Journal of Engineering Sciences
Vol 13, Issue 03, MARCH /2022
ISSN NO:0377-9254

# GQSM - NOMA and Its Application to Vehicular Networks with GWO optimizing mechanism

P. THEJASWINI[1], K. SRINIVASA RAO [2]
1 PG scholar, DECS, Department of ECE, JNTUA.
2 Assistant Professor, Department of ECE, JNTUA.

**Abstract:** Due to the characteristic of transmitting multiplexed signals in superposed mode over the same spectrum, non-orthogonal multiple access (NOMA) technology is deemed as a promising way to improve spectral efficiency in fifth generation (5G) networks. In this paper, we develop a NOMA with generalized quadrature spatial modulation (GQSM) based cooperative system based on the two-path successive relaying concept, in which the data at the source node is divided into two parallel parts and is transmitted to the destination in superposed mode via the assistance of two decode-and-forward (DF) relays. On the condition that the transmit power of the individual nodes and the entire system are all constrained, the maximization of achievable rate is formulated as an optimization problem. Following the guidelines of grey wolf optimization (GWO), the dual decomposition method is adopted to obtain the closed-form expressions of the optimal power allocation. Moreover, to balance the achievable rate between two superposed signals, which is equivalent to minimizing the required spectrum bandwidth, a power allocation scheme between the superposed signals is proposed. The results demonstrate that the proposed NOMA-GQSM-GWO resulted in superior bit error rate (BER) rate performance as compared to conventional methods.

**Keywords:** Vehicular communications, spatial modulation, index modulation, non-orthogonal multiple access, bit error rate.

## 1. Introduction

NOMA techniques will be a key technology of fifth generation (5G) cellular networks [1]. Current orthogonal multiple access (OMA) systems result in low spectrum efficiency, when network resources are assigned to mobile users with poor channel conditions. However, if we consider the power domain, NOMA systems can deliver high spectrum efficiency even with poor channel conditions. In the NOMA scheme, the mobile users may share the same frequency, time, and code, yet they should be differentiated in power levels [2]. To this end, the fundamental concept of NOMA scheme is the use of successive interference cancellation (SIC) technique by the mobile users' receivers with rich channel conditions, to significantly reduce the interference level of mobile users with poor channel conditions. As a result, SIC technique cancels the intra- cell or cluster interference on mobile users' receivers [3]. The user association problem is becoming more challenging in NOMA networks, as some unique power levels of traditional OMA networks, such as co-channel interferences, require re-design. The authors in [4] formulate the user association problem in NOMA networks by grouping the users into orthogonal clusters and associating them different resource blocks using a game theoretic approach. However, game theoretic approaches which are commonly used in user association problems have limitations and work under certain assumptions. On the other hand, evolutionary algorithms (EAs) are global optimizers that work well regardless of the optimization problem in hand. We describe the problem formulation with the network sum rate utility function. A parameter that introduces more complexity to the problem is power control. Usually, as in [4] the power coefficients are considered constant for all network. In our case we find the suitable power coefficients for every NOMA user. Evolutionary algorithms inspired by nature are suitable techniques for solving this problem. In this paper, we apply the GWO [5], which was

recently introduced as a population-based algorithm that mimics grey wolf hunting behavior. Additionally, a comparative study between the GWO obtained results and the legacy particle swarm optimizer (PSO) [6] is performed. The derived results indicate that GWO algorithm outperforms the PSO algorithm in general. Moreover, we conclude that NOMA schemes with power control can be successfully utilized.

## 2. Literature survey

For NOMA-based relaying systems, when relays operate in half-duplex decode-and-forward (DF) mode, many system models and resource allocation schemes already have been proposed. In [7], for a system in which NOMA technique is applied in both direct and relay transmissions, analytical expressions for outage probability and ergodic sum capacity are derived. In [8], a NOMA-based relaying system is proposed to improve spectral efficiency as well as its achievable capacity is investigated. A buffer-aided NOMA relaying system is proposed in [9], its performance is investigated, and an adaptive transmission scheme for such system is proposed in [10]. For a system with slowly faded NOMA-equipped multiple-relay channels, the benefit of joint network channel coding and decoding is studied in [11]. In [12], an analytical framework for a NOMA-based relaying system is developed, and then, its performance over Rician fading channels is studied. In [13], the impact of relay selection on the performance of cooperative NOMA is studied, and then, a two-stage relay selection strategy is proposed. In [14], a novel signal detection scheme for a simple NOMA-based relaying system is proposed, and then, the ergodic sum rate and outage performance of the system are investigated. In [15], based on Alamouti space-time block-coded NOMA technique, a two-phase cooperative DF relaying scheme is proposed. In [16], a dual-hop cooperative relaying scheme using NOMA is proposed, where two sources communicate with their corresponding destinations in parallel over the same channel via a common relay. To maximize the throughput of a NOMA-equipped wireless network with multiple relays, in [17], a novel approach to dynamically select an optimal relay mode and optimal transmit power is proposed.

On the other hand, when relays operate in half-duplex DF (DF) mode, many schemes have been proposed to improve the performance of NOMA-based relaying systems. In [18], a NOMA-based multi-antenna-equipped relaying network is designed, and then, its outage performance is analyzed. When a base station communicates with multiple mobile users simultaneously through the help of a relay over Nakagami-m fading channels, the overall performance is analyzed in [19]. For a NOMA-equipped single-cell relay network, where an OFDM-based DF relay allocates its spectrum and power resources to source-destination (SD) pairs, a many-to-many two-sided SD pair-subchannel matching algorithm is proposed in [20]. In [21], a joint power allocation and relay beamforming design problem is investigated, and then, an alternating optimization-based algorithm is proposed to maximize the achievable rate. In [22], the outage performance of a cooperative NOMA-equipped relay system is studied, and then, an accurate closed-form approximation of the outage probability is derived. In [23], when multiple users transmit messages to two destinations under the help of multiple DF relays, an optimal relay selection criterion is proposed to improve outage performance, and closed-form analytical expressions for the outage probability are derived. In [24], a relay-aided NOMA technique is proposed for uplink cellular networks, where the cooperative relay transmission is used to accommodate more than one user per orthogonal resource block in the context of interference-limited scenarios.

To enhance system flexibility, in [25], for NOMA-equipped cooperative networks with both the DF and AF relaying protocols, where one base station communicates with two mobile users

with the aid of multiple relays, a two-stage relay selection strategy is proposed while considering different quality-of-service (QoS) requirements of the users.

## 3. Proposed Model

We consider a multi-vehicle single-relay cooperative downlink vehicular communication network, comprising one BS with Nt transmit antennas, vehicle 1 and vehicle 2 both with Nr receive antennas, and one DF relay with Nt transmit and Nr receive antennas operating in the half-duplex mode, where the BS aims to transmit two GQSM signal vectors x1 and x2 generated by m1 and m2 bits to vehicle 1 and vehicle 2, respectively. For simplicity, we assume that m1 = m2 = log2 C(Nt, p) + p log2 M. Note that the vehicle 1 can directly receive the signal from the BS due to the near location, while there is no direct transmission link between the BS and vehicle 2 because of the severe propagation attenuation (long distance). Therefore, one DF relay is assumed to be located between the BS and vehicle 2, which leads to two phases for transmission from the BS to vehicle 1 and vehicle 2. To enable this two-phase transmission, we investigate two relaying transmission schemes, C-NOMA-GQSM with GWO optimization as shown in Figure 1.

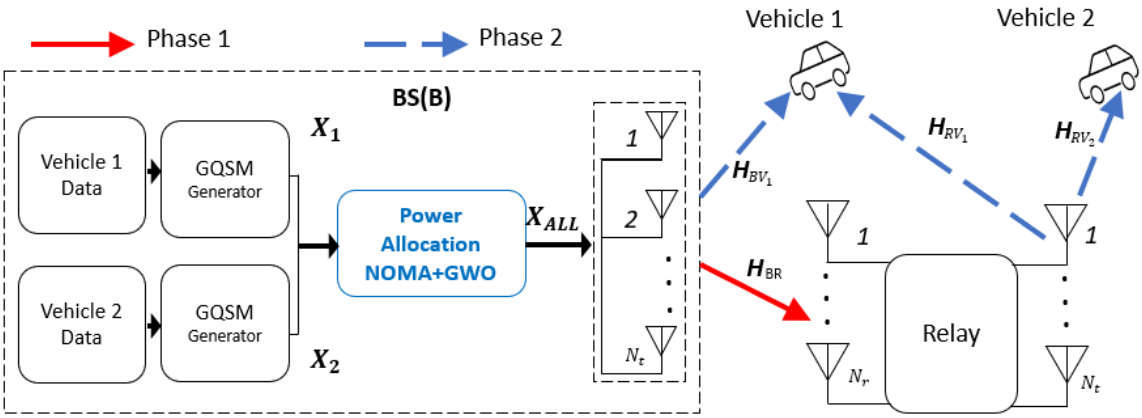


Figure 1. Proposed system model

### 3.1 GQSM

We first propose the GQSM scheme in Figure 2 in this subsection. We consider an MIMO system with Nt transmit antennas and Nr receive antennas.

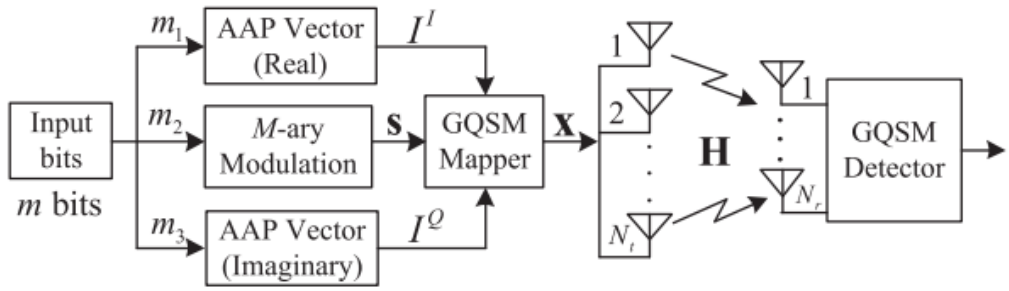


Figure 2. System model for GQSM.

By GQSM, p out of Nt transmit antennas are activated for conveying the real part of the modulated signal vectors with the selected antenna activation permutation (AAP) $I^I$. Similarly, the imaginary part of the modulated signal vectors is transmitted through another p activated transmit antennas, resulting in the corresponding AAP ) $I^Q$.. Note that the total number of AAPs for the real/imaginary part is C (Nt, p), but only L = 2log2 C(Nt,p) AAPs are adopted for modulation purposes. As can be seen in Figure 2, m input bits are split into three parts, m1,

m2, and m3, where m1 and m3 (m1 = m3) bits represent the index bits for the real and imaginary parts, respectively, and m2 bits stand for the modulation bits generating the modulated signal vector. Specifically, the modulated signal vector s = [s1,s2,...,sp] are first generated by m2 = p log2 M bits, where sτ = sI τ + j sQ τ with 1 ≤ τ ≤ p, sτ ∈ X, and X denotes the M-ary constellation set. It should be noted that sI τ and s Q τ are selected from X I and X Q, respectively, where X I and X Q represent the real and imaginary parts of X, respectively. m1 = m3 = log2 C(Nt, p) bits are then utilized to determine the AAP I I and I Q so as to transmit the real and imaginary signals {sI τ } p τ=1 and {s Q τ } p τ=1. Let sI = [sI 1 ,sI 2 ,...,sI p] and sQ = [s Q 1 ,s Q 2 ,...,s Q p ] denote the real and imaginary sets of the the modulated signal vector s. Let I I α and I Q β be the αth and βth legal AAPs for real and imaginary parts, respectively.

### 3.2 Power allocation with NOMA-GWO

We have shown the idea of a NOMA-based novel two-path relaying system, where the target information of the source node is divided into two equal streams and they are transmitted to the destination via two half-duplex DF relays in superposed mode. Because of adopting the idea of superposition model in the NOMA technique, intuitively, lower level of system frequency is required compared to a system with OMA scheme. In such system, while targeting on the maximization of the system capacity, the power allocation among the source and relay nodes is an optimization problem given that there are power constraints at the individual nodes as well as the entire system. The dual decomposition method is adopted to obtain the closed form expressions of the optimal power allocation.

Once the optimal power allocation at each node is known, in order to separate the superposed received messages at the destination, the optimal power allocation between the two data streams is formulated as an optimization problem while targeting on the minimization of the required frequency band. Similar to the solution scheme of the first problem, the dual decomposition method is adopted to obtain the closed form expression of the optimal power allocation. 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, GWO. For GQSM-NOMA systems the optimal power allocation is done probably with the proposed GWO technique that is attained. The power scheduling is performed exploiting the proposed GWO method so that to allocates power through maximum effectiveness to users in an effectual method. The NOMA while employed utilizing GQSM creates a substantial increase in energy effectual power allocation to users.

#### 3.2.1 NOMA

The architecture model of the proposed method in NOMA-GQSM based systems is demonstrated in fig. 1, which still needs two phases to complete the whole transmission. It should be noted that vehicle 1 is near to the BS, and the DF relay is relatively far from the BS, which leads to σ2 BV1 > σ2 BR. Due to the NOMA principle, the BS will combine two signal vectors by $x_{ALL} = \sqrt{\zeta}1x1 + \sqrt{\zeta}2x2,$ where ζ1 and ζ2 denote the power allocation factors for vehicle 1 and vehicle 2, respectively, and ζ1 + ζ2 = 1 as the transmit power constraint. Since vehicle 1 is near to the BS and vehicle 2 as well as the relay are far from the BS, the BS will allocate more power to uesr 2 (x2) and less power to vehicle 1 (x1) by NOMA, which leads to ζ1 < ζ2. By C-NOMA-GQSM, the BS first broadcasts the combined signal xALL to both vehicle 1 and the relay in the first phase. The Nr × 1 received signal vectors at vehicle 1 and the relay can be expressed as

$$\begin{aligned} \mathbf{y}_{\mathrm{BV}_1}^{\mathrm{NOMA}} &= \mathbf{H}_{\mathrm{BV}_1}\mathbf{x}_{\mathrm{ALL}} + \mathbf{n}_{\mathrm{BV}_1} \\ &= \mathbf{H}_{\mathrm{BV}_1}(\sqrt{\zeta_1}\mathbf{x}_1 + \sqrt{\zeta_2}\mathbf{x}_2) + \mathbf{n}_{\mathrm{BV}_1} \end{aligned} \quad (1)$$

$$\begin{aligned} \mathbf{y}_{\mathrm{BR}}^{\mathrm{NOMA}} &= \mathbf{H}_{\mathrm{BR}}\mathbf{x}_{\mathrm{ALL}} + \mathbf{n}_{\mathrm{BR}} \\ &= \mathbf{H}_{\mathrm{BR}}(\sqrt{\zeta_1}\mathbf{x}_1 + \sqrt{\zeta_2}\mathbf{x}_2) + \mathbf{n}_{\mathrm{BR}} \end{aligned} \quad (2)$$

respectively, where nBV1 and nBR denote the the Nr × 1 noise vectors following the distribution CN (0, σ2 BV1 ) and CN (0, σ2 BR), respectively. Vehicle 1 retains the received signal and waits for another upcoming signal in the second phase for detection purposes. With the help of the relay, the transmitted signal vector to vehicle 2 can be easily detected due its larger transmit power by the ML detection.

### 3.2.2 GWO

This study proposed an efficient power level selection method named as GWO. The detailed architecture of GWO power level selection method is presented in the figure 3 respectively. During the first phase, initial positions of population are identified. These positions will be auto update based on the available population in discrete searching space respectively. During the second phase, the variable weights (VW) of each population are estimated and according the variable weights positions will change, it results in selection of optimal power levels. The VW is mainly used to adaptively search the power level space for optimal (best) power level combination. The best power level combination is the one with reduced BER and optimal number of selected power levels.

For this purpose, GWO optimization technique used for enhancive power level selection with NOMA-GQSM specific power levels as its input variable weights respectively. GWO with momentum is a tool that helps move NOMA-GQSM specific power level vectors of gradients in the right directions and thus contributes to faster convergence with reduced BER. So, we can use small power level set to get better BER based on optimization. We describe a momentum, a moveable average of the NOMA-GQSM specific power level gradients. Then, we use it to change the network weight.

**Mathematical model:** GWO algorithm is developed by understanding the hunting mechanism, leadership hierarchy and social behavior of grey wolves. Generally, the wolves' lives as a group in their social behavior and each group contain multiple number of four levels of wolf population. In this group, alpha ($\alpha$) wolves are most dominant members, then beta ($\beta$) followed by delta ($\delta$) wolves are middle dominant members and finally omega wolves are lowest dominant members. These wolves are functioned together and under beta ($\beta$) wolf leadership, they will start the hunting mechanism. The mathematical model of hunting mechanism of grey wolves consists of the following: Encircling, Hunting and attacking the prey.

**Encircling prey:** Encircling prey is the initial phase of hunting mechanism respectively. Based on the prey position in the search space, the grey wolf will change its position automatically. To describe the operation of encircling mathematically, three coefficients are derived as follows:

$$\overrightarrow{D_\alpha} = |\overrightarrow{C_1}.\overrightarrow{X_\alpha(t)} - \overrightarrow{X(t)}|,\ \overrightarrow{D_\beta} = |\overrightarrow{C_2}.\overrightarrow{X_\beta(t)} - \overrightarrow{X(t)}| \text{ and}$$
$$\overrightarrow{D_\delta} = |\overrightarrow{C_3}.\overrightarrow{X_\delta(t)} - \overrightarrow{X(t)}| \quad (3)$$

Here, the position vector of grey wolf is indicated by the $\overrightarrow{X(t)}$ with $\vec{A}$, $\vec{C}$ and $\vec{D}$ as its coefficient vector with respect to each current iteration $(t)$. Then, the alpha position vectors is indicated by $\overrightarrow{X_1}$, beta $\overrightarrow{X_2}$ and delta position vectors is indicated by $\overrightarrow{X_3}$. They are calculated as follows:

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\overrightarrow{D_\alpha}\ ,\ \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_1}.\overrightarrow{D_\beta} \text{ and } \overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_1}.\overrightarrow{D_\delta} \quad (4)$$

$$\overrightarrow{X(t)} = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \quad (5)$$

From the above equation, it is observed that the position vectors play the crucial role in power level selection procedure. If the dominant wolves reach near to the grey wolves, then the grey wolves are run away its original position based on the average weights of delta, beta and alpha. Here, the best power levels are selected by the alpha wolves as it's nearer to prey in social hierarchy. Then, the alpha wolf is treated as the leader. The beta and delta wolves contain the lowest probability power levels.

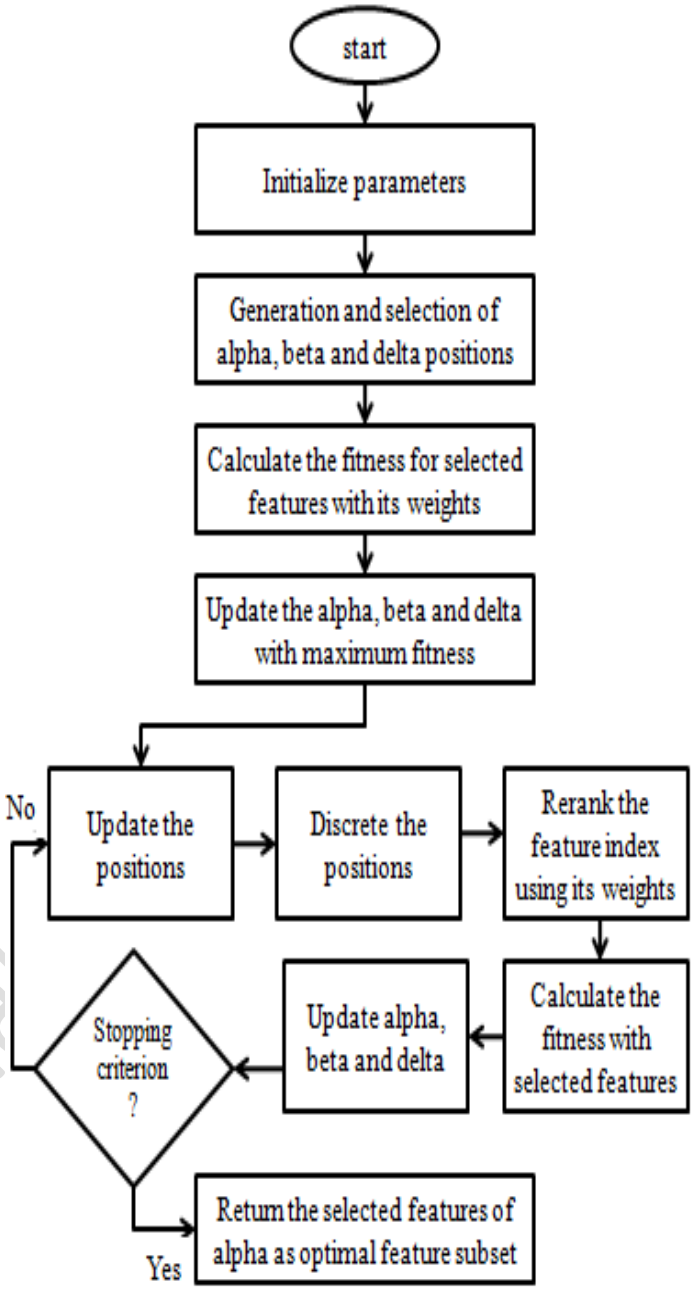


Figure 3. power level selection operation of GWO

Hence, in the equation (3) alpha positions are dominant as its weight are much larger than the other wolves' weights respectively. Based on the above concerns, the proposed work is hypothesized as follows:

- The hunting and searching processes are performed by the alpha wolves, whereas monitoring operation is performed by the beta wolves and finally the less important role is played by the delta wolves respectively.

- The dominant grey wolves are surrounding the prey in the social hierarchy manner. It means alpha is number one in position as it is nearest to the grey wolves, then the beta is ranked as second position as it is nearer to the pack after the alpha. And finally, delta is ranked as third position. Based on the prey location, all the wolves have capability to change their position and the leadership levels also interchanged. Here, the position changeable wolves are treated as the omega wolves.
- This phenomenon can be utilized for the purposed of best power level selection with multi objective optimization. To implement this, fitness function is developed by using the minimum or maximum positions updation.
- During the searching procedure, the temporary prey is selected and NOMA-GQSM power levels are selected. But, during the hunting procedure, accurate prey is selected and based on prey accurate NOMA-GQSM power levels are selected properly.

As the omega wolves are changing its positions, the positions considered as per equation (3) must be updated continuously based on the new weights. For this purpose, the GWO algorithm is extended with the variable weights concept. This process will be explained as follows:

- After the search begins, the wolf which is nearest to the prey is treated as the alpha and remaining all wolves are neglected. Based on the power levels availability, the alpha wolf changes its positions and starts the new prey searching.
- If the power levels are obtained, then the alpha weight is updated as the 1.0 at the beginning of searching procedure, and other wolves' weights are updated as the zero at this time. These initialized weights are the property of auto updating with the prey positions and power level availability.
- During the final state, the delta, beta and alpha are having the equal weight and encircle the prey based on perfect power levels. All the wolves start the prey based power level searching operation from beginning to the end with automatic wolf rank updation.
- It means beta replace the position of alpha and delta replace the position of beta and finally original alpha finds the power levels respectively based on the cumulative iteration number ($it$). As per this principle, as the original alpha receives identifies the prey, then its weight is reduced and beta, delta wolves' weighs are increased respectively. Thus, all of the weights are summed up and results the outcome as 1.

Thus, the equation (3) is changed according to the perceptive of variable weights. The above-mentioned hypothesis is mathematically formulated as follows;

$$\overrightarrow{X(t+1)} = w_1 \overrightarrow{X_1} + w_2 \overrightarrow{X_2} + w_3 \overrightarrow{X_3} \quad (6)$$

$$w_1 + w_2 + w_3 = 1 \quad (7)$$

Here, $w_1$, $w_2$ and $w_3$ indicates the weights of alpha, beta and delta respectively. This weights satisfies the weight updation rule $w_1 > w_2 > w_3$. Even though, alpha having highest priority, its weight decreased from 1 to 0.33 during the searching procedure. Similarly, at the same time the weights of the delta and beta raised from 0 to 0.33 respectively.

For this purpose, cosine function is used with an angle $\theta$ to varied in the range of [0, arcos (1/3)] on the weight $w_1$; and all the weights are changed with the cumulative iteration number. If $it = 0$, then $w_2.w_3 \longrightarrow 0$ and similarly If $it = \infty$, then $w_1.w_2.w_3 \longrightarrow 1/3$ respectively. Thus, this work introduced the arc-tangent function on $it$ and results the outcome as angular parameter $\varphi$ .

$$\varphi = \frac{1}{2} \arctan(it) \quad (8)$$

Here, $it$varied from 0 to $\pi/2$. Mathematically $cos\left(\frac{\pi}{4}\right) = sin\left(\frac{\pi}{4}\right) = \frac{\sqrt{2}}{2}$; if $w_2$ increased from 0 to 0.33 along with $it$, then the above-mentioned condition. The angular parameter majorly depending on $it$ and if $it \longrightarrow \infty$ , then $\theta \longrightarrow arccos(1/3)$, $cos\,\varphi$ and $sin\,\theta$ .

$$\theta = \frac{2}{\pi}.arccos\frac{1}{3}.\frac{2}{\pi} \quad (9)$$

if $it \longrightarrow \infty$, $\theta \longrightarrow arccos\,(1/3)$, $= 1/3$, Then the weight coefficient $w_2$ will be calculated easily. Thus, the new positions by using the new weight coefficients are calculated as follows

$$w_1 = \cos\theta \quad (10)$$

$$w_2 = \frac{1}{2}\sin\theta\cos\varphi \quad (11)$$

$$w_3 = 1 - w_1 - w_2 \quad (12)$$

The omega wolves are changed their position based on the directions of $\vec{A}$ and controlling parameter *a*.

- if $\vec{A} > 1$, then the grey wolves changed its positions or run-away from dominants. At the same time, an omega wolf also changed its positions from the prey and creates the more searching space for other wolves. This phenomenon is treated as the global power level search in optimization.
- if $\vec{A} < 1$, Then the grey wolves changed its positions much nearer to the dominants and finally reaches the prey. This phenomenon is treated as the local power level search in optimization.

The random numbers $\vec{r_1}$and $\vec{r_2}$ are used to indicate the direction of wolves and they are controlled by controlling parameter $\alpha$ and results in the coefficient vectors as follows

$$\vec{A} = 2\alpha\vec{r_1} - \alpha \quad (13)$$

$$\vec{C} = 2\vec{r_2} \quad (14)$$

The controlling parameter $a$ is decreased linearly towards zero from the maximum value of 2. And it can be calculated by using $it$ as follows:

$$a = 2(1 - \frac{it}{N}) \quad (15)$$

Here, N is maximum iteration number of $it$ and N is initialized by the users. Finally, in order to improve the BER, the NOMA-GWO-GQSM architecture needs best and optimal power levels. For this propose, the fitness function is used to generate the best power level selection operation and also increases the classification efficiency.

$$Fitness = aP + (1 - a)\frac{NN-L}{L} \quad (16)$$

Here, total number of power levels available in the overall dataset is denoted by $NN$, length of the selected power level is denoted by $L$ , BER is denoted by $P$ .

## 4. Simulation Results.

In this section, we present MatlabR2016a based simulation results to evaluate the BER performance of GQSM systems under the assumptions of Rayleigh fading channels and perfect channel estimation.

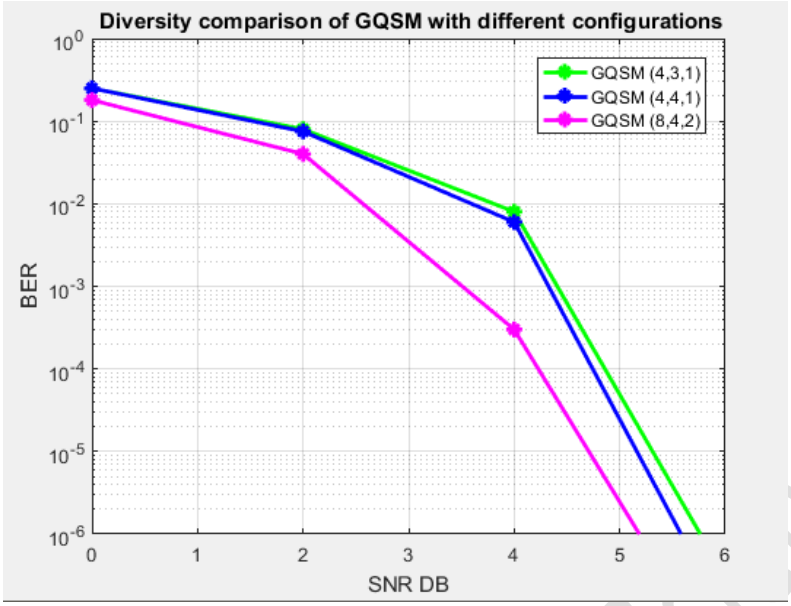


Fig. 4. Diversity comparison of GQSM with different configurations.

For the sake of simplicity, we denote "GQSM (Nt, Nr, p, MQAM)" as the GQSM scheme with Nt transmit antennas, Nr receive antennas, p activated transmit antennas and M-ary QAM constellation. To evaluate the diversity of the proposed GQSM, we compare the BER performance of GQSM (4, 3, 1, 4QAM), GQSM (4, 4, 1, 4QAM), and GQSM (8, 4, 2, 8QAM) in Fig. 6. It is shown from Fig. 4 that GQSM (4, 2, 1, 4QAM) achieves the smallest diversity order as 2 (Nr = 2). To further explore the diversity property, we compare the BER performance between GQSM (4, 4, 1, 4QAM) and GQSM (8, 4, 2, 8QAM), which shows that GQSM (4, 4, 1, 4QAM) achieves the same diversity order (Nr = 4) as that of GQSM (8, 4, 2, 8QAM) by only changing the number of transmit antennas Nt, the number of activated transmit antennas p and the cardinality of constellation M.

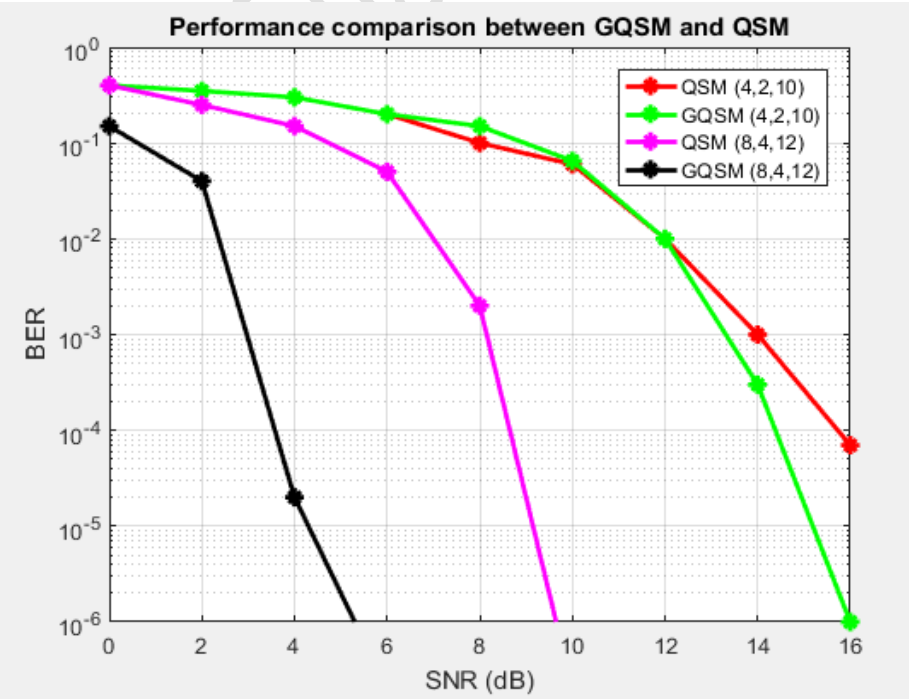


Figure 5. Performance comparison between GQSM and QSM

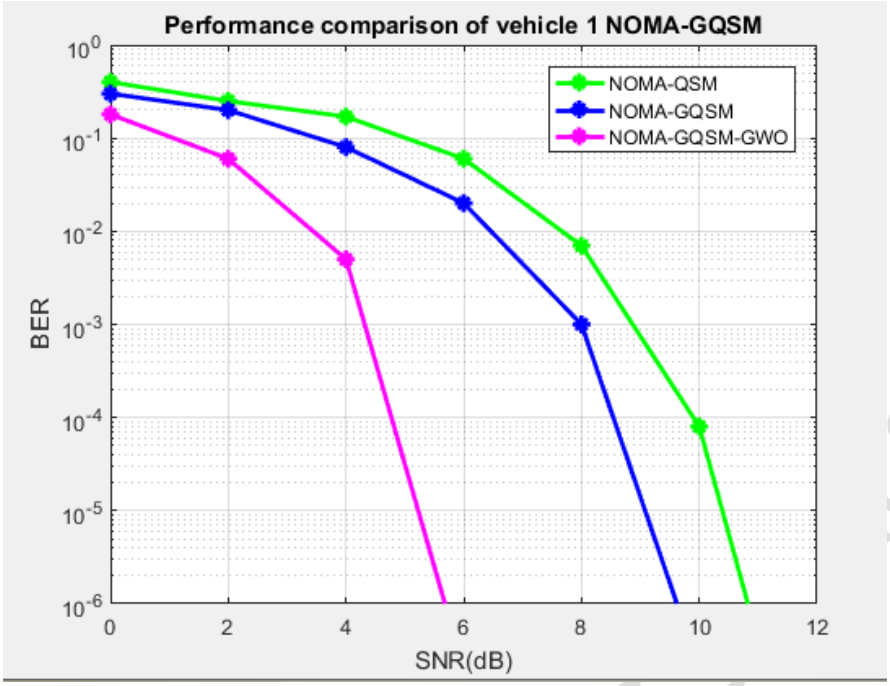


Fig. 6. Performance comparison of vehicle 1

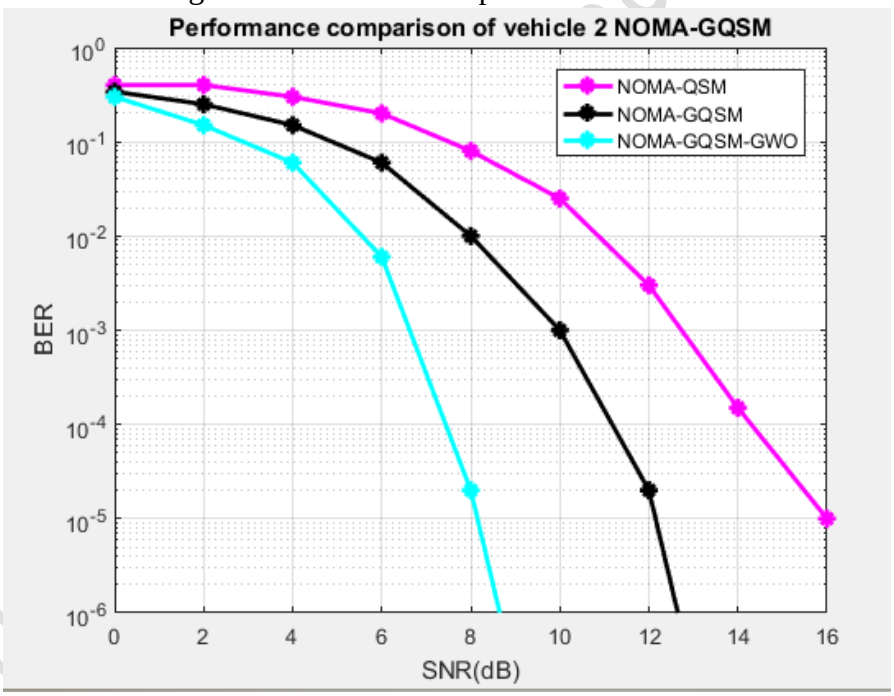


Fig. 7. Performance comparison of vehicle 2

In Fig. 5, we compare the BER performance between GQSM and QSM schemes with Nt = 4 and 8, Nr = 2 and 4. It can be seen that GQSM (4, 2, 3, 4QAM) achieves a large performance gain than QSM (4, 2, 64QAM) both with 10 input bits in the entire SNR region. Specifically, compared to QSM (4, 2, 64QAM), GQSM (4, 2, 3, 4QAM) obtains almost 6 dB SNR gain at BER = 10−2 and obtains up to 8dB SNR gain at BER = 10−4. This is because GQSM significantly increases the length of index bits, which improves the system performance. For both vehicle 1 and vehicle 2, NOMA-GQSM-GWO outperformed as compared to conventional NOMA-QSM, NOMA-GQSM, which is presented in Figure 6 and Figure 7.

## 5. Conclusion

This work proposes GQSM-NOMA Transmitter for multi-user scenario. In the proposed system, a superimposed signal of several constellation symbols is transmitted simultaneously by distinguishing the power domain. Different signal domain is then perceived at each receiver. BER performance is offered in this system when dynamic power allocation is utilized with optimized power coefficients. On the other hand, the spectral efficiency analysis shows that the proposed system outperforms the other existing techniques such as QSM-NOMA system by using the same system configuration over the whole SNR range. In addition, from the simulation results it is shown that the proposed system can cover more users compared with the existing systems. As per the results, it can be concluded that there is a chance to improve the BER by 55% in the new proposed method. As of future research, we would like to extend the single-user scenario to the multi-user one while keeping the same NOMA-GQSM-based cooperative relay idea. Incorporating massive millimeter multiple-input multiple-output (MIMO) technology in such a system could be another possible research direction.

**References:**

[1]. Y. Sun, D. W. K. Ng, Z. Ding, R. Schober, Optimal Joint Power and Subcarrier Allocation for Full-Duplex Multicarrier Non-Orthogonal Multiple Access Systems. IEEE Trans. Commun. 65(3), 1077–1091 (2017)

[2]. S. M. R. Islam, N. Avazov, O. A. Dobre, K. Kwak, Power-domain non-orthognal multiple access (NOMA) in 5G systems: potentials and challenge. IEEE Commun. Surveys Tuts. 19(2), 721–742 (2017)

[3]. Z. Ding, Y. Liu, J. Choi, Q. Sun, M. Elkashlan, C.-L. I. H. V. Poor, Application of non-orthogonal multiple access in LTE and 5G networks. IEEE Commun. Mag. 55(2), 185–191 (2017)

[4]. Z. Ding, X. Lei, G. K. Karagiannidis, R. Schober, J. Yuan, V. K. Bhargava, A survey on non-orthogonal multiple access for 5G networks: research challenges and future trends. IEEE J. Sel. Areas Commun. 35(10) (2181)

[5]. Z. Hasan, H. Boostanimehr, V. K. Bhargava, Green cellular networks: a survey, some research issues and challenge. IEEE Commun. Survey Tuts. 13(4), 524–540 (2011)

[6]. S. Wang, R. Ruby, V. C. M. Leung, Z. Yao, X. Liu, Z. Li, Sump-Power Minimization Problem in Multisource Single-AF-Relay Networks: A New Revisit to Study the Optimality. IEEE Trans. Veh. Technol. 66(11), 9958–9971 (2017)

[7]. J.-B. Kim, I.-H. Lee, Non-orthogonal multiple access in coordinated direct and relay transmission. IEEE Commun. Lett. 19(11), 2037–2040 (2015)

[8]. J.-B. Kim, I.-H. Lee, Capacity analysis of cooperative relaying systems using non-orthogonal multiple access. IEEE Commun. Lett. 19(11), 1949–1952 (2015)

[9]. Q. Zhang, Z. Liang, Q. Li, J. Qin, Buffer-aided non-orthogonal multiple access relaying systems in Rayleigh fading channels. IEEE Trans. Commun. 65(1), 95–106 (2017)

[10]. S. Luo, K. C. Teh, Adaptive transmission for cooperative NOMA system with buffer-aided relaying. IEEE Commun. Lett. 21(4), 937–940 (2017)

[11]. A. Mohamad, R. Visoz, A. O. Berthet, in Proc. IEE ICC. Code design for multiple-access multiple-relay wireless channels with non-orthogonal transmission, (London, 2015), pp. 2318–2324

[12]. R. Jiao, L. Dai, J. Zhang, R. Machenzie, M. Hao, On the performance of NOMA-based cooperative relaying systems over Rician fading channels. IEEE Trans. Veh. Technol. 66(12), 11409–11413 (2017)

[13]. Z. Ding, H. Dai, H. V. Poor, Relay selection for cooperative NOMA. IEEE Wireless Commun. Lett. 5(4), 416–419 (2016)
[14]. M. Xu, F. Ji, M. Wen, W. Duan, Novel receiver design for the cooperative relaying system with non-orthogonal multiple access. IEEE Commun. Lett. 20(8), 1679–1682 (2016)
[15]. M. F. Kader, S. Y. Shin, Cooperative relaying using space-time block coded non-orthogonal multiple access. IEEE Trans. Veh. Technol. 66(7), 5894–5903 (2017)
[16]. M. F. Kader, M. B. Shahab, S. Y. Shin, Exploiting non-orthogonal multiple access in cooperative relay sharing. IEEE Commun. Lett. 21(5), 1159–1162 (2017)
[17]. R.-H. Gau, H.-T. Chiu, C.-H. Liao, C.-L. Wu, Optimal power control for NOMA wireless Networks with relays. IEEE Wireless Commun. Lett. 7(1), 22–25 (2018)
[18]. J. Men, J. Ge, Non-orthogonal multiple access for multiple-antenna relaying networks. IEEE Commun. Lett. 19(10), 1686–1689 (2015)
[19]. J. Men, J. Ge, C. Zhang, Performance analysis of nonorthogonal multiple access for relaying networks over Nakagami-m Fading channels. IEEE Trans. Veh. Technol. 66(2), 1200–1208 (2017)
[20]. S. Zhang, B. Di, L. Song, Y. Li, sub-channel and power allocation for non-orthogonal multiple access relay networks with DF protocal. IEEE Trans. Wirelss Commun. 16(4), 2249–2261 (2017)
[21]. C. Xue, Q. Zhang, Q. Li, J. qin, Joint power allocation and relay beamforming in nonothogonal multiple access amplify-and-foward relay networks. IEEE Trans. Veh. Technol. 66(8), 7558–7562 (2017)
[22]. X. Liang, Y. Wu, D. W. K. Ng, Y. Zuo, S. Jin, H. Zhu, Outage performance for cooperative NOMA transmission with an AF relay. IEEE Commun. Lett. 21(3), 664–667 (2017)
[23]. D. Deng, L. Fan, X. Fei, W. Tan, D. Xie, Joint user and relay selection for cooperative NOMA networks. IEEE Access. 5, 20220–20227 (2017)
[24]. 24. W. Shin, H. Yang, M. Vaezi, J. Lee, H. V. Poor, Relay-aided NOMA in uplink cellular networks. IEEE Sig. Proc. Lett. 24(12), 1842–1846 (2017)
[25]. Z. Yang, Z. Ding, Y. Wu, P. Fan, Novel relay selection strategies for cooperative NOMA. IEEE Trans. Veh. Tehnol. 66(11), 10114–10123 (2017)