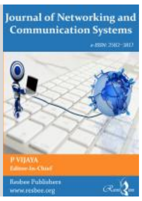
Resbee Publishers

Journal of Networking and Communication Systems

Received 6 December, Revised 19 February, Accepted 13 March



Hybrid Grey Wolf Optimization and Crow Search Algorithm for Power allocation in MIMO-NOMA systems

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Abstract: For 5G communication systems, Non-Orthogonal Multiple Access (NOMA) operates as the shows potential multiple access technologies, and the ability to enhance the system performance. It can be extended with MIMO systems using multi-users to make substantial gains. The Energy Efficiency (EE) of MIMO-NOMA systems require to be enhanced, for that the optimization algorithm called Grey Wolf and Crow Search algorithm for Power allocation (GWCSPA) method is proposed. The GWCS optimization approach is attained from the combination of Grey Wolf Optimization (GWO) and Crow Search Algorithm (CSA) and the proposed GWCSPA techniques schedules user based on EE and Spectral Efficiency (SE) so that it presents an effectual platform to present energy effectual power allocation. The scheduling is carried out exploiting the GWCSPA method which prioritizes users in the best manner based on the objective function. The simulation is carried out by exploiting the estimated measures, like Bit Error Rate (BER), attainable rate, spectral power, and energy. The efficiency of the proposed power allocation algorithm is shown during lesser BER and superior spectral power, achievable rate, and energy correspondingly.

Keywords: NOMA; 5G; MIMO; Energy Efficiency; Optimization Method

Nomenclature

Abbreviations	Descriptions
BER	Bit error ratio
5G	Fifth-generation
SWIPT	Simultaneous Wireless Information and Power Transfer
SE	Spectral Efficiency
MIMO	Multiple Input Multiple Output
D2D	Direct to Direct
WSN	Wireless Sensor Networks
EE	Energy Efficiency
SIC	Successive Interference Cancellation
CUs	Cellular Users
AP	Access Point
OMA	Orthogonal Multiple Access
WSEE	Weighted Sum Energy Efficiency
CSI	Channel State Information
MOP	Multi-Objective Optimization Problem
PEQRD-*M*	Path Elimination QR Decomposition-M
ULD	User Location Distribution
AWGN	Additive White Gaussian Noise Vector
HetNets	Heterogeneous Networks
SUEs	Small Cell Users
CUs	Cellular Users
QoS	Quality of Service
LR-aided DFE	Lattice Reduction-aided Decision Feedback Equalizer
NOMA	Non-orthogonal multiple access
SOP	Single-objective Optimization Problem
WSEE	Weighted Sum Energy Efficiency
BS	Base Station

https://doi.org/10.46253/jnacs.v3i2.a2

1. Introduction

Nowadays wireless communication systems, MIMO-OFDM are a necessary system for high spectral and energy effectiveness. The MIMO-OFDM system raises channel ability with no extra frequency and power resources in prosperous scattering wireless channel environments. In MIMO-OFDM systems, amongst different problems, precise separation of all transmits signals is an important issue at receiver as received signals are a combination model of numerous distorted transmit signals using fading environments.

By the speedy expansion of wireless communication, necessities for spectrum efficiency and data transmission rate are incessantly rising. The NOMA presents a capable spectrum competent solution for promising 5G wireless networks. The downlink NOMA is extensively reported from the viewpoint of information presumption, which is motivated by the development of various research studies. In NOMA, SIC is a typically exploited system to remove co-channel interference reasoned by other users to the preferred signal. In the meantime, the benefits of NOMA was extensively inspected in diverse cases, such as full-duplex wireless communications, wireless broadcast channels, and wireless physical layer security applications. In contrast with the OMA method which only serves one user by means of similar/frequency/time code, NOMA makes sure, which users through weak channels attain preferred target throughput whilst still serving users through stronger channels.

In recent times, there has been an inclination towards Energy Efficient design wireless networks owing to both economic and environmental apprehensions [13][14] [15]. Communication networks were usually considered by means of the endeavor of optimizing throughput, data-rate, latency, and so on [16] [17]. In the past decade, energy effectiveness has to turn out to be a novel principal parameter in the model of communication systems. SWIPT-based cooperative NOMA transmission approach is proposed to manage the energy shortage problem. In recent times, energy competent D2D communication underlying NOMA-based cellular networks is examined. In the model, both CUs and D2D users produce energy from similar AP in downlink and employ it for transmission in uplink. An iterative method to maximize D2D user's energy effectiveness through QoS constraints on CUs is proposed by various researchers. Nevertheless, the EE parameter cannot present any information regarding the individual energy effectiveness of participating links. To overcome this, a substitute form of advantage of WSEE that is described as a summation of links' weighted energy efficiencies might be exploited.

The most important contribution of this work is to propose and develops an energy effectual power allocation technique that works in MIMO–NOMA systems in an effectual way. In this paper, the optimal scheduling of the power allocation principle is shown by exploiting the GWCSPA model. The most important motive for the procedure of GWO in the proposed technique is because of its ease and improved effectiveness. Additionally, it can resolve diverse issues in the area of industrial electronics, WSN, and power systems. It aspires in attaining solutions to issues in space of issue. The scheduling is performed based on the GWCSPA which schedules users based on the objective model in the best manner. It schedules users through SE and EE to present an effectual standard for power allocation.

2. Literature Review

In 2020, Jae-Hyun Ro et al [1], proposed the method which exploits the suboptimal PEQRD approach, and hybrid LR-aided DFE and PEQRD adaptively exploiting channel state. The proposed model chooses the signal recognition model adaptively by computing circumstance number of the wireless channel. The proposed model exploits PEQRD while channel state was reduced whereas its circumstance number was maximal, and reversely exploits the hybrid LR-aided DFE and PEQRD while channel state was encouraging whereas its circumstance number was low.

In 2019, Mahdi Eskandari et al [2], considered the Energy Efficiency maximization and the power allocation issue in point-to-point, MIMO spatial multiplexing models. In contrast with the existing energy-efficient optimization methods which address power loading in ideal CSI supposition, energy-efficient equal power allocation was considered that needs restricted feedback at the transmitter. Additionally, lesser bound expression was derived for optimal EE regarding system parameters like channel circumstances and circuit power.

In 2017, Mohammed A. Abuibaid and Sultan Aldırmaz Colak [3], evaluated the effect of ULD difference on the energy effectiveness of a load-adaptive enormous MIMO system. Subsequently, it recommends a dynamic resource allocation approach that uses the benefits of ULD differences to accomplish an additional energy-effectual design. Every day ULD difference was designed by dividing the cell into a definite number of coverage areas and conveying diverse user densities to everyone for every hour.

In 2018, Shuang Zhang et al [4], examines the tradeoff between EE and SE in a downlink NOMA-based HetNets. The tradeoff issue was devised as a MOP. In the limitations of the maximum transmit power of SUEs and the least number of rate requirements; both SE and EE were increased. To construct MOP dutiful, a weighted sum technique was exploited to convert it into an SOP that set up to dynamically tune weight factor for network providers to acclimatize to diverse SE and EE design requirements.

In 2019, Keming Gan et al [5], proposed the energy utilization minimization issue to receive the smallest number necessary energy utilization for requested effectual transmission throughput performance. In this analysis shows a few imminent into energy competent NOMA-based short packet transmission model. It was revealed that choosing a user that was nearer the Access Point with superior effectual transmission throughput obligation was additional suggested realizing energy competent NOMA based short packet downlink transmission system.

In 2019, Sindhu P et al [6], investigated the issue of WSEE maximization of D2D groups with underlain NOMA cellular networks. Transmitters in the D2D groups can communicate using multiple D2D receivers in comparable spectral sub-band using NOMA protocol in the new network model. In the same way, BS as well communicates with multiple CUs using the NOMA approach. This structure was appropriate for energy-crunch devices, whereas nodes can have diverse energy effectiveness needs. Furthermore, to convene QoS, the constraints rate was compulsory on all receivers in the network.

3. Problem Formulation and System Model

In this section, the problem formulation and the system model for the power allocation models as described.

i) System model: Let a downlink multi-user MIMO system, by means of Base Station linked by means of A indicates the number of antennas that transmit information to a huge number of receivers linked by means of H the number of antennas. Consider A as the total number of users, and NOMA, is used to all users. The BS channel matrix for j^{th} user $[j \in \{1,...,A\}]$ is indicated as $M_j \in C^{H\times A}$ which is deliberated as identically distributed and quasi-static independent. The detection vector for the j^{th} user is indicated as $d_j \in C^{H\times 1}$ and the precoding matrix used by Base Station is indicated as $W \in C^{A\times A}$. The conditions to be fulfilled are, (a) $W = I_A$, whereas I_A indicates the identity matrix $A \times A$. (b) $|d_j|^2 = 1$, and $d_j^M M_j w_g = 0$, for all $g \neq j$, about w_g being g^{th} column of W. To create these circumstances possible, the number of antennas has to assure the state, $H \geq A$. It has to be stated that only scalar value $\left|d_j^M M_j w_g\right|^2$ is required to be subjected back from j^{th} user to the Base Station. For the MIMO-NOMA model are deliberated, intended signals are multiplexed using Base Station for every user simultaneously frequency and resource. Hence, from the BS the equal transmitted signals received are indicated in eq. (1).

$$t = Wr \tag{1}$$

In eq. (1), r indicates the information-bearing vector, $r \in C^A$. Likewise, the observed signal at user j is indicated in eq. (2).

$$n_j = M_j W r + l_j \tag{2}$$

In eq. (2), l_j indicates the identically distributed and independent AWGN, $V(0,\beta^2 I)$. On eq. (2), using the application for the detection vector, the relation attained in eq. (3).

$$d_j^M n_j = d_j^M M_j w_j \sqrt{W_{max}\alpha_j r_j} + \sum_{g=1,g\neq j}^{A} d_j^M M_j w_g r_g + d_j^M l_j \tag{3}$$

In eq. (3), r_g indicates the g^{th} row of r, and the phrase $\sum_{g=1,g\neq j}^{A} d_j^M M_j w_g r_g$ denotes the incidence of interference. Because of the constraint that is in attendance in recognition vector, $d_j^M M_j w_g$, for any $g \neq j$, the aforesaid formulation can be minimized in eq. (4).

$$d_j^M n_j = d_j^M M_j w_j \sqrt{W_{max}\alpha_j r_j} + d_j^M l_j \tag{4}$$

The effectual channel gain, without loss of generalization, is stated as [7]. By all users, the SIC is transmitted for the elimination of interference produced by users by means of poor channel increases at the receiver side. Hence, the data rate obtained at j^{th} user is indicated in eq. (5).

$$K_{jq} = \log_2\left(1 + \frac{\eta \alpha_{jq}\left|d_{jq}^{M} M_{jq} w_j\right|^2}{1 + \eta \sum_{q=1}^{D} \alpha_{jq}\left|d_{jq}^{M} M_{jq} w_j\right|^2}\right) \tag{5}$$

In eq. (5), q states the transmitter and $\eta = \frac{W_{max}}{\beta}$ states the transmit signal to noise ratio.

ii) Objective function: The flexible transmit power W_k and the fixed circuit power utilization W_e mutually comprises the total power utilization. The phrase W_k is indicated in eq. (6).

$$W_k = W_{max} \sum_{j=1}^{A} \alpha_j \tag{6}$$

whereas, α_j indicates the signal and the power allocation coefficient for j^{th} user. For the system, the EE is indicated in eq. (7).

$$\delta_{EE} = \frac{K_{sum}}{W_e + W_k} \tag{7}$$

whereas, K_{sum} indicates the attainable sum rate, and it is indicated in eq. (8).

$$K_{sum} = \sum_{j=1}^{A} K_j \tag{8}$$

The EE system has to be exploited because of the reality that every user comprises the least number of pre-defined rates. Hence, this issue can be devised in eq. (9).

$$\max_{\alpha_{jq}} \delta_{EE} \tag{9}$$

$$\text{So that, } K_j \geq K_j^{min}, \quad j \in \{1, \ldots, A\} \tag{10}$$

$$\sum_{j=1}^{A} \alpha_j \leq 1 \tag{11}$$

whereas, eq. (10) denotes the least rate obligation of the user, and eq. (11) denotes transmit power constraint. In eq. (9) the objective model is in fractional form, and therefore it represents a non-convex issue. Therefore, the attainment of the optimal solution is non-trivial in this scenario, and therefore the issue is required to be resolved. To resolving this issue, the maximization of the SE issue is required to be indicated for the equivalent energy efficiency. Based on eq. (8), for EE maximization, equivalent SE value is needed to be increased in any value of presented power. To overwhelm this principle of power allocation, the proposed technique is modelled about the deliberation of user-dependent and channel gain based power W_a in the Energy efficiency of the system.

4. Power Allocation using Proposed GWCS Approach

The power allocation model is the most important aspire is to make most of the energy efficiency of the system during the proposed optimization method, GWCSPA. For MIMO-NOMA systems the optimal power allocation is done probably with the proposed GWCSPA technique that is attained from the combination of GWO and CSA. The power scheduling is performed exploiting the proposed GWCSPA method so that to allocates power through maximum effectiveness to users in an effectual method. The NOMA while employed utilizing MIMO creates a substantial increase in energy effectual power allocation to users. The architecture model of the proposed method in MIMO-NOMA-based systems is demonstrated in fig. 1.

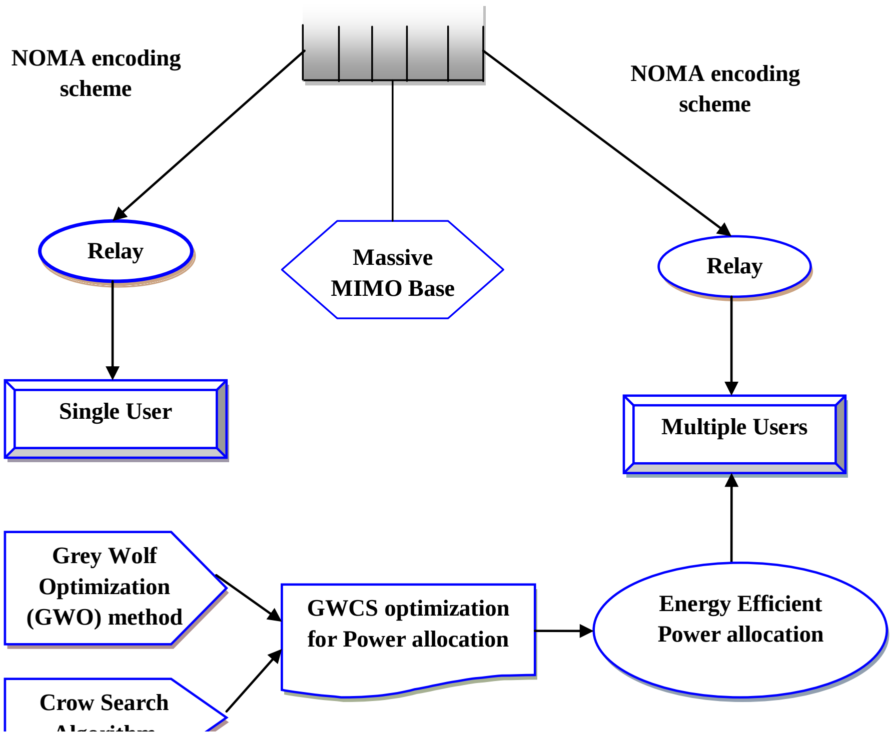

Fig. 1. *Block diagram of a proposed method for power allocation*

a) Fitness calculation: In the optimal allocation of users a system to be effectual based on the power with maximum Energy Efficiency, the system fitness has to be maximum. The maximum fitness measure closes the effectual user's allocation that is done in the best manner. In [8] the objective model is in fractional form, which creates issue non-convex, and hence the progress of optimal solution, is serious. To resolve this issue, user-dependent, and channel gain based power, W_a is comprised of fitness estimation of a system that maximizes the Energy Efficiency of the system, and the aforesaid criterion, is devised as in eq. (9), where EE term δ_{EE} is indicated in eq. (12).

$$\delta_{EE} = \frac{Q_{mean}}{W_k + W_e + W_a} \tag{12}$$

whereas, W_a indicates user-dependent and channel gain based power. The phrase W_k is indicated in eq. (13).

$$W_k = W_{max} \sum_{j=1}^{A} \sum_{q=1}^{D} \alpha_{jq} \tag{13}$$

In eq. (13), α_{jq} indicates signal and power allocation co-efficient for j^{th} user.

$$Q_{mean} = \sum_{j=1}^{A} \sum_{q=1}^{D} K_{j,q} \tag{14}$$

In eq. (5) the phrase $K_{j,q}$ is indicated. The relative between electrical power chosen to the user j and $j+1$ is denoted in eq. (15).

$$W_a = \sigma \bullet \left(\frac{q_{1,j+1} + q_{2,k+1}}{q_{1,1} + q_{2,1}} \right) W_{a,j+1} + (1-\sigma) \left(\frac{q_{1,1} + q_{2,1} - q_{1,j+1} - q_{2,k+1}}{q_{1,1} + q_{2,1}} \right) W_{a,j+1} \tag{15}$$

whereas, $\sigma = h(q_1, q_2)$ and $h(\bullet)$ indicates the correlation factor.

4.1 Enhanced position updation model

In traditional GWO, the leading topic of apprehension is that all search agents are updated based on α (optimal search agent), β (optimal best search agent) and γ (optimal search agent) incomplete optimization procedure as stated in Eq. (16), it denotes the updating position of the grey wolf.

$$\vec{Y}(t+1)=\frac{\left(\vec{Y}_1+\vec{Y}_2+\vec{Y}_3\right)}{3} \tag{16}$$

On the whole, this location updating method tends to early convergence since the search agents were not allowable to discover search space competently. In addition, a similar optimization procedure as stated in Eq. (16) presents restricted exploitation ability in afterward phases of optimization that tends to sluggish convergence.

Consequently, to conquer the aforesaid limits of the traditional GWO, it is merged with CSA to attain an additional appropriate balance among exploration and exploitation. Particularly, CSA integrates a control parameter fl in its location updation formulation as stated in Eq. (17) that permits search agents to determine the magnitude of step movement to other search agents. This parameter plays an important function in obtaining global optima as the great value of fl tends to global exploration when a diminutive fl value outcome to local exploitation.

$$y^{i+1,t+1}=y^{i,t}+r_i\times fl^{i,t}\times\left(m^{j,t}-y^{i,t}\right) \tag{17}$$

Where, the new location of crow is computed as $y^{i,t}$, r indicates an arbitrary number, t indicates the iteration number, m^j indicates flock crow.

As aforesaid, GWO has high-quality exploitation capability other than poor exploration ability, so in the proposed GWO-CSA, a higher value fl is used to use CSA's outstanding exploration excellence as stated in Eq. (10). It refers, the proposed technique can efficiently exploit the two approaches benefits and thus, it can attain strong universal applicability.

In the proposed method, rather than updating from α, β and γ, a search agent is permitted to update its location only exploiting α and β as stated in Eq. (18).

$$\vec{Y}(t+1)=\vec{Y}_1+f1\times rn\times\left(\left(\vec{Y}_1-\vec{Y}\right)+\left(\vec{Y}_2-\vec{Y}\right)\right)/2 \tag{18}$$

One more implication calculation, to preserve population diversity, not all individuals are updated by α and β updating direction in population, other than by α only in the proposed method. This represents a shrinking approach that sets up the proposed method to get away from the local optimum.

$$\vec{Y}(t+1)=\vec{Y}_1+f1\times rn\times\left(\vec{Y}_1-\vec{Y}\right) \tag{19}$$

4.2 Adaptive Balance Probability Scheme

Even though the proposed method has the outstanding abilities of exploitation and exploration of GWO and CSA, on the other hand, an appropriate balance of these two stages is obliged to attain superior performance. In a perfect state, a technique has to achieve the capability to discover an enormous search space in the untimely optimization phase to evade early convergence whereas using miniature areas in the afterward optimization stages to competently process the concluding solutions. It indicates, to achieve the necessary exploitation-exploration, a fixed balance probability among Eq. (18) and Eq. (19) is not constructive. Hence, in this paper, an adaptive balance probability is proposed that permits the proposed method to attain acceleration all through premature steps of optimization procedure wherein the afterward phases of optimization show potential solutions will have a maximum probability to be used. The adaptive balance probability (ρ) is calculated as below:

$$\rho=1-\left(1.01\times t^3/max\_itr\right) \tag{20}$$

Whereas, t indicates current iteration and max_itr indicates a maximum number of iterations.

4.3 Nonlinear Control Parameter (α) scheme

As stated in the preceding segment that parameter A states an important role in balancing exploration and the exploitation of a search agent. In particular, the parameter A is seriously based on $\vec{a}$ that eventually controls the search process direction. A superior $\vec{a}$ value makes easy exploration stage, while a lesser value makes easy exploitation. It represents an appropriate chosen $\vec{a}$ can present an erect balance of exploitation and exploration that can cause better performance. In traditional GWO, the value of $\vec{a}$ is linearly minimized from 2 to 0 exploiting Eq. (21). The component $\vec{a}$ value minimizes from 2 to 0 throughout iterations.

$$\vec{A}=2\vec{a}\cdot\vec{r}_1-\vec{a} \tag{21}$$

So far, numerous method of updating control parameter $\vec{a}$ was presented, for instance [11] and [12]. Consequently, it can be seen that better performance can be attained if the values of the control parameter $\vec{a}$ are chosen by exploiting a nonlinearly minimizing technique, rather than a linearly decreasing technique. Using the aforesaid information, an enhanced scheme, as exhibited in Eq. (22), is used to produce the control parameter values $\vec{a}$ throughout the optimization procedure. This approach permits the adopted method to efficiently discover the search space in contrast with conventional GWO.

$$a = 2 - (\cos(rn(\ )) \times 1 / max - itr) \tag{22}$$

The pseudo code of the proposed method is stated in Algorithm 1.

Algorithm 1: Psuedo code of the proposed algorithm

Initialize grey wolves population $Y_i\,(i = 1,2,....,n)$

Initialize parameters a, A and C

Compute fitness of each Search_agent

Y_α = Best search_agent/wolf

Y_β = Second best search_agent/wolf

while ($t <$ Max-iterations)

  for each search_agent

    if p >rand

      Update the position of current search_agent using Eq.(10)

      else

      Update the position of current search_agent using Eq.(19)

    End if

  end for

By Eq. (21)**update** the value of p

By Eq. (22)**update** the value of a

Update parameters A, C

Compute the fitness of all

Update Y_α , Y_β

t=t+1

end while

return Y_α

5. Result and Discussion

5.1 Experimental Procedure

In this section, the analysis of the proposed technique of power allocation and its efficiency in power allocation exploiting performance analysis was discussed. Here, the proposed method was analyzed exploiting the measures, namely energy achievable rate, spectral power, and BER.

5.2 Performance Analysis

Table 1 summarizes performance analysis of techniques for power allocation, like Grey Wolf Optimization (GWO), Artificial Bee Colony (ABC), and Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and the proposed GWOCS based on estimation measures that are the achievable rate, spectral power, BER, and energy for 64 numbers of transmitting antennas through deviation in SNR. Table 2 exhibits the analysis of techniques for 128 numbers of transmitting antennas by means of variation in SNR. Table 3 exhibits the analysis of the techniques for variation in the number of users. From the overall analysis, it is obvious that achievable rate, spectral power, and energy rise with a rise in the number of users, and BER minimizes using raises in the number of users. Thus, achievable rate, spectral power, and energy are maximum, and the BER is least for the proposed technique as evaluated with the existing models.

***Table** 1: Analysis of the proposed and conventional models for 64 transmitting antennas*

Algorithm	BER	Energy	Achievable rate	Spectral power
GWO	0.0006	7.9727	37.7722	79.7723
ABC	0.0006	13.9176	94.9949	117.995
GA	0.0006	16.7737	96.9099	127.91
PSO	0.0006	17.6164	97.697	129.697
Proposed method	0.0004	17.942	99.9679	131.968

***Table 2:** Analysis of the proposed and conventional models for 128 transmitting antennas*

Algorithm	BER	Energy	Achievable rate	Spectral power
GWO	0.00059	7.5743	91.742	7.5743
ABC	0.00057	15.073	92.7539	15.073
GA	0.00055	19.5555	94.0013	19.5555
PSO	0.00055	19.5953	95.4359	19.5953
Proposed method	0.00045	19.5593	94.029	19.5593

Table 3: *Analysis of the proposed and existing models for variation in number of users*

Algorithms	Achievable rate	Spectral power	Energy	BER
GWO	1.9179	2.1947	0.2799	0.0007
ABC	5.2599	17.4104	4.474	0.00057
GA	5.2907	17.4104	7.4559	0.00057
PSO	5.2907	17.4107	9.4477	0.00052
Proposed method	**5.4959**	**17.4107**	**9.7029**	**0.00051**

6. Conclusion

In this work, a model for optimal power allocation with layered transmission modeled was proposed for MIMO- NOMA systems. The NOMA, while extending using MIMO systems were exploited to create considerable improvements in the attendance of multiple users. The EE power allocations to users were done probably using the MIMO-NOMA systems exploiting the proposed optimization approach. The power scheduling was performed exploiting the proposed GWCSPA approach so that to allocate power to users in an effectual way. The simulation of the proposed GWCSPA technique was estimated to exploit 4 estimation measures, namely achievable rate, spectral power, BER, and energy. The proposed GWCSPA approach on evaluation through the existing technique was able to produce superior outcomes of lesser BER, and maximum spectral power, achievable rate, and energy correspondingly. This reveals the efficiency of the proposed GWCSPA approach in optimal power allocation.

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