Spectral efficient network and resource selection model in 5G networks

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ABSTRACT

This work addresses the challenges in modern communication networks, emphasizing the need for improved efficiency, higher data transfer rates, and reduced delays. In 5G networks, advanced resource optimization, network selection, and relaying techniques are crucial for expanding multi-cellular coverage and enhancing network performance. However, implementing these techniques in mobile environments with high interference levels increases computational demands for radio resource management (RRM). Machine learning (ML) and deep learning (DL) are proposed as solutions to enhance consumer applications, reduce communication overhead, and improve RRM. Current ML/DL methods, however, struggle with identifying key features for network selection and balancing system throughput with spectral efficiency. This paper introduces the spectral efficient network and resource selection (SENRS) model for 5G multiple input multiple output-orthogonal frequency division multiplexing (MIMO-OFDM) networks. Tested using the Stanford University Interim (SUI) channel fading model in a highway scenario, the SENRS model demonstrates superior performance compared to existing network and resource selection systems.

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1. INTRODUCTION

The emergence of 5G technology has assisted individuals in a new era of connectivity, promising unprecedented data speeds, lower latency, and enhanced reliability [1]. However, a significant challenge arises in the current resource management optimization methods, which predominantly assume static user behavior [2], [3]. In reality, users in 5G networks are highly mobile, especially in scenarios involving fast-fading channels such as those encountered by users traveling in vehicles or trains. These dynamic environments exhibit high signal fluctuation, frequent changes in network conditions, and dynamic channel variations, posing substantial challenges to resource management [4]. In response to this challenge, the focus shifts towards multiple input multiple output (MIMO)-orthogonal frequency division multiplexing (OFDM) technology [5], which proves to be instrumental in provisioning multi-service to mobile users. Unlike conventional OFDM [6], MIMO-OFDM enables multiple data streams to be transmitted simultaneously, significantly enhancing spectral efficiency and system performance [7]. The emphasis on MIMO-OFDM lies in its ability to mitigate the adverse effects of fast-fading scenarios, providing a more stable and reliable communication channel for mobile users. In 5G, MIMO-OFDM plays a pivotal role in improving the overall efficiency of the network, especially when users are moving [8], [9]. Further, the traditional resource management methods in wireless communication systems are predominantly designed with the assumption of static users, where the location and conditions of users remain relatively constant over time [10]. In such scenarios, resource-allocation strategy can be pre-determined or adjusted periodically, relying on the stability of the communication environment [11]. However, the advent of 5G technology brings with it a paradigm shift, introducing a multitude of use cases with diverse requirements, including high-mobility scenarios [12]. When users are mobile, as in the case of vehicular or train-based communications, traditional resource management methods face significant challenges. One key limitation is the dynamic variation of channel conditions [13]. In a fast-fading channel, where users are moving at high speeds, the signal strength experiences rapid fluctuations due to factors such as distance changes, obstacles, and interference from other wireless sources [14]. To address this, the work introduces an effective network-selection and resource-allocation design that adapts to the dynamic nature of mobile users.

Moreover, the current machine learning (ML) methods have gained prominence in the domain of wireless communication for tasks such as network-selection and resource-allocation due to their ability to adapt and learn patterns from data [15], [16]. However, one persistent challenge faced by these methods, particularly in the context of network-selection, is the issue of class imbalance because of load balancing [17]. Class imbalance occurs when the distribution of instances across different classes is not uniform. During the process of network-selection, some networks may have significantly more instances (users or scenarios) than others. This imbalance can lead ML models to be biased towards the majority class, resulting in suboptimal performance for minority classes [18]. In the case of network-selection, this imbalance could manifest as a bias towards popular or more frequently used networks, neglecting the optimal utilization of other available networks. Further, when working with heterogeneous networks, where multiple networks with diverse characteristics coexist, the imbalance in the number of samples from different classes hinders the learning process. Hence, the proposed work aims to develop a novel ML that not only enhances the current methods for network-selection and resource-allocation but also effectively handles class-imbalance issues, ensuring a more robust and accurate decision-making process. Furthermore, in the current 5G, the physical layer deals with the transmission and reception of signals [19], while the medium access control (MAC) layer governs access to the shared communication medium [20]. In 5G, where diverse services with varying requirements coexist, an effective cross-layer optimization strategy becomes imperative [21], [22]. Hence, this work proposes a spectral efficient network and resource selection (SENRS) approach, ML model, to address the drawbacks and challenges posed by the dynamic nature of 5G networks. As 5G networks become increasingly integral to our daily lives, it is crucial to evaluate and optimize their performance for superior spectral efficiency and channel resilience in real-world deployments. This necessitates a comprehensive understanding of the waveforms and signals employed in 5G systems. In the pursuit of maximizing the potential of 5G networks, currently researchers and engineers have delved into the complexities of waveforms and signals, aiming to design and simulate end-to-end 5G networks [23], [24]. This involves considering various factors and various system parameters to create a holistic representation of the network. The evaluation of performance metrics like throughput, latency, and reliability becomes paramount in assessing the effectiveness of these simulated 5G networks. Hence, the contribution of this work is as follows: i) introduction of MIMO-OFDM channel for multi-service provisioning considering user mobility; ii) implementation of an effective network-selection and resource-allocation design; iii) development of a novel ML algorithm addressing class-imbalance issues in network-selection; and iv) enhanced system throughput, and spectral efficiency i.e., (minimal latency and improved reliability).

The manuscript is organized as follows. In section 2, the literature survey is discussed. In section 3, the SENRS approach is presented which discusses the system and network model, network-selection optimization, and resource-selection optimization. In section 4, the results are discussed for the SENRS approach comparing it with existing work for throughput, spectrum access failure, and spectrum access success performance. In section 5, the conclusion along with the future work is discussed.

2. LITERATURE SURVEY

This section studies various current network and resource selection methodologies designed for heterogenous 5G networks using MIMO-OFDM. Liu *et al*. [14] looked at how well the sparse code multiple access (SCMA)-OFDM networks handled bit-error rates (BER) across multi-path Rayleigh faded-channels including Gaussian-channels when carrier-frequency-offset (CFO) was present. They also demonstrated how SCMA-OFDM networks suffer greatly from BER loss whenever the standardized CFO was more than 0.02. Bartsiokas *et al.* [15] examined the issue of placing and selecting relay-nodes (RNs) while taking subcarrier allotment and power-consumption restrictions into account. They investigated and integrated different deep learning (DL)-based techniques with overall energy and spectrum-efficiency were increased by up to 30%. When the reinforcement-learning (RL) approach was used to choose RN selection, it enhanced energy efficiency by 80% and spectrum-efficiency by 75% in comparison with an approach that relied solely on

DL-enabled placement. Ahmed *et al*. [16] introduced a novel integrating technique that skillfully combined the car to car network-hierarchical deep neural network (CtCNET-HDRNN) framework with 5G's millimeter-wave (mmWave) and Monte-Carlo for dedicated-short-range-communications (DSRC) networks to ensure communication efficiency. In comparison to non-diversity decision-making situations, they found that using multiple antennas over 5, 30, 45, 50, and 60 kHz significantly improved data rates, especially during lane shifts at velocities reaching as high as 188 km/h.

Dangi *et al.* [24] presented an innovative technique to guarantee quality of service (QoS) across a multi-service environment while focusing on battery efficiency improvements. They suggested a method that utilized double-deep reinforcement learning (D-DRL) for achieving the best network-selection strategy. The findings gathered within this study indicated that the suggested technique showed significant improvement in utility-reward compared to DRL, random and greedy techniques. Xie *et al.* [25] introduced a network selection method that utilized dueling-double deep q-network (D-DQN) with DRL. Finding the system choosing advantages for various services created by users involved using the analytical hierarchy method to determine the weighting connection among network characteristics and user-services. According to the experiment's findings, the method effectively minimized switching of the network, optimized network resource utilization, and ensured users gain from network-selection. Lee and Kim [26] addressed the issue of allocating resources for different types of movement in the context of road side unit (RSU)-deployed vehicle to everything (V2X) networks. They introduced a distributed multi-agent reinforcement learning (MARL) centered resource-allocation method using restricted resource sharing under both overload and underload scenarios. Srivastava *et al*. [27], presented a method that combined transfer and detection of sidelink control information (SCI), where sidelink-transmit user-experiences (SLTxUEs) send and get SCI within an extra combined strategy opposing to the main one. This assisted in minimizing overlooked node disturbance and decreasing the number of subjected with enhanced the mean packet reception rate (PRR) by 27% compared to the cutting-edge under the most demanding traffic conditions. Moroever, the method allowed for enhanced utilization of resources and boosted efficiency, resulting in a minimum of 95% mean PRR across every circumstance.

Iqbal *et al*. [28] introduced a radio resource management (RRM) Q-learning method, which was assessed for distributed and collaborative approaches, utilizing collaborative and distributed learning. Results of simulations using the ultra-dense heterogeneous networks (UDHN) within a metropolitan structure indicated that collaborative learning with an impressive rise of 37.9 and 48.57% was noted in the sum-cell user-capacity and small-cell user-capacity of the Q-learning small user-cells, respectively when utilizing collaborative learning instead of distributed learning. González *et al*. [29] presented a resource-allocation strategy for NR VV2X Mode 2 and their effectiveness was assessed in numerous situations. According to the study, larger numerologies outperformed lesser subcarrier distances. Despite the standard specifying an arbitrary approach for V2X resource decision-making, it was noted that the different sensing processes result in increased PRR levels. Bruun *et al*. [30] presented two collaborative resource utilization strategies: group scheduling and device-sequential scheduling, along with an administrative communication architecture. It was noted that a lack of reception of these regulatory signals resulted in uncooperative behavior and a noticeable decrease in performance. It was demonstrated that while communication, possesses a notable effect on resource distribution efficiency, the suggested group and sequential scheduling of resource allocation methods enhanced reliability significantly when compared with SL mode-2. In conclusion, various methods of network and resource selection in 5G networks have been studied; MIMO and OFDM networks have been studied considering user mobility. The current method is predominantly aimed at dealing in providing better spectral efficiency; however, extreme user mobility and usage of dynamic spectrum allocation results in high interference; as a result, failed to bring a tradeoff between maximizing spectral efficiency and throughput maximization. The ML-based network section exhibits poor results as it fails to identify features contributing to frequent handoffs. In addressing the research problem, in the next section proposed methodology of SENRS is presented.

3. PROPOSED METHODOLOGY

This section introduces a SENRS design under a 5G MIMO-OFDM network [15], [16]. First, the system and network model are presented, second, the network resource selection using a novel multi-split K-fold cross-validation extreme gradient boosting (XGB) model. Finally, the resource selection maximizes system throughput with enhanced back-off time optimization to mitigate interference to achieve enhanced spectral efficiency.

3.1. System network model

Consider a dense 5G network designed using a MIMO-OFDM network where two MIMO-OFDM 5G networks overlap each other with radius s. Let the mobile-terminal be deployed arbitrarily across the MIMO-OFDM network following a poisson distribution (PD) [31] considering a uniform mobility pattern. In the 5G network, any MIMO-OFDM network-connected mobile-terminal will notify the corresponding base stations (BSs) for observed downlink radio-frequencies (RFs) for adjusting the measurement-gap. The anticipated size of the mobile-terminal can be effectively managed within a given area. The anticipated size is determined through the intensity variable φ and the processing variable μ. The μ for each mobile-terminal O in MIMO-OFDM network X is discussed in this work. To collect the data from the mobile-terminals O, the (1) is utilized to represent the PD having a mean of φX. In (1) s represents MIMO-OFDM network area radius. The location of j^{th} mobile-terminal is attained using the continual constant distribution $\mathbb{S}^2$ by utilizing the polar-coordinates $\left(s_j, \theta_j\right)$, where $j = 1,2,3, \dots, O$ and $0 \leq \theta_j \leq 2\pi$, and $0 \leq s_j \leq s$.

$$\varphi X = \varphi \pi s^2) \tag{1}$$

3.2. Network-selection optimization

To initialize the radio resource control (RRC) X2, the mobile-terminal monitors the MIMO-OFDM network's reference-signal received-power (RSRP), which is lower in comparison with the handover quality specification, according to the MIMO-OFDM standard presented in [16], [31]. Hence, due to this reason, the RRC measurement gap has to be reconfigured for the MIMO-OFDM network. In addition to this, mobile terminals record a higher RSRP in comparison to the handover quality specifier, which triggers the initialization of RRC X1. When the MIMO-OFDM power exceeds the predetermined quality specifier threshold, the mobile-terminal triggers the RRC Y2 initialization, chooses an available slot in the MIMO-OFDM distribution channel for communication, and completes the handoff efficiently. The network-selection process using the conventional model is presented in Figure 1. Figure 1 illustrates that the handoff request occurs in phase X, whereas the handover operation takes place in phase Y, after which the MIMO-OFDM network decides to permit the handoff. However, the conventional model induces higher signaling overhead. Hence, this work presents a novel ML-based handover operation approach. This work adopts a similar ML-based method introduced in [31] to reduce signaling overhead. However, the ML-based network selection prediction method failed to provide accurate results when data is imbalanced; further, failed to identify which characteristic plays a major role in attaining higher network-selection accuracy. The ML-based network selection algorithm is given in Figure 2.

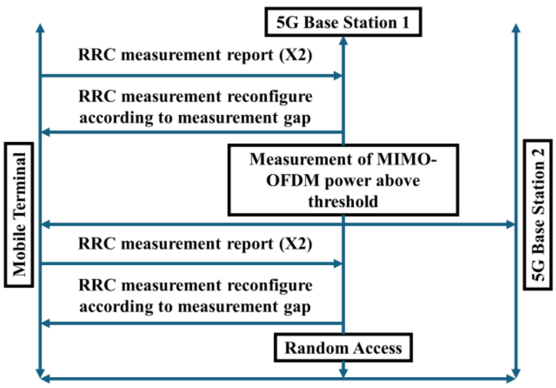

Figure 1. Conventional network-selection in MIMO-OFDM network

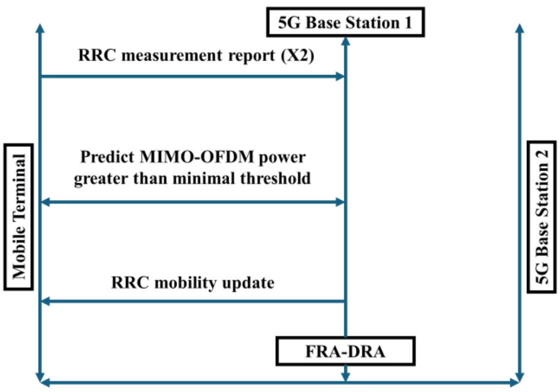

Figure 2. ML-based network-selection for reducing signaling-overhead in MIMO-OFDM network

Deciding whether to allow a mobile-terminal measurements-gap approach or utilize ML for handover efficient performance is determined using Figure 2. The receiver-operating-characteristic (ROC) curve is utilized to predict the success or failure of handoff which involves computing it with the multi-split k-fold cross-validation xgboost (MSKF-XGB) classification model. By utilizing the past data on the likelihood of successful handovers for each mobile-terminal, the MSKF-XGB model is presented in this work for decision-making during handovers using collected data U. The objective-function of XGB [32] is defined using (2).

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(u-1)} + f_t(x_i)\right) + \Omega(f_t) \tag{2}$$

In (2), l defines the loss-function which denotes the error between the anticipated and collected data. Moreover, l is the representation of the t^{th} tree of a basic decision-tree (DT). u is used as the iterative index during the optimization process. The regularization-function presented in (2) can be described using the (3) [32]:

$$\Omega(f_t) = \gamma U + \frac{1}{2}\lambda\left|\left|w\right|\right|^2 \quad (3)$$

In (3), U denotes the different leaves within the DT. γ and λ defines the penalty-factor which consists of the score of vectors for different leaves. Further, the XGBoost method is laid out in detail in the work of Chen and Guestrin [32]. In (3), it is essential to establish or assign specific values to U, γ and w to improve the method of optimization before beginning the training phase [33]. The incorporation of regularization-function helps to minimize computational difficulties and prevent overfitting issues. The n×0 matrix for characteristic-set that have to be trained as describe in (4).

$$Y = \left[Y_j\right]_{j=1}^{o} \quad (4)$$

Where o represents the overall characteristic-sets taken into account for training and Y_j represents the multi-dimensional characteristic vector acquired during a given time instance. In this work, 1 indicates that the handover has been executed, and 0 indicates that it has not, by utilization of supervised labeled-vector y. In MIMO-OFDM, the RSRP is among one of the five characteristics that are taken into account throughout this study. The other three characteristics are mobile-terminal distance from the BS, mobile-terminal coordinates, and reference symbol measurement updates according to X1 and X2, respectively. The final three characteristic attributes are gathered from mobile-terminals whereas the initial two characteristics are acquired through RRC messages employing recorded arriving time variance or global positioning system (GPS). Here, enhancing the hyper-parameters involves using MSKF to enhance the accuracy of the network selection operation. By randomly splitting the dataset into equal-sized subsets, the characteristic-subset for training the MSKF-XGB model is constructed through a typical KF-CV. Next, the rest of the K-1 samples are utilized to build the network-selection operation. After careful consideration, the model which minimizes the anticipated error is chosen based on the grid l. The conventional equation for CV is denoted using the following equation. Using the conventional CV presented in (5), the MSKF-CV is optimized as (6).

$$CV(\sigma) = \frac{1}{M}\sum_{k=1}^{K}\sum_{j\in G_{-k}} P\left(b_j, \hat{g}_{\sigma}^{-k(j)}\left(y_j, \sigma\right)\right) \quad (5)$$

$$CV(\sigma) = \frac{1}{SM}\sum_{s=1}^{S}\sum_{k=1}^{K}\sum_{j\in G_{-k}} P\left(b_j, \hat{g}_{\sigma}^{-k(j)}\left(y_j, \sigma\right)\right) \quad (6)$$

Initially, a primary characteristic is selected coming from subsets of characteristics, which is then utilized to develop a network selection prediction model with better performance. In (5) and (6), for the selection of better $\hat{\sigma}$ for optimizing the network-selection prediction design, in (7) is utilized.

$$\hat{\sigma} = \underset{\sigma\in\{\sigma_1,\ldots,\sigma_l\}}{\arg\min}\ CV_s(\sigma) \quad (7)$$

Where, M denotes the size of the dataset considered for training, $P(\cdot)$ represents loss-function, $\hat{g}_{\sigma}^{-k(j)}(\cdot)$ indicates the approach employed for coefficient calculation. In this way the best networks are selected wind minimize interference effect a novel resource slection optimization is presented in next section.

3.3. Resource selection optimization

The study tries to maximize the throughput of the network by resource optimization process within the MIMO-OFDM network. Consider a mobile-terminal x which achieves the given throughput S_x and its respective resource-allocation e_{xy}. In a scenario where the resource y is given to mobile-terminal y, in this scenario $e_{xy} = 1$, else $e_{xy} = 0$. Hence, from this scenario, the overall throughput-gain issue is represented using (8). In (8), R represents overall mobile-terminals present in the MIMO-OFDM network. Additionally, in this work, a limit has been set for fixed resource allocation (FRA) which is represented using (9).

$$\underset{E}{max} \sum_{x}^{R} S_x. \quad (8)$$

$$\sum_{x}^{R} e_{xy} = 1 \ \forall y \quad (9)$$

Using the (8) and (9), the overall throughput that can be achieved by a given mobile-terminal x for FRA is evaluated using the following considerations. Consider a resource-set V_x which has been exclusively given to a mobile-terminal x. Let l_{xy} define the probability of resource y which can be accessed only by the given mobile-terminal x. In this study, l_{xy} is considered independent. Hence, from this throughput S_x is evaluated using (10).

$$S_x = 1 - \prod_{y \in V_x} l'_{xy} = 1 - \prod_{y=1}^{T} \left(l'_{xy}\right)^{e_{xy}} \tag{10}$$

In (10), $l'_{xy} = 1 - l_{xy}$ denotes the probability that the resource y cannot be accessed by mobile-terminal x and $1 - \prod_{y \in V_x} l'_{xy}$ denotes the probability that at least one resource can be accessed by mobile-terminal x. This work proposes an efficient approach and low-complexity approach for FRA and dynamic resource allocation (DRA) aware MIMO-OFDM network using throughput gain considering optimal resources are allocated as defined in (11).

$$\delta S_x = S_x^z - S_x^q = \left[1 - \left(1 - l_{xy'_x}\right) \prod_{y \in V_x} \left(1 - l_{xy}\right)\right] - \left[1 - \prod_{y \in V_x} \left(1 - l_{xy}\right)\right] = l_{xy'_x} \prod_{y \in V_x} \left(1 - l_{xy}\right) \tag{11}$$

It is evident from (11) that δS_x decreases with each iteration of allocation. This happens because V_x keeps on increasing, causing $\prod_{y \in V_x} \left(1 - l_{xy}\right)$ to approach to zero. In (11) is modiefied considering MAC overhead $\mathcal{D} < 1$ is given (12).

$$\delta S_x^{\mathbb{V},b}(y) = \left(1 - \frac{1}{\mathbb{V}}\right) (1 - \mathcal{D}) l_{xy} \left(\prod_{o \in V_x} \bar{l}_{xo}\right) * \left(1 - \prod_{o \in V_*^c} \bar{l}_{xo}\right) \sum_{n=1}^{\mathbb{V}} \left[\bar{l}_{x_n y} \left(\prod_{m=1, m \neq n}^{\mathbb{V}} l_{x_m y}\right)\right] \tag{12}$$

In (12) allows one to simulate the parameter $\mathcal{D}$ while taking contention-window $\mathcal{A}$ into account, which is the average MAC protocol overhead. Consider h to be the average value for the back-off variable that each mobile-terminal can choose. Because the back-off variable is evenly chosen among zero alongside the $\mathcal{A} - 1$ interval (i.e., $[0, \mathcal{A} - 1]$), this work deduces that $\mathrm{h} = {}^{(\mathcal{A} - 1)}/_{2}$. This allows us to calculate the average overhead as (13).

$$\mathcal{D}(\mathcal{A}) = \left(([\mathcal{A} - 1]\varphi/2) + \mathrm{s}_{\mathrm{SENS}} + \mathrm{s}_{\mathrm{SYNCH}} + \mathrm{s}_{\mathrm{RTS}} + \mathrm{s}_{\mathrm{CTS}} + 3\mathrm{s}_{PDT}\right)/\mathrm{S}_{\mathcal{J}} \tag{13}$$

Where s_{SENS} is the time of sensing, s_{SYNCH} is the size of synchronization packets,s_{RTS} defines request to send, s_{RTS} defines ready to send, s_{PDT} defines propagation delay time, $S_{\mathcal{J}}$ stands for the cycle time and φ represents the period of time corresponding to a single back-off variable. Depending on how resources are distributed, the overhead $\mathcal{D}$ will vary. As a result, the DRA model is modified with the present channel allocation for $\mathcal{D}$. Because $\mathcal{D}$ is rather stable, our DRA approach works efficiently and without problems leading to improved throughput, spectrum access failure, and spectrum access success-all of which are demonstrated empirically in the next section.

4. RESULTS AND DISCUSSION

This section presents an experiment analysis of the proposed SENRS and existing system network and resource selection (ES-NRS) model [16]. The proposed and existing model is implemented using the SIMITS simulator [34]. The SUI channel fading model [35] from NYUSIM implemented in MATLAB is used to validate the proposed model under the MIMO-OFDM network. The scenarios are created similarly to DeepMIMO [16]. The simulation is studied under mobility patterns representing the highway scenarios. The SIMITS simulator allows live spectrum access and failure monitoring considering mobile-terminal mobility. In this work, the 5G propagation simulation is utilized with the following parameters: a central frequency of 28 GHz, a bandwidth of 100 MHz, a network cellular area of 350 meters, a BS power level of 46 dBm, along with RRC even Y2, X1, and X2, of -95 dBm, -125 dBm, and -130 dBm, respectively. The duration of the simulation has been set at 50 milliseconds. Here experiment is conducted to evaluate performance in terms of throughput, spectrum access failure, and spectrum access success under varied mobile-terminal sizes.

4.1. Throughput performance

This section studies the throughput performance of both SENRS and ES-NRS considering mobile terminal sizes of 20 and 40. The throughput is measured in terms of total number of packets transmitted per channel. A higher value indicates better performance. Figure 3 shows the throughput performance of both ES-NRS and SENRS for 20 mobile terminals. Similarly, Figure 4 shows the throughput performance of both ES-NRS and SENRS for 40 mobile terminals. From the results, the proposed SENRS model can attain better throughput in comparison with ES-NRS considering 20 and 40 mobile terminal sizes. An average throughput enhancement of 16.17% is seen for 20 mobile terminal and an average throughput enhancement of 9.25% is seen for 40 mobile terminals.

4.2. Spectrum access failure performance

This section studies the spectrum access failure performance of both SENRS and ES-NRS considering mobile terminal sizes of 20 and 40. The spectrum access failure is measured in terms of the total number of times the mobile-terminal fails to transmit the packets on a given spectrum. A lower value indicates better performance. Figure 5 shows the spectrum access failure performance of both ES-NRS and SENRS for 20 mobile terminals. Similarly, Figure 6, shows the spectrum access failure performance of both ES-NRS and SENRS for 40 mobile terminals. From the results, the proposed SENRS model can reduce spectrum access failure in comparison with ES-NRS considering 20 and 40 mobile terminal sizes. An average spectrum access failure reduction of 54.41% is seen for 20 mobile terminals and an average throughput enhancement of 14.96% is seen for 40 mobile terminals.

4.3. Spectrum access success performance

This section studies the spectrum access success performance of both SENRS and ES-NRS considering mobile terminal sizes of 20 and 40. The spectrum access success is measured in terms of the total number of times the packets are successfully transmitted. A higher value indicates better performance. Figure 7 shows the spectrum access success performance of both ES-NRS and SENRS for 20 mobile terminals. Similarly, Figure 8, shows the spectrum access success performance of both ES-NRS and SENRS for 40 mobile terminals. From the results, the proposed SENRS model can attain better throughput in comparison with ES-NRS considering 20 and 40 mobile terminal sizes. An average spectrum access success enhancement of 16.17% is seen for 20 mobile terminals and an average throughput enhancement of 9.25% is seen for 40 mobile terminals.

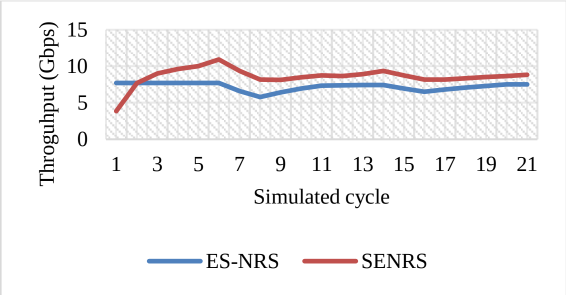

Figure 3. Throughput performance for 20 mobile terminals

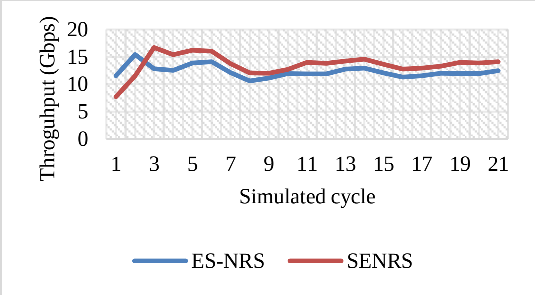

Figure 4. Throughput performance for 40 mobile terminals

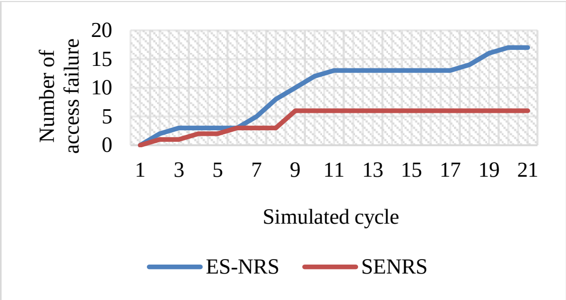

Figure 5. Spectrum access failure performance for 20 mobile terminals

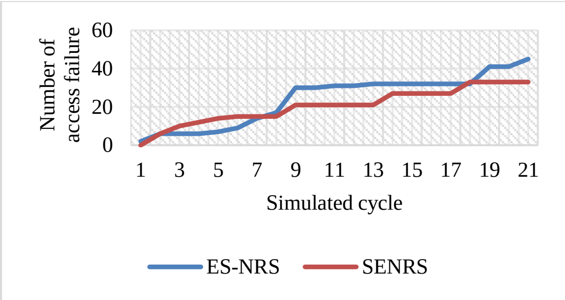

Figure 6. Spectrum access failure performance for 40 mobile terminals

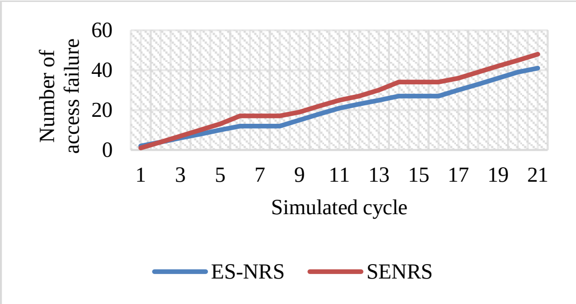

Figure 7. Spectrum access success performance for 20 mobile terminals

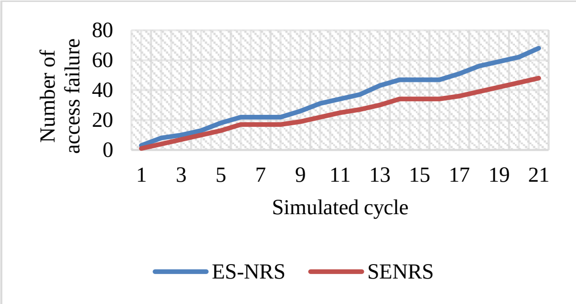

Figure 8. Spectrum access success performance for 40 mobile terminals

5. CONCLUSION

In this work, a novel network and resource selection method is introduced to improve spectrum efficiency. The proposed model simulated results showing significant improvement in throughput, and better spectral access success with minimal spectrum access failure. The significant spectral efficiency aids in increased resource availability, thereby reducing overall latency and improving system reliability. The model is tested using scenarios created employing DeepMIMO and the SUI channel fading model is used for studying the model in practical highway-like mobility and path-loss scenarios. The proposed SENRS model is compared with existing NRS methodologies showing significant enhancement in terms of throughput and spectral usage performance. The performance enhancement is due to multi-split cross-validation XGB-based network-selection and improved resource selection that maximizes the system throughput with minimal spectrum access failure with enhanced backoff time optimization using both FRA and DRA. Future work would consider incorporating software-defined radio to dynamically optimize the contention window according to network traffic and the mobile nature of the user under different real-world environment scenarios will be studied, including assessment of signal quality, coverage, interference resilience, error rates, and spectral efficiency.

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