p}_2 \in \mathcal{P}_2$ prefers p_1, it would chooses p_1 again, but p_1 would have rejected again. Thus, no mutually preferred buyer-seller pair outside this matching is possible. Hence, the matching game converges to an optimally stable matching.

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References

[1] A. Geetha and P. Kumari, "Network virtualization," in *Towards Wireless Heterogeneity in 6G Networks*. CRC Press, 2024, pp. 226–242.
[2] W. Rafique, J. Barai, A. O. Fapojuwo, and D. Krishnamurthy, "A survey on beyond 5g network slicing for smart cities applications," *IEEE Communications Surveys & Tutorials*, 2024.
[3] R. A. Banez, H. Xu, N. H. Tran, J. B. Song, C. S. Hong, and Z. Han, "Network virtualization resource allocation and economics based on prey–predator food chain model," *IEEE Transactions on Communications*, vol. 66, no. 10, pp. 4738–4752, 2018.
[4] M. Amine, A. Kobbane, and J. Ben-Othman, "New network slicing scheme for ue association solution in 5g ultra dense hetnets," in *ICC 2020-2020 IEEE International Conference on Communications (ICC)*. IEEE, 2020, pp. 1–6.
[5] P. Vamvakas, E. E. Tsiropoulou, and S. Papavassiliou, "On controlling spectrum fragility via resource pricing in 5g wireless networks," *IEEE Networking Letters*, vol. 1, no. 3, pp. 111–115, 2019.
[6] S. A. Kazmi, N. H. Tran, T. M. Ho, and C. S. Hong, "Hierarchical matching game for service selection and resource purchasing in wireless network virtualization," *IEEE Communications Letters*, vol. 22, no. 1, pp. 121–124, 2017.
[7] F. Debbabi, R. L. Aguiar, R. Jmal, and L. Chaari Fourati, "Game theory for b5g upper-tier resource allocation using network slicing," *Wireless Networks*, vol. 29, no. 5, pp. 2047–2059, 2023.
[8] F. Pase, M. Giordani, G. Cuozzo, S. Cavallero, J. Eichinger, R. Verdone, and M. Zorzi, "Distributed resource allocation for urllc in iiot scenarios: A multi-armed bandit approach," in *2022 IEEE Globecom Workshops (GC Wkshps)*. IEEE, 2022, pp. 383–388.
[9] A. Filali, Z. Mlika, S. Cherkaoui, and A. Kobbane, "Dynamic sdn-based radio access network slicing with deep reinforcement learning for urllc and embb services," *IEEE Transactions on Network Science and Engineering*, vol. 9, no. 4, pp. 2174–2187, 2022.
[10] A. Abouaomar, A. Kobbane, and S. Cherkaoui, "Matching-game for user-fog assignment," in *2018 IEEE global communications conference (GLOBECOM)*. IEEE, 2018, pp. 1–6.
[11] P. Gorla, D. R. Paithankar, V. Chamola, S. Bitragunta, and M. Guizani, "Optimal spectral resource allocation and pricing for 5g and beyond: A game theoretic approach," *IEEE Networking Letters*, vol. 3, no. 3, pp. 119–123, 2021.
[12] J. Du, C. Jiang, J. Wang, Y. Ren, and M. Debbah, "Machine learning for 6g wireless networks: Carrying forward enhanced bandwidth, massive access, and ultrareliable/low-latency service," *IEEE Vehicular Technology Magazine*, vol. 15, no. 4, pp. 122–134, 2020.
[13] H. Z. Khan, M. Ali, I. Rashid, A. Ghafoor, and M. Naeem, "Cell association for energy efficient resource allocation in decoupled 5g heterogeneous networks," in *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*. IEEE, 2020, pp. 1–5.
[14] A. Ndikumana, S. A. Kazmi, K. Kim, M. S. Munir, W. Saad, C. S. Hong *et al.*, "Pricing mechanism for virtualized heterogeneous resources in wireless network virtualization," in *2020 International Conference on Information Networking (ICOIN)*. IEEE, 2020, pp. 366–371.
[15] A. Perveen, M. Patwary, and A. Aneiba, "Dynamically reconfigurable slice allocation and admission control within 5g wireless networks," in *2019 IEEE 89th Vehicular Technology Conference (VTC2019-Spring)*. IEEE, 2019, pp. 1–7.
[16] F. Debbabi, J. Rihab, L. Chaari, R. L. AGUIAR, R. Gnichi, and S. Taleb, "Overview of ai-based algorithms for network slicing resource management in b5g and 6g," in *2022 International Wireless Communications and Mobile Computing (IWCMC)*. IEEE, 2022, pp. 330–335.
[17] D. Basu, S. Sanyal, G. Das, U. Ghosh, and R. Datta, "Simulation Code and Data Directory for RA in SNS," 2024, [https://github.com/Samriddha21/Hierarchical-Matching-1.git].
[18] V. Bansal, A. Agrawal, and V. S. Malhotra, "Stable marriages with multiple partners: efficient search for an optimal solution," in *Automata, Languages and Programming: 30th International Colloquium, ICALP 2003 Eindhoven, The Netherlands, June 30–July 4, 2003 Proceedings 30*. Springer, 2003, pp. 527–542.
[19] A. E. Roth, "Deferred acceptance algorithms: History, theory, practice, and open questions," *international Journal of game Theory*, vol. 36, pp. 537–569, 2008.