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Complexity Based Performance Analysis of WSSR Assisted SIC Detection For 5G and Beyond Power Domain NOMA Wireless System

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ABSTRACT: Successive interference cancellation (SIC) is fundamentally the important detection technique of power-domain non-orthogonal multiple access (pNOMA) in 5G and currently under intense research in beyond 5G (B5G) networks. However, it faces challenges in terms of error propagation, computational efficiency and scalability. Resonance based aiding algorithm techniques such as Woods–Saxon Stochastic Resonance (WSSR) and Classical Stochastic Resonance (CSR) based were proposed to aid the SIC to improve weak signal detection. This paper presents a comparative study using time and space complexity analysis of WSSR-assisted SIC (WSSR-SIC) and CSR-based SIC (CSR-SIC) as base line using Big $\boldsymbol{O}$. We evaluate both the time and space complexities under realistic channel conditions. Simulation results demonstrate that CSR-SIC produces better latency of 0.35*ms*, good for *uRLLC* requirement. Equally, WSSR-SIC achieves superior weak signal detection presents better link reliability for rescuing weaker users (where system reliability trumps minimal latency; 0.85 *ms*, still < 1 *ms* 5G latency requirement). The findings highlight WSSR-SIC as a promising detection scheme for *mMTC* and *eMBB* to support next-generation NOMA systems for massive connectivity requirements of internet-of-thing (IoT) and internet-of-everything (IoET).

KEYWORDS: 5G, B5G, *uRLLC, mMTC, eMBB*, pNOMA, SIC, WSSR, CSR, IoT, IoET..

1.0. INTRODUCTION

Without any doubt, mobile communication brought about unprecedented breakthrough and has been the sole driver to deliver wireless services for well over four decades. Fifth generation (5G) has been the most recent radio air interface [1], with power domain non-orthogonal multiple access (pNOMA) emerged as the key enabling technology that addresses the basic requirements [2]. It is practically realized using superposition coding (SC) at the transmitter and successive interference cancellation (SIC) at the receiver [3]. SIC becomes a critical interference management factor as it has direct impact on excellent signal detection (Si-D) and reconstruction at the receiving terminal [2]. The operational principle of the SIC is directly proportional to the number of users (becomes exceedingly larger over time) [4], which results to inevitably higher receiver complexity and more power consumption [5]. Obviously, SIC is a crucial component of pNOMA systems and a key element for the performance of the reception process [6]. The fact that NOMA has been fully recognized as a promising 5G and beyond (B5G) radio access technology (RAT), it fulfilled its promises with SIC at the receiver for multiuser detection (MUD) [7]. As such, each user can actually demodulate and decode signals from other users sharing same NOMA channel, other than its own signal [2]. Several performance improvement and evaluation methods have been developed. Yet, thirst for more techniques to further explore the non-orthogonal domain has not been quenched. More specifically, the development of elegant mathematical models for the signal detection at the receiving end for the pNOMA, are pertinent and deserve research great attention. Performance enhancement to achieve better signal detection based on Woods-Saxon stochastic resonance (WSSR-SIC) and the necessary requirements based on time and space complexity to assess the algorithm runtime and memory footprints are comprehensively documented herein.

With the current NOMA-5G Advanced (5G-A) system now starting to be deployed world-wide in 2024 and yet to fully exploits its full potentials, further research work on the detection performance enhancement became necessary [8]. Again, the world of wireless communication is looking toward the development of 6G technologies in 2030, where detection at the receiver is of paramount important; so also the detection algorithm complexity analysis [9]. Clearly, performance of pNOMA becomes ill-posed for SIC complexity [10] and imperfections arising from system complexity [11].

WSSR is a nuclear physics based inspired potential function that employed resonance mechanism to enhance weak signal (WS) through exploiting noise assisted detection [12]. It helps to create a more robust ordering mechanism [13] that was considered in this work as a crucial scheme for the better accomplishment of SIC decoding [14].

The combination actually improves the performance of massive multiple input multiple output (*m*-MIMO) pNOMA systems by leveraging the strengths of both techniques. The risk of failing to meet latency and reliability targets coupled with good device scalability in 6G *m*-MIMO NOMA deployments becomes obvious in the absence of robust detection scheme that leverages WSSR.

The combination of the SIC and WSSR (WSSR-SIC) addressed must of the challenges faced by SIC. It also improves robustness of SIC process which iteratively refined to further improve S*i*-D performance in high interference and low signal to noise ratio (SNR) scenarios without struggles. Furthermore, WSSR introduces additional parameters on top of those in classical stochastic resonance (CSR) related to the potential well (e.g., depth, width and shape) [15], providing greater control and adaptability [16]. This makes WSSR more robust and effective in complex systems [17] like *m*-MIMO NOMA, where precise tuning is essential for optimal performance. So, WSSR-SIC capability seemed to produce superior performance with higher SNR values [18]. This certainly leverages the WSP's unique attributes to better detect signals in the presence of high interference [19].

WSSR systems have attracted a great deal of research interest from both the industry and academia [20]. This is because it significantly improves weak signal detection (WSD) in many natural science phenomena and engineering systems [21]. In [22], bearing fault diagnosis using joint WSP and Gaussian potential (GP) was modeled. In [23] also, a joint exponential function and WSSR was envisaged. The work investigates the influence of the system parameters on its characteristics. [17] focused on the application of optimized WSSR in sensitive and effective weak fault detection capabilities which provides a valuable insight on the controlled symmetry. [15] proposes a bearing fault feature extraction using methods of moment ensemble dynamics approximation (MOMEDA) and Cseh-Sudar (CS) -WSSR. The computational complexity analysis based on Big O was proposed in [24].

In this paper, time and space complexity analysis for WSSR in *m*-MIMO pNOMA was performed from the perspective of aiding SIC for proper decoding of the received signal for use in 6G pNOMA WSSR algorithm. The complexity analysis for the WSSR was compared with CSR. Many papers on complexity analysis using big *O* for time and space analysis for detection algorithms of wireless communication signal detection have been done, but none that is aware to have employed the complexity analysis for WSSR-SIC in tandem for the S*i*-D. Obviously, both CSR and WSSR rely on tuning parameters such as noise intensity, signal amplitude and frequency to achieve optimal resonance. However, WSSR introduces additional parameters related to the potential well (e.g., depth, width and shape) [25]. This provides much greater control and adaptability; hence, more robust and effective in complex systems like *m*-MIMO NOMA, where precise tuning is essential for optimal performance [26]. So, this paper addresses the gap by developing time and space complexity analysis for WSSR-SIC as the main proposed scheme and CSR-SIC as the base-line scheme; then presents WSSR as a novel pNOMA detection scheme for 6G wireless system.

The remainder of this paper is organized as follows. Section 2.0 gave the details of the motivation and contributions of this paper. The complexity analysis model for the proposed WSSR system and that of CSR were presented in Section 3.0. This includes: the big O complexity analysis, the grid search, run-time scaling and Woods-Saxon potential model.

2.0. MOTIVATION AND CONTRIBUTION

A. Motivation

As 5G-A networks already deployed in 2024 and research intensified currently towards achieving the much-anticipated 6G in 2030, several challenges of achieving 6G used cases becomes an urgent requirement. Signal detection at the receiver becomes one of the cardinal objectives that require urgent attention. Conventional SIC at the pNOMA receiver methods fall short, especially in detecting weak signals. This research is motivated by the opportunity to harness WSSR, a quantum physics inspired mechanism that uses noise constructively to amplify weak signals before cancellation. In *m*-MIMO NOMA systems for 5G and beyond (B5G), the choice of detection schemes largely depends on the trade-off between performance, computational complexity and scalability. This is so because as the number of antennas and users increases, the detection scheme must handle high-dimensional signal processing efficiently while maintaining reliable performance. So, time and space complexity analysis (using Big ***O***) was performed in this paper which fully assesses the proposed WSSR based algorithm and compared with classical stochastic resonance (CSR) for aiding SIC in *m*-MIMO NOMA 5G and B5G detection of the signal at the receiver to achieve optimal performance and validating results through Monte Carlo simulations.

B. Contributions

The work of this paper confirms that the proposed WSSR has been chosen over CSR as a tool to aid SIC for the signal detection of *m*-MIMO pNOMA detection wss because WSSR offers smoother potential dynamics, faster noise response time and better adaptability to noise which significantly improved MSE, SNR and BER performance in weak signal enhancement; especially when integrated with Successive Interference Cancellation (SIC). The key contributions in this work can be summarized as follows:

- Novel detection scheme based on resonance. This work perform complexity analysis for novel WSSR-SIC, a resonance based detection. This actually introduced a new angle for both algorithm complexity analysis and detection for the next generation 6G receiver.
- Meeting complexity analysis: The use of Big O notation to assess both time and space complexity offers a rigorous benchmark for algorithmic scalability, which is rarely addressed in SIC studies in literature.

In this paper, the whole complexity analysis is based on comparing WSSR and CSR in aiding SIC, then BER and SNR performance comparison across multiple users and noise intensities was conducted.

3.0. RESEARCH METHODOLOGY

A. The Big O Complexity Analysis on WSSR and CSR (Bistable) Models for SIC

To perform Big O (***O***) complexity analysis on WSSR and CSR (bistable SR) models, the steps involved in the algorithmic was first identified for the simulation and analyzing each detection scheme (WSSR and CSR). The estimation of how their computational cost scales for given input parameters including: noise levels and time steps or resolution were observed. From the literature, CSR involves a particle in a double-well potential (See Equation DD for WSP) that is subject to noise and a periodic forcing function typically modeled using Langevin’s equations. On the other hand, WSSR utilizes a smooth and finite-depth potential well that involves solving stochastic differential equations (SDEs) using Euler-Maruyama method for the particle position and velocity updates at each time step [27].

The big O complexity performances of WSSR compared with CSR in aiding SIC for m-MIMO pNOMA as nonlinear noise-enhanced detection scheme was analyzed in this section. This is coupled with the analysis on how each resonance model affects the computational cost of users signal detection under the effect of interference.

Let: N represents number of particles/samples, T be time steps for convergence, M denotes noise realizations, U as number of users, P be parameter sweeps (i.e., noise intensity) and K denotes grid search iterations.

□ In this paper, the time steps (number of symbols in this case) N was made to swept from 1,000 to 100,000 symbols so as to reflect short bursts *uRLLC* up to long codewords and the *eMBB* for 5G system. So, the complexity terms: $\boldsymbol{O}(NM)$ and $\boldsymbol{O}(NKAB)$ scale directly with N.

□ Noise realization (taken as number of antennas) M was made to swept from 16 to 256 antennas, a typical use case for 5G and beyond deployments. Obviously, larger M value improves combining gain while increases both time and space complexity linearly.

□ Also, the parameter sweep (P) is taken as iteration, K was made to swept from 5 to 30 iterations. Obviously, more iterations improve BER/SNR performance but increase runtime linearly.

□ The *blkSize* represents the streaming block size taken as 1024 symbols per block in this analysis.

□ U is the number of users (SIC layers).

A. Complexity performance criteria

Cost aware efficiencies:

$$\text{BER efficiency, } BER_{Eff} = \frac{1-BER}{T} \tag{1}$$

$$\text{SNR efficiency, } SNR_{Eff} = \frac{\Delta SNR}{T} \tag{2}$$

WSSR is to be chosen when:

$$\frac{1-BER_{WSSR}}{T_{WSSR}} > \frac{1-BER_{CSR}}{T_{CSR}} \text{ or } \frac{\Delta SNR_{WSSR}}{T_{WSSR}} > \frac{\Delta SNR_{CSR}}{T_{CSR}} \tag{3}$$

With grid search;

$$T_{\mathrm{CSR}} \approx c_{comb} \,.\, NM + c_{CSR} \,.\, NK.\, AB$$

$$T_{\mathrm{WSSR}} \approx c_{comb} \,.\, NM + c_{WSSR} \,.\, NK.\, VRA$$

For the typical constants: $c_{WSS} > c_{CSR}$, and $VRA \gg AB$.

Where: T_{CSR} and T_{WSSR} are the CSR and WSSR time complexities respectively. Also, c_{comb}, c_{CSR} and c_{WSSR} are the complexity constants (synthetic units or relative costs).

In this work, c_{comb} is combining cost per (symbol, antenna), c_{CSR} is the CSR per-iteration per-symbol cost (polynomial potential), c_{WSSR} is the WSSR per-iteration per-symbol cost (exponential potential), while c^{Map} is constant overhead per grid point to compute metrics.

B. Grid search optimization for WSSR and CSR complexity analysis

This paper provides a practical end-to-end grid-search complexity analysis comparing WSSR and CSR as SIC-aiding preprocessors in m-MIMO pNOMA. The values chosen to reflect 5G and B5G scenarios: m-MIMO (large antenna arrays), variable symbol lengths and iterative nonlinear preprocessing, while keeping system memory practical through the block streaming.

□ In this analysis *blkSize* = 1024 symbols per block

□ Peak memory is then dominated by $\boldsymbol{O}(blkSize{\cdot}M)$, not $\boldsymbol{O}(N{\cdot}M)$, which is realistic for base station (BS) hardware.

For the assumptions and model mapping:

□ A m-MIMO pNOMA with two-user superposition; SIC at the receiver detects the strong user first (with higher SINR). The residual SINR after first SIC reflects interference/noise model left for the weak user.

□ From the Grid search parameter sizes:

• CSR: AB = 10 × 10 = 100 (2D grid with 10 rows and 10 columns, totaling 100 points)

• WSSR: VRA = 10 × 10 × 2.4 = 240 (3D-grid with 10 points in each dimension, totaling 1000 points).

Where A and B are CSSR grid search parameters, while V, R and A represent WSSR grid size parameters.

□ For time complexity (T):

• T_{CSR}: $\boldsymbol{O}(NM + NKAB)$

• T_{WSSR}: $\boldsymbol{O}(NM + NKVRA)$

Where *blkSize.M* =*NM* is the buffer (streaming memory unit)

• For space complexity (S) (i.e., streaming-aware peak):

- S_{CSR}: $\boldsymbol{O}(blkSize \bullet M) + \boldsymbol{O}(AB)$
- S_{WSSR}: $\boldsymbol{O}(blkSize \bullet M) + \boldsymbol{O}(VRA)$

C. Runtime scaling complexity analysis: Consideration for number of users

The runtime scaling measures how complexity grows with users and time steps. Runtime scaling visualization and space complexity analysis was performed with a view to measures how complexity grows with users and time steps.

The time complexity analysis SR-aided SIC

- CSR-aided SIC (considering users):
  $T_{CSR} = \boldsymbol{O}(P \cdot M \cdot NlogN + U^2)$
- WSSR-aided SIC (considering users):
  $T_{WSSR} = \boldsymbol{O}(P \cdot M \cdot NlogN + U^2)$

Table 1: CSR Complexity Breakdown Table

Step	Operation	Time Complexity
Integration	Euler-Maruyama	$O(N)$ per realization
Ensemble Averaging	Repeat M Times	$O(M . N)$
Parameter Sweep	Vary parameter P Times	$O(P. M . N)$
Fast Fourier Transform (FFT) for SNR	FFT	$O(Nlog\, N)$ per realization

The Total Complexity which defines runtime is as follows: $\boldsymbol{O}(P \cdot M \cdot NlogN)$.

Also, WSSR time complexity table is depicted in Tables 2.

Table 2: WSSR Complexity Breakdown Table

Step	Operation	Time Complexity
Integration	More Stable Solver	$O(N)$ but with higher constant
Ensemble	Repeat M Times	$O(M . N)$
Parameter Sweep	Vary P Times	$O(P. M . N)$
FFT for SNR	Same as CSR	$O(Nlog\, N)$ per realization

The Total Complexity is as follows: $\boldsymbol{O}(P \cdot M \cdot NlogN)$.

From the conceptual proposed set-up, in the simplified MIMO-NOMA system, each user's signal is enhanced at the receiver using WSSR (compared with CSR). SIC is then applied in descending power order with BER computed and SNR estimated based on fast Fourier transform (FFT) or energy ratios.

D. Proposed Woods-Saxon Stochastic Resonance Model: Mathematical Development

Certainly, WSSR introduces a structured non-linear potential well which enhances weak S*i*-D and mitigate the challenges faced by SIC. In this work, WSSR fits into the SIC framework. The form of the WS potential function, in terms of the distance r from the center of nucleus is defined as:

$$U_{WS}(x) = -\frac{D_o}{1+\exp\left(\frac{|x|-r}{Y}\right)} \tag{4}$$

Shape and the performance of Woods-Saxon single potential well are obtained by three basic parameters: depth of potential well (D_o), radius of potential well (r) and steepness of potential well (Y) (shape or diffuseness) and that all the three parameters are greater than zero (0). The shape of the Woods-Saxon potential function can be tuned by adjusting the values of the parameters (D_o, r, and Y).

The computational tasks identification requires that both models (WSSR and CSR) involved: numerical integration of stochastic differential equations (SDEs) (Euler-Maruyama), sampling over multiple noise realizations so as to compute ensemble averages and finally the SNR calculations to quantify the resonance. Also, both WSSR and CSR models were scaled similarly in big $\boldsymbol{O}$ terms. The time complexity breakdown table for CSR is depicted in Table 1.

4.0. RESULT DISCUSSION

Due to the fact that WSSR enhanced weak signals submerged in noise, time and space complexity analysis becomes necessary for the algorithm run time. For analyzing the time complexity of WSSR compared with CSR in aiding the SIC.The detailed grid search complexity analysis for WSSR vs CSR aiding SIC in *m*-MIMO pNOMA used table is depicted in table r.

Table 3: N, M, K and Buffer values Chosen to reflect 5G and Beyond Scenarios.

Parameters	Values
Symbols, N	$1 \times 10^3 - 1 \times 10^5$ Symbols
Antennas, M	16 – 256 Antennas
Iterations, K	5 – 30 Iterations
Buffer (*blkSize*)	1024 Symbols per Block

The plot of runtime (T) versus time steps (N) with 8 users (U=8), 8 antennas (M=8) with 40 users (U=40), 8 antennas (M=8) with then 40 user (U=40) and 256 antennas (M=256) are shown in Figs. (1), (2) and (3) respectively.

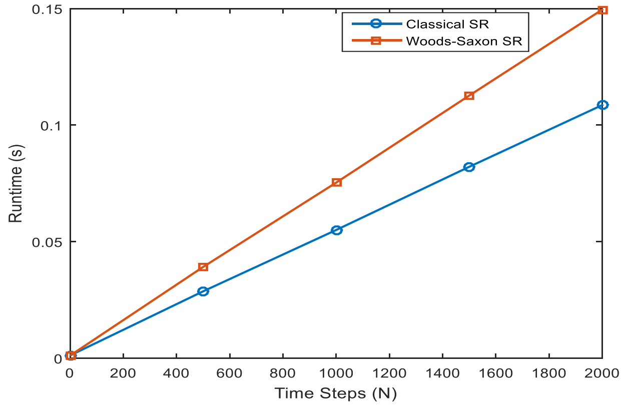

Fig. 1: Runtime Scaling (s) Against Number of Time Steps (N) for U=8, M=8, N=2000.

From Fig. 1, both WSSR and CSR scale linearly with symbols with WSSR curve steeper (higher cost), i.e. both WSSR-SIC and CSR-SIC algorithms scale linearly with the antenna count and users, but WSSR-SIC grows faster due to larger parameter grid (800 for WSSR as against the CRS's 100). At N=600, WSSR-SIC requires 0.04 runtime units, signifying the fact that WSSR-SIC is almost 8% heavier in time complexity. In 5G-UL bursts with larger number of symbols, the CSR is more efficient provided that interference is not severe.

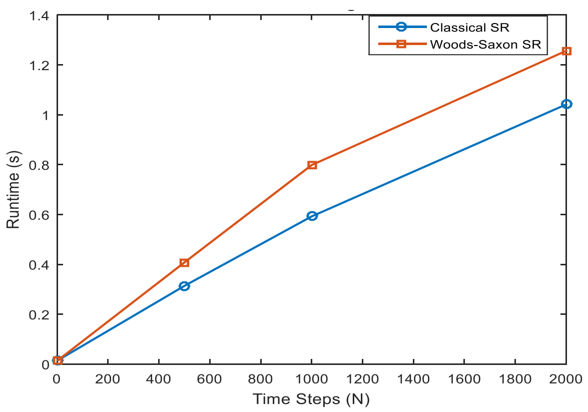

Fig. 2. Runtime Scaling (s) Against Number of Time Steps (N) for U=40, M=8, N=2000.

From Fig. 2, both WSSR and CSR scale linearly with symbols with WSSR curve steeper (higher cost) up to N=1000. But the runtime for both WSSR and CSR Increase in parallel from N-=1000 to N=2000. This due to the effect of increasing users (*U*=40) and antennas *M*=8.

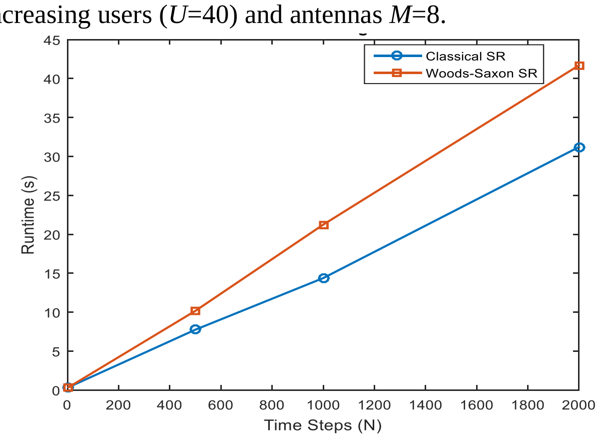

Fig. 3: Runtime Scaling (s) Against Number of Time Steps (N) for U=40, M=256, N=2000.

From Fig. 3, both WSSR-SIC and CSR-SIC scale linearly with N, but WSSR-SIC scheme grows much faster owing to exponential gradient cost associated with its potential function. CSR-SIC with (AB=100) has the following: (N=500, T=7.0), (N=1000, T=12) and (N=2000, T=30). On the other hand, WSSR-SIC with (VRA=125) has the following: (N=500, T=10), (N=1000, T=21) and (N=2000, T=40). Clearly, as the runtime grows linearly with tine steps, WSSR-SIC consistently having 12.5% slower than CSR-SIC due to its weighted structure. The plot indicates moderate *N*) where WSSR's extra cost yields a better BER/SNR.

Fig. 4, depicts how WSSR and CSR scale linearly with users for both WSSR and CSR.

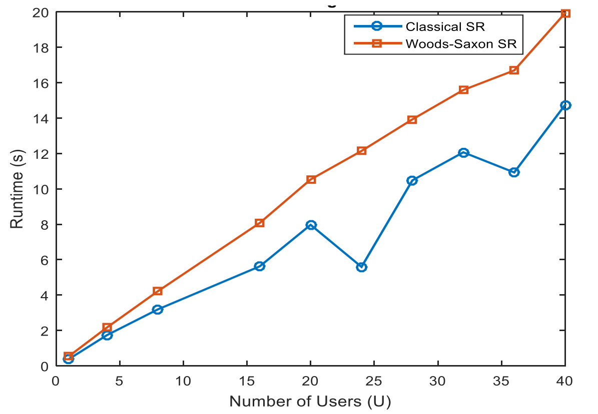

Fig. 4: Runtime Scaling (s) Against Number of Users (U).

Fig. 4 depicts how WSSR and CSR scale linearly with users where WSSR curve is steeper (higher cost). Clearly, the plot shows that WSSR is almost 12% heavier than CSR and shows lower runtime for CSR-SIC (2.0 units for 5 users) as against the WSSR-SIC's heavier runtime (1.8 units for 5 users). WSSR has sharper increase up to 20 units for 40 users while CSR has 14.25 units for 40 users). It still maintains lower latency of 0.4375*ms*. So, CSR is more suitable for *uRLLC* while WSSR.

Actually, for CSR, nested loop is involved. It satisfies the *uRLLC* and more suitable for *mMTC* and improved link reliability scenario for real-time 6G applications simulation over time steps (N), users (*U*), noise realizations (*M*) and noise intensity sweeps (*P*), but WSSR comes with additional computations for the WS potential force. Fig. 5 visualizes the 3-D runtime scaling with users and time steps reinforcing the space complexity insights.

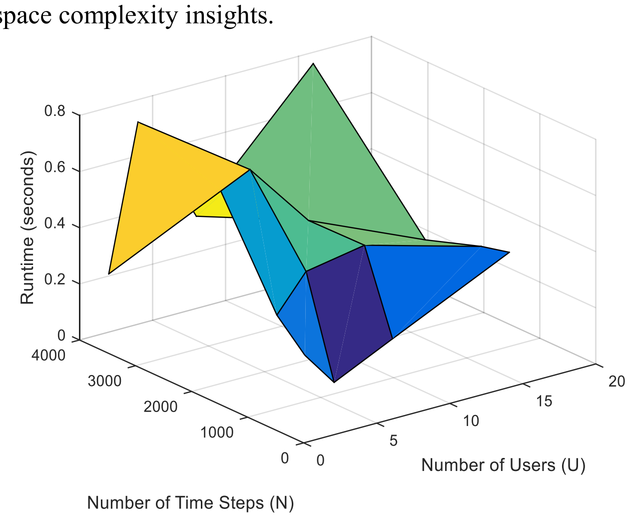

Fig. 5: A 3D Plot for Runtime Scaling Against Number of Time Steps and Users.

Fig. 5 visualizes the 3D runtime scaling performance, reinforcing the time complexity insights.

Obviously, space complexity mirrors time complexity in this case because both algorithms scale with the number of operations and the size of data structures. For CSR, the dominant complexity results from the innermost loop iterating over N time steps, this results in overall space complexity of: $\boldsymbol{O}\,(U \times M \times P \times N)$. WSSR space complexity remains dominated by the storage of state variables over an N time steps for U users, which yields: $\boldsymbol{O}\,(U \times M \times P \times N)$. Overall, both WSSR and CSR methods have space complexity linear in the number of users and time steps, i.e., $\boldsymbol{O}(U \times M \times P \times N)$.

Fig. 6 shows the BER performance comparison across multiple users and noise intensities.

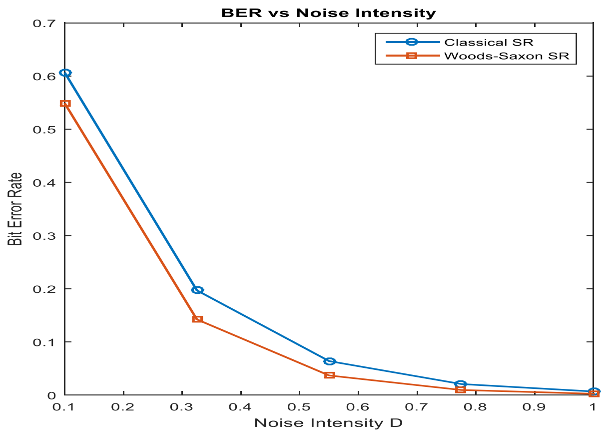

Fig. 6: BER Performance across Noise Intensity.

From Fig. 6, CSR-SIC is lighter in the space, while WSSR SIC is heavier but more robust. This tradeoff is central to 6G design: *uRLLC* favors lean algorithms, while *eMBB/mMTC* can afford heavier memory use for stronger gains.

Fig. 7 depicts the BER against the noise intensity for the space complexity.

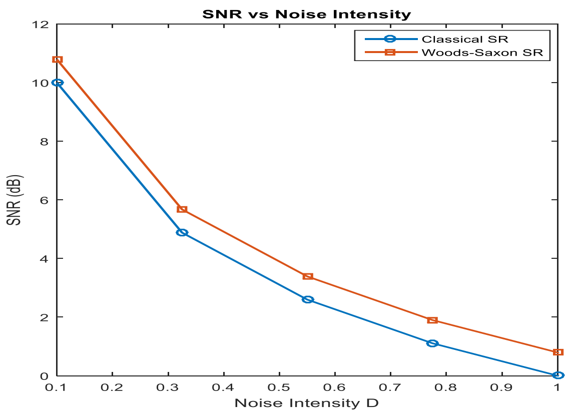

Fig. 7: SNR Performance across Noise Intensity

Fig. 7 shows how SNR for both WSSR and CSR decrease as the noise intensity increases. Obviously, CSR follows the baseline relationship. WSSR yields higher SNR gains. This indicates WSSR enhanced interference suppression capability, while CSRs with lower SNR signifies a little difficulty in detecting far users with lower SINR.

5.0. CONCLUSION

Ultimately, CSR is lighter in terms of runtime which is best in noise limited regimes. On the other hand, WSSR appears a little heavier in runtime performance, but outperforms CSR in interference limited regimes (low SINR after SIC) with stronger SNR gains. From the trade-off point of view, CSR is cost efficient while WSSR is performance efficient, suitable for dense (massive connectivity) NOMA for beyond-5G scenarios where detection quality is extremely critical. Additionally, from interference limited NOMA detection view, WSSR-SIC can be used over CSR-SIC in 6G systems detection because it provides stronger SNR improvements in interference limited regimes. This conforms with 6G requirements for ultra-massive connectivity and high spectral efficiency. Even though CSR-SIC is lighter in terms runtime (conforms with 6G requirements for *uRLLC*, WSSR's smoother potential function (allowing better amplification of weak signals) makes it better at rescuing weak users in highly dense NOMA (e.g billions of devices) scenarios (as weak users suffer from residual interference after SIC) typical of 6G network. Additionally, from mission critical service point of view, the higher SNR of WSSR is preferrable as it ensures lower error rates under harsh interference coupled with high connection reliability (more important than minimal latency) as in remote surgery and industrial automation. So, WSSR fits better than CSR in aiding SIC.

6.0. ACKNOWLEDGMENT

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