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# AN EFFICIENT DYNAMIC RESOURCE SHARING FOR A MULTI-VENDOR WIRELESS NETWORK VIRTUALIZATION

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## ABSTRACT

**Service diversity in the fifth generation of mobile communication (5G) has introduced crucial challenges in the resource management and Radio Access Network (RAN) infrastructure. To overwhelm these difficulties, Wireless Network Virtualization (WNV) has been proposed as a promising key technology to enable emerging services and respond to user and operator demands. WNV reduces operator implementation and operation costs and utilizes the resources to be distributed dynamically among virtual operators by decoupling hardware infrastructure and service providers into different entities.**

**In this work, a typical WNV system is designed and simulated to visualize system operation and task management among the Infrastructure Providers (InPs), Mobile Virtual Network Operators (MVNO), and user equipment (UE). In the system design, multiple InPs own the hardware resources and provide isolated slices to the MVNOs, where several MVNOs purchase channel resources from InPs and service their UEs. A new system model is derived mathematically where a dynamic inter-user inference is considered for the first time with multiple InPs under 5G radio conditions. Moreover, an economic model is integrated with the proposed WNV system to evaluate overall expenses and revenue for each player. The process of selecting MVNOs by different InPs and dynamically allocating resources to the UEs is proposed to be two levels; paring UEs with the MVNOs at the first Level and then distributing InP resources to the UEs via pre-selected MVNOs at the second Level.**

**For this purpose, hierarchical game-matching and Particle Swarm Optimization (PSO) algorithms are proposed to address dynamic resource allocation complexity and provide optimum resources to the UEs, maximizing InPs revenue and user throughput. The simulation results show both algorithms' robustness in optimizing the expenses and gaining UEs throughput. Furthermore, integrating the economic scheme with the derived WNV model facilitates the optimization of profits and cost reduction for the involved players. This methodology guarantees the financial viability of the network and ultimately provides advantages to all stakeholders. As well as the obtained UEs engagement reached 98% of the total users who contributed to the resource request. It is a high rate of user admission within acceptable time intervals and complexity. Results indicated a trade-off between the two proposed algorithms regarding convergence and accuracy; PSO obtained faster convergence, while the matching game provided higher throughput and better end-user performance.**

***KEYWORDS:*** WIRELESS NETWORK VIRTUALIZATION; RESOURCE ALLOCATION; MATCHING GAME; PSO; RESOURCE PRICING.

## 1. INTRODUCTION

In the ever-changing world of wireless communication technologies, the arrival of 5G and RAN has started a new era of connection and services. As the demand for various applications rises, the efficient administration of network resources becomes essential to ensure optimal performance and user satisfaction. In this light, WNV emerged as a paradigm shifter with the potential to fundamentally change resource allocation and pricing strategies in 5G network slicing within RAN contexts (Oladejo et al., 2021; Oladejo & Falowo, 2019).

WNV changes network design by virtualizing physical resources. This virtualization creates various simulated networks for different services and applications. WNV's interaction with dynamic resource allocation and pricing models allows network operators to distribute resources in real-time, depending on user and service needs. Dynamic resource allocation with WNV enables the development of more adaptive, responsive, and economically feasible network systems (Hirayama et al., 2022).

The economic effects of this dynamic resource allocation and pricing method are significant. Network operators may optimize resource utilization, reduce congestion, and improve quality of service (QoS) by adapting resource delivery to the individual demands of applications and users. This new approach allows diverse service offers based on variable pricing structures and quality levels, promoting competition. As a result, network operators can generate sustainable income while providing the most outstanding possible user experience across the varied array of services in 5G and RAN ecosystems (Jayaraman et al., 2023; Yarkina et al., 2022).

The effects of WNV and dynamic resource allocation are not limited to centralized systems; they also affect distributed ones (Awada et al., 2022). The smooth merging of WNV with distributed systems improves scaling, robustness, and flexibility. It lets complicated and decentralized network platforms handle their resources more efficiently (Alevizaki). In InP environments with numerous nodes, WNV-based dynamic resource allocation intelligently allocates resources based on geographical and temporal demand patterns to reduce interference. This improves network performance and lets cooperative communication paradigms minimize interference and optimize resource allocation (Lieto et al., 2022).

Matching game theory and PSO in WNV provide creative optimization techniques and advanced resource allocation and management tactics (Farhat et al., 2022). The distribution of resources is essential for efficient and optimized 5G network slicing in WNV (Adiraju & Rao, 2022; Mohammed & Shaikhah, 2022). Research communities have investigated various resource allocation algorithms that utilize game theory and PSO principles. The researchers (Kazmi et al., 2017) studied a matching game approach to allocate resources in an OFDMA virtualized wireless network. The results illustrated improved integration, better user experience, and higher bandwidth utilization, and in (Wang et al., 2019) outperformed Hierarchical matching fixed sharing techniques by 32% and 97% of the ideal solution in the average total rate for WNV. A resource pricing scheme was developed (Kazmi et al., 2020; Tun et al., 2019) to balance InP profit with network social welfare and improve resource usage and stability. The method covered dynamic network slices and used matching theory and auctions for system allocation. Simulations improved social well-being, financial pairing, and profitability. In (Nguyen, 2021), a Generalized Kelly mechanism was proposed to solve the two-level allocation problem in network slicing, achieving efficient resource utilization and inter-slice and intra-slice isolation while maintaining high performance. Besides the matching game, several works (Paul et al., 2021; Sheena & Snehalatha, 2022; Waleed et al., 2021; Wei, 2022) have presented the benefits and impact of metaheuristic algorithms in WNV, such as Ant Colony Optimization, Genetic, and firefly Algorithm, to improve dynamic slicing and resource allocation in 5G networks with Pareto optimum solutions. Despite the work done in this field, the topic is still in the initial steps toward applying virtualization in practical RAN due to the open challenges.

In this work, a new typical wireless network for 5G RAN is comprehensively designed with virtualizing resources, power and channels provided by multiple InP and shared among several MVNOs and hundreds of UEs. The design includes RAN Optimizations and economic models. A new mathematical method is developed as a primary contribution to this work, derived from the three sub-models and integrated into a practical model. In the air interface of RAN, a new model for the channel gain is proposed that considers interference from all users to the victim user to consider Inter-user Interference (IUI). Therefore it is a unique model in this field.

The study utilizes a combinatorial approach, employing a matching game and metaheuristic optimization algorithms, to address two-faced selections between users and MVNOs for services and preferred Resource Blocks (RBs). At the first level, pairing is done between UEs and MVNOs to select desired services; in the second level, MVNOs are dynamically paired with InPs to allocate to shared virtual RBs. This approach optimizes user selection, enhances resource utilization, and manages the trade-off between user throughput and revenue for MVNOs and InPs. Furthermore, achieving this goal involves integrating practical economic frameworks to determine the expenses of MVNO users and the income of InPs. In addition, a non-convex optimization technique is proposed to solve mixed integer linear programming issues (MLIP), enabling optimal values for cost-minimization and throughput enhancement.

The rest of the paper is structured as follows; section two presents the system model of the virtual network, section three outlines the methodology employed in the study, and the fourth section presents the experiment results. Finally, the fifth section pertains to the conclusion.

## 2. SYSTEM MODEL

The optimization and enhancement of mobile networks' performance is crucial for stakeholders like InPs, MVNOs, and UEs. A combinatorial strategy is used to achieve this objective, integrating hierarchical matching algorithm selection with an economic model and comparing it with a metaheuristic optimization algorithm using PSO techniques. The game-matching algorithm is run twice for service selection and resource allocation, focusing on aligning service providers with users and optimizing service distribution while maximizing revenue. The second phase distributes network resources to individuals based on their needs, maximizing network throughput. The economic model ensures that every participant operates within the most advantageous economic regions, considering profit functions, costs, and revenue. This methodology ensures the network's financial viability, providing advantages to all stakeholders.

The graphical model inspected in Figure 1 is assumed to employ a downlink wireless system based on OFDMA. The method comprises a set of InPs $\mathcal{N}$ $(n = 1, 2, 3, \ldots \mathcal{N})$ that each InP owns a bandwidth $\mathcal{BW}$ and gNodeB base station (BS), as well as a set of MVNOs $M$ $(m = 1, 2, 3, \ldots M)$. The InPs provide services to a group of MVNOs under some individual contracts called service level agreements (SLAs). Additionally, an MVNO$m$ offers its facility to a set of UEs denoted by $\mathcal{K}_m$ $(k = 1, 2, 3, \ldots \mathcal{K}_m)$. Then, $k = U_m \mathcal{K}_m$ indicates the total number of UEs, where $U_m$ is considered a cardinality of UEs. Each InP$n$ holds a set of $\mathcal{C}_n$ Orthogonal channels, each channel with a bandwidth $W$. It is assumed that the transmit power on each channel of InP$n$ is $P_n$, where $P_n = \frac{P_n^{Total}}{|\mathcal{C}_n|}$ and $P_n^{Total}$ is the total transmit power of the gNodeB of InP$n$ (Kazmi et al., 2017).

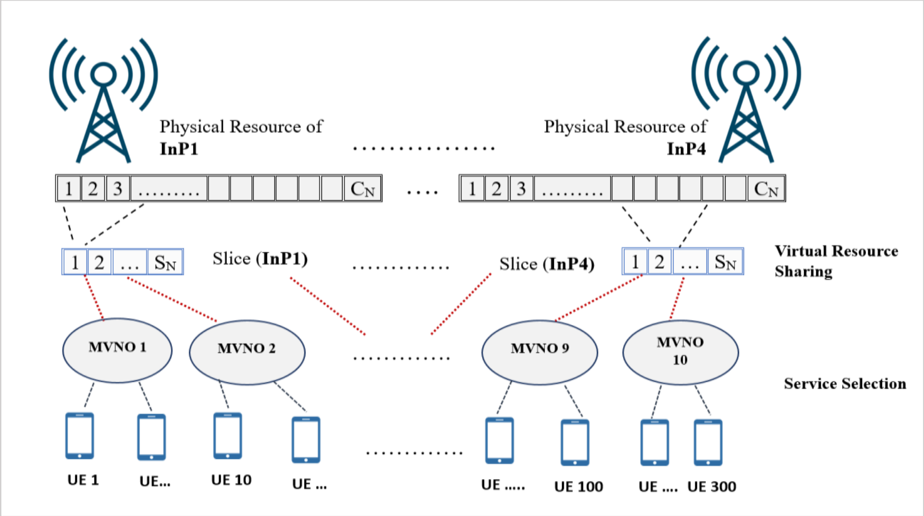

**Fig.( 1):-** Graphical System model.

Moreover, InPn enables independent services employing a set of $\mathcal{S}_n$ slices; the $\mathcal{S}_n$ is allocated by InP$n$ to MVNOs$m$ and has an adjustable amount of channels dependent on the MVNOs need. The binary variables $\mathcal{X}_{\mathcal{K},m}$ for user association and $\mathcal{Y}^{\mathcal{S}_n}_{n,m}$, for Slice distribution are introduced as follows:

$$\mathcal{X}_{k,m} = \begin{cases} 1, & if\ user\ k\ assosiated\ with\ MVNO\ m \\ 0, & otherwise \end{cases} \tag{1}$$

$$\mathcal{Y}^{\mathcal{S}_n}_{n,m} = \begin{cases} 1, & if\ slice\ \mathcal{S}_n\ is\ allocated\ to\ MVNO\ m\ from\ InP\ n, \\ 0, & otherwise \end{cases} \tag{2}$$

The data rate for a UE $k \in \mathcal{K}_m$ distributed to a slice $\mathcal{S}_n$ can be calculated using Shannon's formula as:

$$\mathcal{R}_{n,m,k}^{\mathcal{S}_n} = \sum_{\mathcal{C} \in \mathcal{S}_n} \mathcal{BW} \ log_2 \ (1 + SINR) \qquad (3)$$

Where $\mathcal{R}_{n,m,k}^{\mathcal{S}_n}$ is the achievable data rate of user $k$ belongs to MVNO$m$, served by InP$n$ through the slice $\mathcal{S}_n$. The received signal-to-interference noise ratio (SNIR) $\gamma_{m,k}^{\mathcal{C}_n}$ relating to the transmission of MVNOs$m$ user $k$ over a $\mathcal{S}_n$ with transmit power $\mathcal{P}_n^{\mathcal{S}_n}$ is:

$$\gamma_{m,k}^{\mathcal{C}_n} = \frac{P_{n,m}^{\mathcal{S}_n} \ \mathcal{G}_{m,k}^{\mathcal{C}_n}}{\sum_{j \epsilon M,,j \neq m} P_{n,j}^{\mathcal{S}_n} \ \mathcal{G}_{j,k}^{\mathcal{C}_n} + \left(\sum_{u \in \mathcal{K}_m, u \neq k} P_{n,m}^{\mathcal{S}_n} \ \mathcal{G}_{m,u}^{\mathcal{C}_n}\right) + \sigma^2} \qquad (4)$$

$\mathcal{G}_{m,k}^{\mathcal{C}_n}$ is the gain amongst the BS of InP$n$ and UE $k$ over the channel $\mathcal{C}_n$that allocated for the slice $\mathcal{S}_n$, $P_{n,j}^{\mathcal{S}_n} \ \mathcal{G}_{j,k}^{\mathcal{C}_n}$ represents the interference caused by the synchronized transmissions on the other slices and the co-channel $\mathcal{G}$ interference caused by the broadcasts of other MVNO$j$ on the same UEs group in the other InP$n$ and other channels allocated to the slice $\mathcal{S}_n$ and $\mathcal{P}_{n,m}^{\mathcal{S}_n} \ \mathcal{G}_{m,u}^{\mathcal{C}_n}$ presents the interference caused by the simultaneous transmissions on the same slice and the channel interference caused by the broadcasts of the same MVNO$m$, InP$n$ and slice $\mathcal{S}_n$ but different users $u$ on the same UEs set; through this point, dynamic interference can be managed, and better results can be calculated for user data rate.

## 2.1 Problem Formulation

In this work, the problem focused on optimizing users' performance while maximizing the profits of InPs and MVNOs. The solution should take a non-convex approach to maximize the interests of all the players involved in multiple infrastructure networks. In this context, the UE seeks to reduce the cost incurred in the network while maximizing throughput, while MVNO M should aim to minimize costs while maximizing throughput. On the other hand, InP N should maximize their profits. It is here defining the decision variables for each player. For the UE k, we can define a binary variable. $\mathcal{X}_{k,m}$To indicate whether UE $k$ chooses to use the services of MVNO $m$. The objective function for UE $k$ should minimize the cost incurred in the network while maximizing throughput.

**UE:**

$$\text{s.t.} \min_{\mathcal{X}_{k,m} \in [0,1]} \sum_{m \in M} \mathcal{X}_{k,m} \beta_m^M d_k \qquad (5)$$

$$\sum_{m \in M} \mathcal{X}_{k,m} = 1, \qquad (6)$$

Some constraints must be imposed on the decision variables to ensure the proposed solution is feasible. UE $k$ can evaluate the condition (6); only one MVNO can service each UE. The objective function for MVNO $m$ should maximize its profit, which is a function of the cost of serving its UEs and buying slices from InP$n$.

**MVNO:**

$$\text{s.t.} \max_{\mathcal{X}_{k,m} \mathcal{Y}_{n,m}^{\mathcal{S}_n} \in [0,1]} \sum_{k \in \mathcal{K}} \mathcal{X}_{km} \beta_m^M d_k - \sum_{n \in N} \sum_{\mathcal{s}_n \in \mathcal{S}_n} \mathcal{Y}_{n,m}^{\mathcal{S}_n} \beta_n^I |\mathcal{S}_n|, \qquad (7)$$

$$\sum_{m \in M} \mathcal{X}_{k,m\,,} \leq 1 \,, \forall k, \qquad (8)$$

$$\sum_{k \in \mathcal{K}} \mathcal{X}_{k,m} \, \ell_{k,n} \leq \mathcal{Y}_{n,m}^{\mathcal{S}_n} |\mathcal{S}_n|, \forall n, \qquad (9)$$

For MVNO$m$, The goal is to provide its UEs at the lowest possible cost while maximizing bandwidth based on the slice pricing supplied by the InP. For this, it can be described by decision factors as $\mathcal{X}_{k,m} \mathcal{Y}_{n,m}^{\mathcal{S}_n} \in [0,1]$ to indicate whether the proposal of UE $k$ is accepted by

MVNO$m$ and whether MVNO$m$ intends to buy a slice of $\mathcal{S}_n$ InP n, respectively. For MVNO$m$, to guarantee that UE *k* is serviced by at most one MVNO constraint (8). Also, to ensure assigned goods on the slice are fewer than the competency percentage provided to MVNO$m$ constrain (9). Then computing the required channels to fulfil user demands $d_k$ on InP $n$ consuming the formula: $\ell_{k,n} = d_k / \mathcal{R}_{n,m,k}^{\mathcal{S}_n}$ where $\ell_{k,n}$ is the number of channels required to serve UE *k* on a slice $\mathcal{S}_n$ of InP$n$.

For InP$n$, it is required to confirm that allocated slices are less than the total InP slices and that the contract agreement is not unsettled. The objective should satisfy the requirements of all MVNOs concerning the contract agreements that are not desecrated. The decision variables $\mathcal{Y}_{n,m}^{\mathcal{S}_n} \in \{0,1\}$ indicates whether InP$n$ accepts the slice ordering offer of MVNO$m$. The objective function for InP$n$:

**InP:**

$$\max_{\mathcal{Y}_{n,m}^{\mathcal{S}_n} \in [0,1]} \sum_{m \in M} \sum_{s_n \in \mathcal{S}_n} \mathcal{Y}_{n,m}^{\mathcal{S}_n} \left( \sum_{k \in \mathcal{K}} log \;\; \mathcal{R}_{n,m,k}^{\mathcal{S}_n} \right) + \omega \beta_n^I |\mathcal{S}_n| ) \qquad (10)$$

$$\text{s.t. } \sum_{m \in M} \sum_{s_n \in \mathcal{S}_n} \mathcal{Y}_{n,m}^{\mathcal{S}_n} |\mathcal{S}_n| , \qquad (11)$$

$$\sum_{k \in \mathcal{K}} \sum_{s_n \in \mathcal{S}_n} \mathcal{Y}_{n,m}^{\mathcal{S}_n} \;\; \mathcal{R}_{n,m,k}^{\mathcal{S}_n} \geq d_m , \forall m \quad , \qquad (12)$$

Here, the objective function (10) for the InP$n$ is to raise its income, a weighted sum of the logarithm of the requested resources by the UEs and the price per unit of the slices allocated to the MVNOs. The weight$\omega$ represents the transaction between disinterest and InP income. The first term in the objective function means proportional fairness among the UEs, where the logarithm of the requested resources reflects the idea that users with higher demands will have higher benefits from the network. The second term in the objective function represents the revenue earned by the InP from selling slices to the MVNOs. Constraint (11) ensures that the number of slices allocated to the MVNOs by the InP$n$ does not exceed the total number of portions available. Constraint (12) provides that the allocated resources to the MVNOs are sufficient to meet the demands of the UEs, where $\mathcal{R}_{n,m,k}^{\mathcal{S}_n}$ represents the number of resources allocated to the slices of the MVNO$m$ on InP$n$ used by UE *k*.

## 3. PROPOSED METHODOLOGIES

### 3.1. Matching Game Formulation

The proposed methodology involves a combinatorial approach that is divided into two stages. Initially, MVNO users solicit services from the MVNO, which evaluates proposals based on specific criteria and forwards them to the next stage as a request to various InPs. This stage is commonly referred to as service selection. Upon acceptance of a proposal, the resulting output serves as the input (i.e., initial values) for the subsequent stage, which involves resource procurement between MVNOs and InPs. This work design corresponds to *Definitions1,2 and 3*(Kazmi et al., 2020).

#### *1.1.2. Pairing UEs to MVNOs at the Lowest Level*

In the initial phase, we employed the user association algorithm described by (Kazmi et al., 2020) to determine the number of users requiring the service based on their profile preferences and utilization functions. The matching game involves pairing UEs and MVNOs, representing two distinct entities. By generating a set of $n$ imaginary variables for each MVNO, denoted by $m_n$, and considering the preferred perspectives of the UEs and MVNOs represented by $P_k$ and $\mathcal{P}_{m_n}^{l}$, respectively. From (4), a UE $k$ ranks an MVNO $m_n$ Based on its accessible amount in a non-reducing instruction assumed by:

$$U_k(m_n) = \beta_{m_n}^M , \qquad \forall m_n \quad (13)$$

Through (4), an MVNO *m* ranks all UEs based on the profit they yield in a non-increasing order by:

$$U_{m_n}(k) = max\,(\beta_{m_n}^M d_k - \beta_n^l l_{n,k}, 0), \quad \forall k \qquad (14)$$

In (13) MVNO $m_n$ evaluate values of $d_k$ and $\mathcal{G}_{n,k}^{\mathcal{S}_n}$ determines the necessary channels (i.e., $l_{n,k}$) for a UE k and places them according to the profit they generate in $\mathcal{P}_{m_n}^{l}$. Moreover, a UE *k* is assumed to be indifferent towards all the channels delivered by a single InP-BS *n* because the same channel gain values can diverge for altered InP-BSs. Additionally, a UE is not ranked in the list if its earnings are unfavourable in $\mathcal{P}^{l}_{m_n}$. Nevertheless, from (9), each MVNO can only assist restricted UEs, i.e., through the quota $q_{m_n}$ is determined as the upper limit slice for supplied InP.

### *1.1.3. Pairing MVNOs with InPs at the highest Level*

MVNOs need slices from certain InPs to service their acceptable UEs. The MVNO demand signifies as $d_{m_n} = \sum_{k\in\mu(m_n)} d_k$. Now both MVNOs and InPs define their respective preference profiles as $\mathcal{P}^{\mathcal{U}}_{m_n}$ and $\mathcal{P}_n$. Then, each MVNO targets to reduce its cost. Therefore from (7), MVNO$m$ grades InPs based on their price in a non-decreasing order as:

$$U_{m_n} = \beta^{I}_{n}, \qquad \forall n \qquad (15)$$

Through (10), InPs maximize expenses by exporting slices, achieving equality among UEs, and ranking purchasers non-increasingly.

$$U_n(m_n) = \sum_{k\in\mu(m_n)} \log\left(\mathcal{R}^{S_n}_{n,m,k}\right) + \omega\beta^{I}_{n}\, \mathcal{Y}_{m_n}, \ \ \forall m_n \ (16)$$

Here, assume that the values of $d_{m_n}$ and the set of UEs matched in the low- Level (i.e., k ∈ μ($m_i$ )) are sent to the InPs in the tender phase. Then InP computes the required slice scope, i.e., $\mathcal{Y}_{m_n}$ to meet MVNO$m_n$ demand, ranking InPs based on constraints (15). Matching and selecting InPs under the SLA involves considering the price range, throughput, available RBs, and bandwidth.

### 3.2. Particle Swarm Optimization (PSO) algorithm formulation

PSO is a metaheuristic optimization method encouraged by the collective behaviour of bird clustering or fish training. It is widely used in various domains; in network slicing, the PSO is used to optimize the distribution of resources, such as bandwidth, computing power, and storage, among multiple InPs and their respective slices for each MVNO (Oladejo & Falowo, 2018). The fitness function uses constraints such as InP capacity, slice delay, resource allocation expenses, and MVNO profitability for assessing particles. The convergence to a globally prime result that satisfies resource allocation criteria for all MVNOs and slices is attained via iteratively updating particle locations and measuring fitness (Waleed et al., 2021).

Mathematically, the particles are employed by the subsequent equations:

$$\mathrm{v}_i\,(\mathfrak{t}+1) = \mathfrak{W}v_i + \mathfrak{H}_1\mathfrak{r}_1[\mathfrak{p}_i(\mathfrak{t}) - \mathfrak{Z}_i(\mathfrak{t})] + \mathfrak{H}_2\mathfrak{r}_2\big[\mathfrak{p}_j(\mathfrak{t}) - \mathfrak{Z}_i(\mathfrak{t})\big] \quad (17)$$

$$\mathfrak{Z}_i\,(\mathfrak{t}+1) = \mathfrak{Z}_i\,(\mathfrak{t}) + \ \mathrm{v}(i)\,(\mathfrak{t}+1) \qquad (18)$$

$$\mathfrak{W} = \mathfrak{W}_{\max} - \frac{(\mathfrak{W}_{\max} - \mathfrak{W}_{\min})}{\mathfrak{T}_{\max}} * \ \mathfrak{T}_{\mathfrak{Q}} \qquad (19)$$

Where $v_i$ is the velocity of participle $i$, $\mathfrak{H}_1$ and $\mathfrak{H}_2$ are positive constants called acceleration coefficients, and $\mathfrak{r}_1$ and $\mathfrak{r}_2$ are randomly generated numbers in the range [0,1], $\mathfrak{Z}$ is the position of particle $\mathfrak{p}$ in time $\mathfrak{t}$ and $\mathfrak{W}$ is the inertia weight defined by (19), where ($\mathfrak{W}_{max}$ is the initial weight, $\mathfrak{W}_{min}$ is the final weight, $\mathfrak{T}_{max}$ denotes the maximum iteration number, and $\mathfrak{T}_{\mathfrak{Q}}$ is the existing recurrence number (Tian, 2017).

**ALGORITHM 1-A; MATCHING GAME**

```
1. Initialize t_S and G(t_S,:)
2. Initialize Beta_M_m = unifrnd(4, 8, [M, 1])
3. Initialize Beta_I_i = unifrnd(2, 4, [N, 1])
4. Initialize Dk_k with the demand of UEs,
5. Calculate L_L(n,k) based on the demand per unit price for   MVNO m and InP n
6. Initialize Xv = zeros(K, M)to do service selection
7. Initialize flag = true // Initialize flag to true
8. while flag is true:
9. Increment t_S by 1
10. Loop over all ihi from 1 to Sn:
11. Loop over all jhi from 1 to K:
```

```
12. Loop over all lki from 1 to M:
13. If mu_mn_k(ihi,jhi,lki) < 0, then set mu_mn_k(ihi,jhi,lki) to 0
14. For each UE k from 1 to 10:
15. Find the most preferred MVNO-InP pair for UE k using the preference list Pk
16. Do Low-Level UEs-MVNOs
17. Propose to that pair by setting mu_mn_k(t,mn_ind,k) = 1,
18. Update t to be min(t,5) to limit t to 15
19. Pad Pk with zeros so that it has size [K, max(t-8,0), M]
20. For each UE k from 1 to K:
21. Sort the matrix mu_mn_k(:,k,:) in descending order and obtain the indices of the sorted elements
22. Use the indices to update the preference list Pmn(t,:,k)
23. For each MVNO-InP pair mn from 1 to M*N:
24. Sort the matrix mu_mn_k(:,:,mn) in descending order and obtain the indices of the sorted elements
25. Use the indices to update the preference list Pk(t,:,mn)
26. If t > 0 and t_S > 0:
27. If G(t_S,:) is not equal to G(t_S-1,:), then set flag to false
28. Do   high-level matching using the Gale-Shapley algorithm
29. Update G(t_S,:) based on the current matching till convergence
30. End While
```

## ALGORITHM 1-B; ECONOMIC MODEL

```
31. Initialize:
32. Set X11v to a matrix of size K x M, with all elements set to 0.
33. Set q to a matrix of size M x N, with values of Q_kn for each MVNO.
34. Set P_I to a matrix of size N x M, with all elements set to 1:M.
35. Set P_M to a matrix of size M x N, with all elements set to 1:N.
36. Set Revenue_InP and Revenue_MVNO to 0.
37. Perform low-level matching game:
38. While there exists an MVNO that is unmatched:
39. For each MVNO m:
40. For each UE k in MVNO m:
41. Calculate the utility U_M(n) for each InP n based on R_M, C_M, and Beta_M_m(n).
42. Calculate the utility U_I for each InP n based on Beta_I_i(n) and the number of matched MVNOs.
43. Find the InP n that maximizes U_M(n).
44. If no InP maximizes the utility function of MVNO m, remove the MVNO m from the game.
45. Find the UE k that maximizes R_M in InP n.
46. If UE k is already matched to another MVNO in InP n, remove the MVNO m from the game.
47. Match UE k to MVNO m in InP n and remove the old match, if any.
48. Update the demand q(m,n) of MVNO m in InP n and remove the InP n from the game if the demand is met.
49. Calculate the total revenue of InPs and cost for MVNOs.
50. Check if matching is group stable for all InPs:
51. For each InP n:
52. For each MVNO m:
53. If InP n is worse off with MVNO m than its current match, update its preference list.
54. If matching is group stable for all InPs:
55. Display the total revenue of InPs and MVNOs.
56. Do upper matching to MVNO and InP:
57. For each MVNO n:
58. For each InP m in its preference list:
59. If InP m prefers MVNO n to its current match, update the game.
60. Display the final matching result.
```

## ALGORITHM 2:PSO

```
61. Define PSO parameters: nParticles, nItrations,w, c1&c2
62. Define PSO search space Lower and upper boundaries
63. Initialize PSO variables and cost function
64. Run PSO algorithm
65. for iteration = 1 to nIterations
66. for particle = 1 to nParticles
67. Evaluate objective function of the particle
68. Run cost function and iterate for = end
69. Update particle best position and cost &global best position and cost
70. end
71. for particle = 1 to nParticles
72. Update particle velocity and position
73. Enforce search space boundaries
74. Iterate till convergence
75. end
76. end
77. Print optimized results
78. Calculate optimizedDataRate based on globalBestPosition
79. Calculate optimizedObjective as sum of optimizedDataRate
80. Print "Optimized Average Data Rate: ", optimizedObjective
```

**81.** ***end***

## 4. SIMULATION RESULTS

In this section, the derived system model in the previous part is simulated, integrating with the proposed algorithms. The unique standard parameters adopted for the system simulation are listed in Table 1. The network encompasses several MVNOs and InPs, serving a variable quantity of UEs K distributed randomly within a coverage area of (9000x9000) meters, as presented in figure1. The user demands are assumed to display a random distribution ranging from 1 to 20 bps/Hz. The effect of path-loss and Rayleigh distribution is considered on the channel between the UEs and BS. The link gain is given between user $k$ of MVNO$m$ by (Kazmi & Hong 2017):

$$\mathcal{G}_{m,k}=\mathfrak{I}\,\mathcal{PL}^{-\mathfrak{B}}_{\mathfrak{D}_{(m,k)}} \qquad (20)$$

Where $\mathfrak{I}$ is a function of path-loss ( $\mathcal{PL}$ ( $\mathfrak{D}_{m,k}$ )) and arbitrary value created according to the Rayleigh spreading, $\mathfrak{D}_{m,k}$ the geographical space between BS of MVNO $m$ and user $k$, and $\mathfrak{B}$= 3 is the path loss factor. The pricing structures of MVNOs and InPs demonstrated a uniform distribution within the respective ranges of $\beta_m^M$= {4 ~ 8} and $\beta_n^N$ = {3 ~ 5} budgetary units per bps/Hz.

**Table( I)**:- System Simulation Parameters

| **Parameters** | **Values** |
|---|---|
| Carrier | 4 GHz |
| InP Bandwidth | 5,10, 15 and 20 MHz |
| No. of MVNO | 10 |
| No. of InP | 4 |
| Total no. of users | 300 |
| RB Bandwidth | 180 KHz |
| Subcarrier spacing | 15 KHz |
| No. of Subcarrier per RB | 12 |
| No. of RB in InP | 100 |
| gNodeB Noise Power | $10^{-13}$ W |
| gNodeB Tx Power | 46 dBm |
| Coverage area | 9000 m *9000 m |
| User distribution | Uniform |

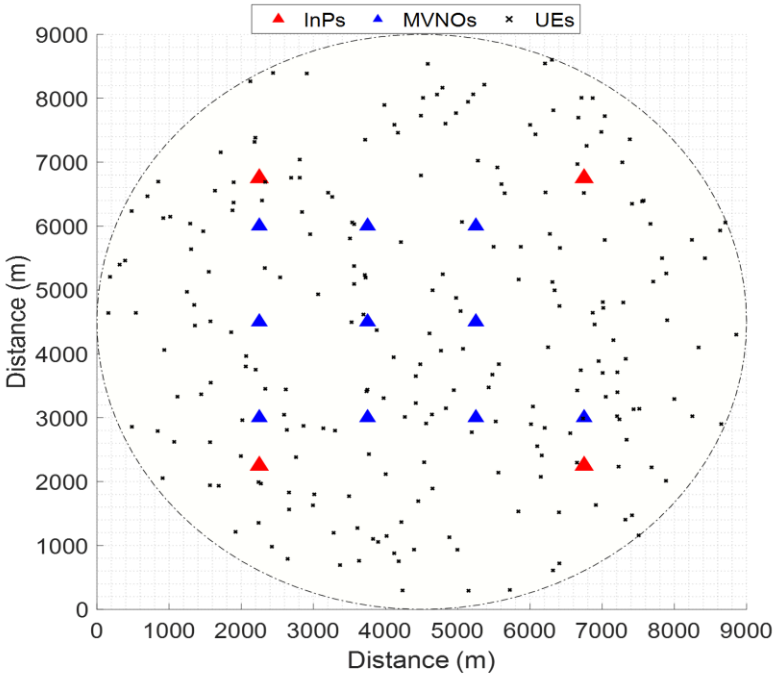

**Fig.( 2)**:- InPs, MVNOs and UEs distribution over a geographical area

### 4.1. User Association and Matching Game Algorithms

To reduce resource loss and gain revenue, InPs offer limited and shared resources. Therefore, in a dense UE environment such as the proposed, designed network in this work, UE establishment to the network and accessing services is a challenge. Figure 2 illustrates the UE establishment over different system bandwidths of InPs with 100 available RBs. It is shown that the establishment percentage is %100 steady state for the low range of UEs up to 80 UEs for all adopted InP bandwidths. When the UEs increase to 300, the user accessing ratio drops gradually, such as stair behaviour. The ratio degrades within a transient period, then becomes a steady state for the following range of UE increase. However, the establishment ratio for all the bands follows the same trend, but the scale of dropping this ratio is higher in low system bandwidths. The establishment percentage records 92% for the 5MHz bandwidth at 300 UEs; concurrently, it is 98% for the bandwidth 20 MHz. It can be concluded that at a low number of UEs, low bandwidth adoption is motivated as the establishment ratio is near the high bandwidth, while, at dense UE scenarios, a bandwidth lower than 5 MHz is not recommended.

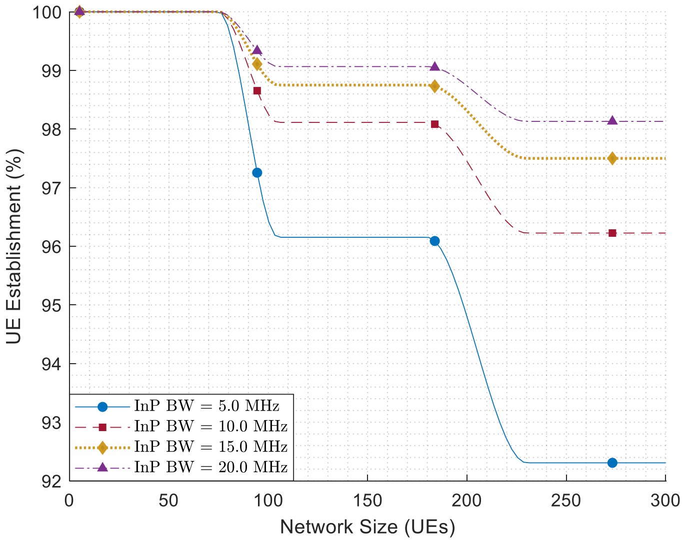

**Fig.( 2):-** UE Network Access Rate (UNAR) over different InP bandwidth

Figure 3 displays the total sum rate achieved for all users attached to all InP across various system bandwidths. The sum rate of InPs is the summation of all users in all InPs. Users gradually join the network, adding their data rate to the total sum rate, resulting in a logarithmic trend for each InP's bandwidth. The graph shows that the data rate increases significantly at low user densest, up to 100. Conversely, As the user count grows, the total sum rate approaches constant due to resource management system allocation until fully utilized; the rest of the users are rejected that they exceeded the network's capacity to achieve SLA in terms of user capacity. By this, for adding more users at a level, the sum rate will not be increased as the newly added users be rejected by the system.

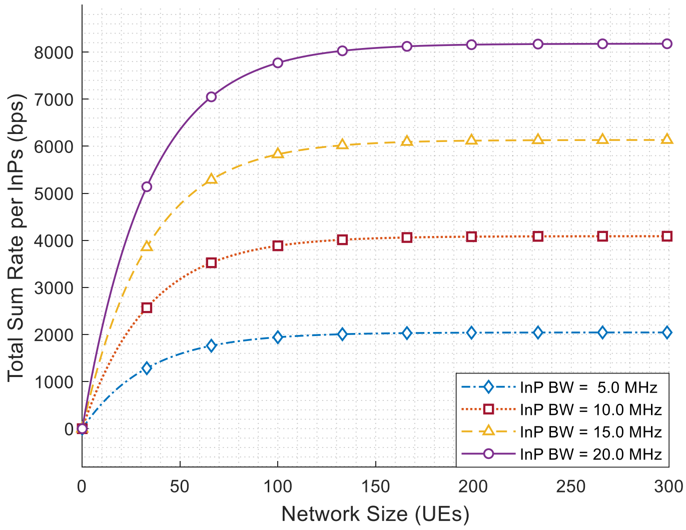

**Fig.(3):-** Network Sum-rate for each InP system Bandwidth.

### 4.2. PSO and Matching algorithm integrating with the economic model.

The average network throughput of all InPs for PSO and Matching Game algorithms is presented in Figure 4. Increasing UEs gain additional average throughput. Obtained average throughput for the system is much higher for the Matching Game than PSO, especially at dense UEs. The superiority of the Matching Game algorithm can be attributed to several factors; Matching Game optimizes resource allocation by considering user-specific characteristics, resulting in higher throughput for all users. It prioritizes fairness and objectivity, enhancing overall system performance and leading to higher throughput. The algorithm design principles are tailored to the network scenario, ensuring superior throughput outcomes. However, the PSO algorithm may show limitations or lack necessary adaptations, leading to lower throughput performance.

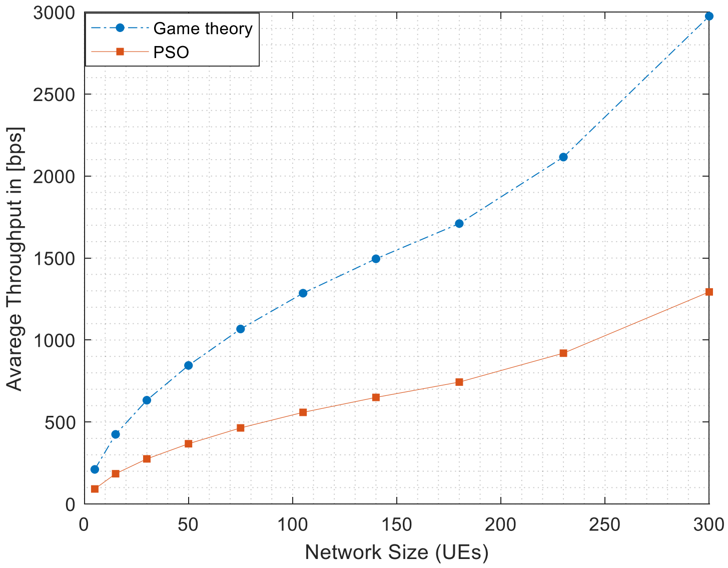

**Fig.( 4):-** Average System Throughput based on PSO and Matching game.

The bar chart in Figure 5 demonstrates the offered average price per InP for all the ten MVNOs in different system bandwidths. The measurement could be any unit price (UP) to show the effect and scale of the price in terms of bandwidth and MVNO number. Each InP offered various prices depending on its bandwidth and shared RBs. For instance, the InP with 20 MHz provided their price from 0 to 300 UP across all MVNOS; the same scenario for other InPs applied. MVNO users can select the system that best meets their requirements. As the bandwidth increases, more RBs are shared with users, enhancing performance while maintaining the same price range for MVNOs. This efficient calculation of prices is achieved through a user association algorithm utilizing a Matching game approach.

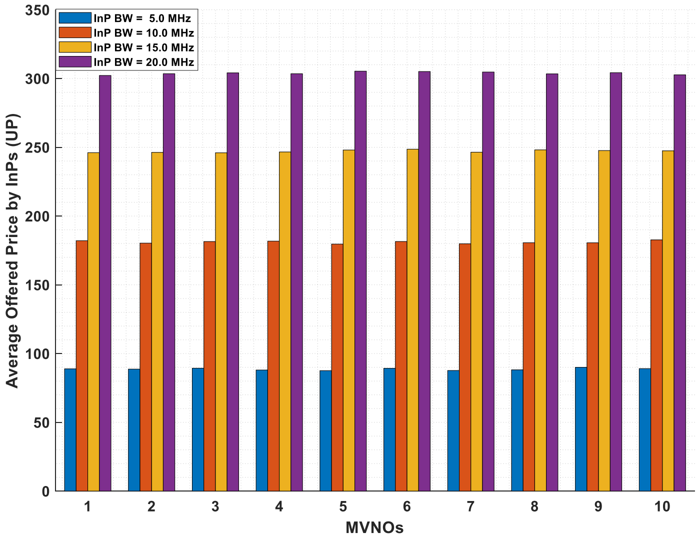

**Fig.(5):-** InP Selection Prices are based on Bandwidth and Sliced RBs among MVNOs.

Figure 6 illustrates the proposed algorithms' convergence with the number of iterations. Convergence of the Algorithm is the state that each user pairs with its MVNO channel to get resources. It is noted that the number of UEs in the network directly relates to the time-consuming algorithms iterations to match service providers with the users. As much as the UEs increase, the time to reach convergence is increased simi-linearly up to 100 iterations. Beyond that, increasing UEs has no significant effect on the convergence time due to the system's stability with 100 iterations for 300 UEs. PSO converges faster in 30 seconds than the Matching Game, which takes 45 seconds for 300 users in 300 iterations. As users increase, both algorithms require more iterations and computational effort. However, once the user count reaches 300, convergence stabilizes in iteration 100 for both algorithms. PSO's faster timing convergence is attributed to its dynamic search space exploration, while the Matching Game ensures user satisfaction with available resources, resulting in slightly longer convergence time and system stability.

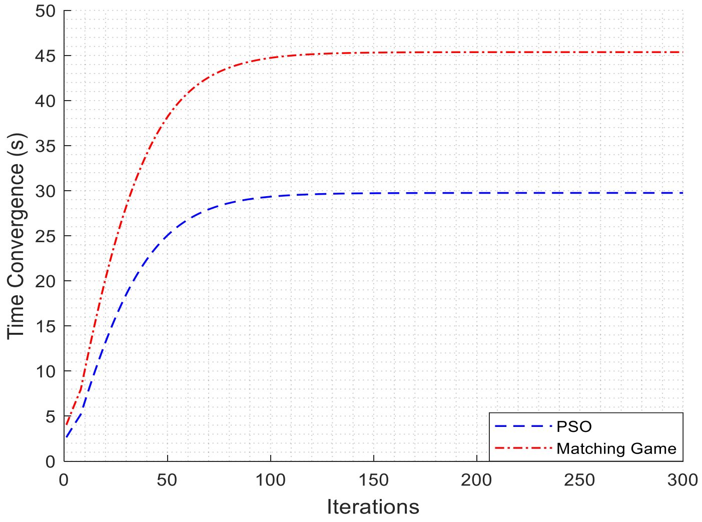

**Fig.(6):-**Average convergence for all InPs per Algorithm.

Figure 7 demonstrates the revenue of MVNOs in terms of the number of users for both proposed algorithms. It is noted that increasing users gain more income for the MVNOs comparably. In terms of earning more revenue, the matching game outperforms PSO. This outcome of Figure 6, where MVNOs adopting Matching Game provides more data rate than the PSO, so if we consider the cost per bit mechanism, MVNO revenue is increased by increasing air interface throughput.

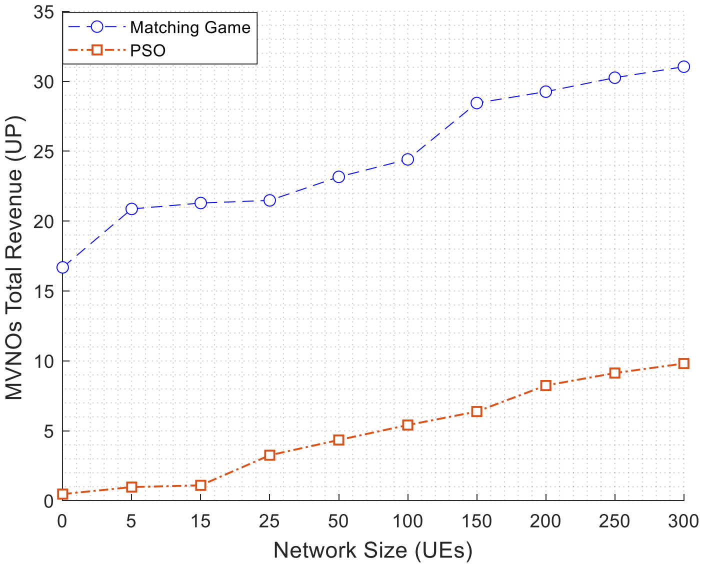

**Fig. (7):-** The total Optimal Average Pricing for UEs per MVNO.

Figure 8 depicts the total InP income per Algorithm according to the number of RBs. As RBs are added, revenue increases incrementally. When RBs reach 100, for instance, the InP with 20 MHz in the matching game gains up to 350 UP, while others with 5 MHz gain only 120 UP. The Matching Game algorithm surpasses the PSO algorithm in revenue generation and data rate services because of its customizable price choices, cost-effectiveness, and efficient RB allocation methods. Due to not fully exploiting RBs, the PSO algorithm may have data rate restrictions. However, the Matching Game algorithm maximizes revenue and improves data rate services, making it the most outstanding choice for revenue development and customer satisfaction.

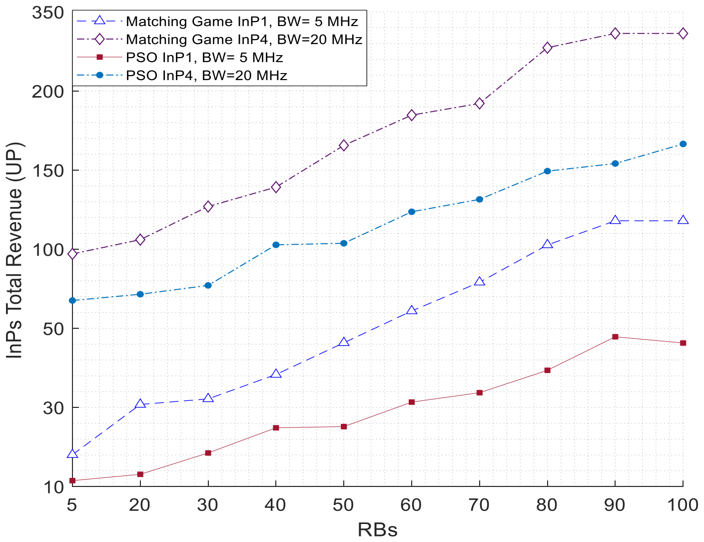

**Fig.(8):-** Total Revenue of InPs per algorithms.

## 5. CONCLUSION

WNV is an exciting new technology that addresses resource management and RAN architecture obstacles in 5G network slicing. It accomplishes dynamic resource allocation by decoupling hardware infrastructure and service providers, thereby reducing the operational expenses of operators. This work addresses a crucial challenge in WNV: dynamic resource allocation from multiple InP to several MVNOs and sharing with hundreds of UEs.

Multiple InPs, each with hardware resources, sell isolated slices to MVNOs, who buy channel resources from InPs to provide service to UEs. This paper presents a unique system model that considers dynamic inter-user interference and an economic model to assess costs and returns. The findings demonstrate the resilience of hierarchical game-matching and Particle Swarm Optimization (PSO) algorithms in minimizing expenditures and enhancing UE throughput. Integrating the economic model with the WNV system maximizes earnings and saves expenses for all stakeholders, assuring financial viability. High user admittance within acceptable time intervals and complexity are shown by the obtained UEs engagement rate, reaching 98% of total users contributing to resource demands. The trade-off between the suggested algorithms is noticed, with PSO displaying quicker convergence and the matching game giving better throughput and boosting end-user effectiveness. This study highlights the relevance of WNV in 5G for controlling resources and RAN facilities, and it suggests that hybrid techniques that combine the best features of both algorithms can generate higher-quality outcomes in 5G network slicing. In particular, the research focuses on how mixed methods that combine both algorithms' strengths could produce enhanced results.

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