# Maximizing Downlink Channel Capacity of NOMA System Using Power Allocation Based on Channel Coefficients Using Particle Swarm Optimization and Back Propagation Neural Network

**Shailendra Singh and E. S. Gopi**

**Abstract** One of the methods among the pool of technologies for the 5G wireless communication is the NOMA (Non-orthogonal Multiple Access). Conventionally, the channel between the base station and the various mobile station users are shared based on the orthogonality principle. To increase the capacity of the channel, NOMA has been technologically enhanced and explored for 5G standards. In this case, the channel is shared between the users based on the difference in the transmitted power allocated to the individual users. The Successive Interference Cancellation (SIC) is adopted to detect the signal during the uplink and the downlink. In SIC, during the uplink scenario, the base station usually collects and detects the symbol in the decreasing order of the channel gain (between a particular user and the base station). In the same order, during the downlink scenario, the SIC uses the increasing order of the channel coefficients or gain. The power is allocated based on the corresponding channel gain. If the channel gain is larger, then less power is allotted and vice versa. In NOMA, the method used is Multiplexing in Power Domain and after allocation of Power to the users, it has been changed to the problem of Constraint Optimization. In this paper, an attempt is made to demonstrate the proposed methodology used for power allocation and handling the given constraints in NOMA downlink scenario using Particle Swarm Optimization (PSO) and Back propagation Neural Network (BPNN). The experimental results have shown the importance of the proposed technique for power allocation in the Downlink NOMA scenario.

**Keywords** PSO · ANN · NOMA · SIC · Power allocation · Channel capacity

## 1 Introduction

In wireless communication systems, various multiple access methods have been the key technologies ranging from the very first generation that is called (1G) to the advanced fourth generation (4G) that is called LTE-Advanced. The multiple access

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technologies include Frequency Division Multiple Access (FDMA), Time Division Multiple Access (TDMA), Code Division Multiple Access (CDMA) and Orthogonal Frequency Division Multiple Access (OFDMA). In all the above methods, access to the channel has been shared by using orthogonality in Frequency, Time and Codes, respectively, allocated to the individual users. In the fourth generation of mobile communication systems such as long-term evolution (LTE) and LTE-Advanced, OFDMA has been widely adopted and very much popular to achieve higher data rate. The near future demand for mobile traffic data volume could be expected to be 500–1,000 times larger than that in 2010. The technologies like mm wave transmission, Full duplex, Multicarrier transmission, Non-Orthogonal Multiple Access (NOMA) are being explored in 5G to increase the channel capacity. The working principle behind NOMA is Power Domain Multiplexing that means access to the channel is shared by using different Power levels allocated to the individual users, because of Power Domain Multiplexing in NOMA, it discards the Orthogonality principle and that helps in the improvement of the channel capacity, compared to other orthogonal multiple access (OMA) schemes.

## 2 Literature Survey

How fascinatingly things are changing, lets take the brief history of cellular phone over 50 years which itself is a milestone. The 1G based phones were big, heavy and analogue with heavy price. The 1990s saw the second generation i.e. 2G cell phones, embedded digitally with that we could make calls, send text messages, and a smiling face. In 2000, the third generation, i.e. 3G, cell phones were revolutionized and came with an Internet browser. MIMO technology was used in the 3G cell phones and for the data transmission packet switching was used. Now forth generation, i.e. 4G cellular system came in 2010. Methods that were used in 4G: long-term evolution (LTE), WiMAX, internet protocols, and packet switching were the key technologies. We could say it was a new computer or digital machine in our hands. Now it's time to move to a new generation, 2020 will be the fifth-generation era, i.e. 5G. It can be 100 times faster than the 4G. The downlink maximum throughput can offer a 10–20 Gbps, which means we can easily download 2–3 HD DVD movies in just 1s. Some technologies among others possibly used for 5G cellular networks are millimetre-wave for 5G 24–100 GHz is proposed, Massive MIMO, Beam forming and NOMA. It is highly anticipated that the connection density would become 106 connections for a square kilometre area in future. In the typical OFDM, we have the sub carriers, and different users are given different sets of sub carriers but in case of NOMA, a particular sub carrier or group of sub carriers can be given to more than one user. In [1–5], it has been observed and surveyed that all the NOMA schemes such as Single carrier, Multi carrier, Power Domain, Cognitive radio-NOMA and including Single Input Single Output (SISO) and Multiple Inputs Multiple Outputs (MIMO) don't use the multiple antennas for transmitting and receiving the particular sub carrier or group of sub carriers, it usually combine the signals and transmit it through the single transmitting antenna and receives by the single receiving antenna. While the MIMO system requires multiple antennas for transmitting and receiving the signals, this is the main difference between MIMO and NOMA. In case of OMA, if one user only needs to be served with low data rate, e.g. sensors, then OMA gives the more data rate than it's needed but NOMA provides a satisfactory solution for this problem faced by OMA. Because of the availability of new power dimensions, NOMA systems can be amalgamated with present multiple access (MA) models. NOMA consists of two types of Multiplexing. The Code Domain Multiplexing and other one is Power Domain multiplexing. In the NOMA the allocation of power can be initialized or performed by implementing different methods based on the channel conditions of users. Taking single input single output (SISO) system, the algorithm for power allocation has been determined by the parent source for maximizing the rate simply considering the Downlink NOMA [6]. However, most of the previously used methods are applied to only two users. To increase its domain and reach to more users, the proposed system is based on Pascal's triangle for the power allocation. The well-known French mathematician and philosopher Blaise pascal had proposed the Pascal's triangle method [7]. But the Power allocation in NOMA creates the problem for constrained optimization because the allocation must satisfy the distribution according to the channel conditions, and the distributed power among the users must be equal to the power at the base station. There are many classical methods that have been already developed by the researchers to solve the problems of constrained optimization. In the case of multiple input multiple output (MIMO) system, the powers are being allocated optimally to the 'n' number of communication channels for maximizing the sum rate by using Karush-Kuhn-Tucker (KKT) conditions subjected to the total power constrained and non negativity constrained. Similarly, the power allocation in NOMA to maximize the sum-rate is also the important task having same Power constrained like MIMO, but the power allocation is just opposite in NOMA for channel conditions as compared with MIMO. The same KKT conditions have proposed by the researchers to find the optimum power values by taking the weighted sum of received rates for the individual users after applying lagrangian Optimization [8]. The optimum power values for NOMA have also achieved by the researchers by using Jensen's inequality criteria to calculate Ergodic Capacity by applying closed form lower bound and after that a scheme for power allocation is applied to satisfy the ergodic capacity according to the requirements for all the users just by solving a problem of convex optimization [9]. In [10], a scheme for power allocation in NOMA called Proportional Fairness Scheduling (PFS) has discussed. Some other techniques that have proposed to allocate the power by satisfying the given constrained are dynamic power allocation and users scheduling [11, 12]. When the conventional methods or classical methods fail or not suitable for estimation then computational intelligence comes into the picture. It provides the solution to a complex problem by imitating the human behaviour. Recognition, classification and clustering can be done by using computational intelligence. The objective of this paper is to allocate the power for a novel power domain (PD) NOMA using machine learning techniques (PSO and ANN) according to the estimated channel conditions. PSO generate the optimum solution for any kind of optimization problem by minimizing or maximizing the problem [13, 14]. In this paper, we have allocated the power such that the total sum rate is maximized so that PSO is suitable for it. Back propagation neural network is used to make the results obtained from PSO more efficient. There are many applications like constraint satisfaction, associative storage, Optimization, planning control and classification, for the Neural Networks that have been designed. Because of having special characteristics like robustness, ability to learn and massive parallelism etc. Neural networks are being preferred [15].

The further discussion in this paper is as follows. Section 3 discusses about Conventional Power Domain NOMA in detail. Section 4 elaborates the Power allocation algorithm and optimization with constraints. The Experiments and the Results are presented in Sect. 5 followed by Conclusion.

## 3 Power Domain NOMA

In the Power Domain NOMA, different levels of power are allotted to the individual users based on the channel conditions, it means, the channel state information (CSI) must be required at the base station for the power allocation. If the channel is good between the base station and the receiver, then the receiver usually detects the signal of less strength, so the users having good channel conditions are supposed to allocate less power values and users having poorer channel conditions are supposed to allocate more power values. However, in case of conventional OMA, the water filling policy is used for the power allocation. The Superposition Coding (SC) and Successive Interference Cancellation (SIC) are the two key enabling technologies for NOMA, keeping the generality, SC is used at the base station that permits it to transmit the combined Superposition coded messages to all the users. SIC helps in efficiently managing the interference at the receiver end. It has been observed that using SIC at receiver end users rate can be improve up to Shannon limit. SIC technology mitigates the interference from the users with poorer channel conditions.

### *3.1 Downlink NOMA*

Let $h_r$ be the Rayleigh channel coefficient between the base station and the $r$th user with $r = 1, 2, 3$. Figure 1a illustrates the typical power domain NOMA with three users with $|h_1| > |h_2| > |h_3|$ in downlink scenario. The channel link between the base station and the 3 receivers are represented as $|h_1|$, $|h_2|$, $|h_3|$, respectively, with $|h_1| > |h_2| > |h_3|$. Let the total power used to broadcast is given by P and let $a_i$ be the fraction of the power alloted for the $i$th user with $a_1 + a_2 + a_3 = 1$

$$u_i = h_i(\sqrt{(}a_1)X_1 + \sqrt{(}a_2)X_2 + \sqrt{(}a_3)X_3) + N \tag{1}$$

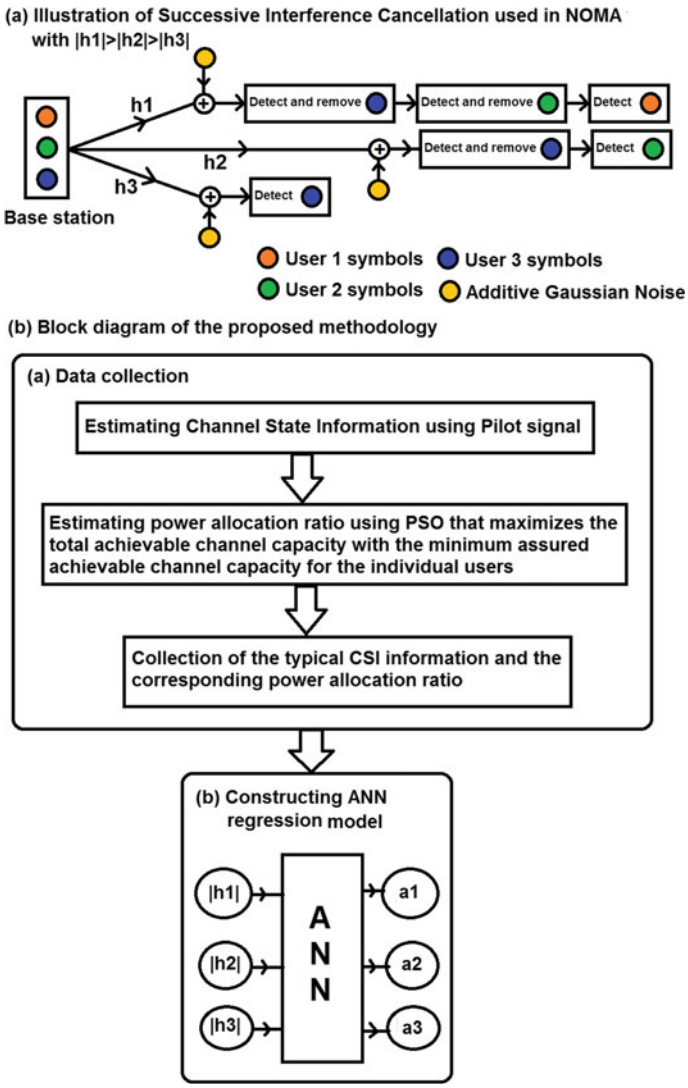


**Fig. 1** **a** Illustration of successive interference cancellation used in power domain NOMA, **b** proposed methodology for power allocation using PSO and ANN

where $N$ is the additive Gaussian noise with mean zero and variance $\sigma^2$. Let $X_i$ be the symbols associated with the $i$th user. The Successive Interference Cancellation (SIC) (refer Fig. 1a) is used in the receiver section as described below. As $|h_1| > |h_2| > |h_3|$, user 1 detects $X_3$ and is removed from the received signal. Further $X_2$ is detected from the remaining signal and is also removed from the remaining signal. Finally, detect $X_1$ from the remaining signal. Thus, the channel capacity attained between the base station and the user 1 is computed as follows:

$$C_3^d(1) = \log_2\left(1 + \frac{|h_1|^2 a_1 P}{\sigma^2}\right) \tag{2}$$

In the similar fashion, user 2 detect $X_3$ and removed from the received signal, which is followed by detecting $X_2$ from the remaining signal. The channel capacity attained between the base station and the User 2 is computed as follows:

$$C_2^d(2) = \log_2\left(1 + \frac{|h_2|^2 a_2 P}{|h_2|^2 a_1 P + \sigma^2}\right) \tag{3}$$

Finally, user 3 detect $X_3$ directly, and hence channel capacity is computed as follows:

$$C_1^d(3) = \log_2\left(1 + \frac{|h_3|^2 a_3 P}{|h_3|^2 a_1 P + |h_3|^2 a_2 P + \sigma^2}\right) \tag{4}$$

$c_r^k$ is the maximum achievable rate attained by the user $k$th user using SIC technique, $r$ is the order at which the data corresponding to the $k$th user is the detected. The Quality of service (QOS) is determined based on the demand of the data rate. Let the demand rate requirement of the User 1, User 2, User 3 are, respectively, represented as the $R_1$, $R_2$, $R_3$. We would like to obtain the optimal values for $a_1$, $a_2$ and $a_3$, such that $C_3^d(1) + C_2^d(2) + C_1^d(3)$ is maximized, satisfying the constraints $C_3^d(1) > R_1$, $C_2^d(2) > R_2$ and $C_1^d(3) > R_3$. It is noted that the order in which the data are detected is from weak signal to the strong signal (3, 2, 1), i.e. $|h_1| \geq |h_2| \geq |h_3|$.

## 3.2 Uplink NOMA

During the Uplink, the base station receives the signal as shown below.

$$s = h_1\sqrt{(}a_1)X_1 + h_2\sqrt{(}a_2)X_2 + h_3\sqrt{(}a_3)X_3) + N \tag{5}$$

The Successive Interference Cancellation (SIC) is used in the receiver section (base station) described below. In the case of uplink, the strongest signal is detected first, i.e. $X_1$ is detected first, followed by $X_2$ and $X_3$.

Thus, $X_1$ is detected first and is removed from the received signal. From the remaining signal, the signal $X_2$ is detected and is removed. Finally, the signal $X_3$ is detected from the remaining signal. The channel capacity attained between the base station and all the users during the uplink is computed as follows:

$$C_1^u(1) = \log_2\left(1 + \frac{|h_1|^2 a_1 P}{|h_2|^2 a_2 P + |h_3|^2 a_3 P + \sigma^2}\right) \tag{6}$$

$$C_2^u(2) = \log_2\left(1 + \frac{|h_2|^2 a_2 P}{|h_3|^2 a_3 P + \sigma^2}\right) \tag{7}$$

$$C_3^u(3) = \log_2\left(1 + \frac{|h_3|^2 a_3 P}{\sigma^2}\right) \tag{8}$$

## 4 Proposed Methodology

The block diagram illustrating the proposed methodology is given in the part (b) of Fig. 1 that is Fig. 1b. In the very first part, Particle Swarm Optimization is used to estimate the power allocation ratio corresponding to the given magnitude of the channel state information (CSI). Pilot signal is transmitted through the channel one after another to the individual users and the corresponding CSI (between the base station and the individual users are obtained). For the given CSI, power allocation ratio is estimated using PSO that maximizes the maximum achievable channel capacity (refer Sect. 3.1). It is also noted that the minimum achievable channel capacity of the individual users are incorporated while using PSO.

### *4.1 Constrained Optimization*

A plethora of classical methods existed for constraint optimisation problems, basically depend on the nature of the constraints whether they are equality or inequality or together. Some of the methods among the pool are Lagrange's multiplier, Penalty Function method and augmented Lagrange method. Suitability of usage depends on the constraints; these mentioned methods has been useful for a problem with inequality constraints. Methods such as gradient projection and quadratic projection are very much useful for equality constraints differences existed between Constrained optimization and unconstrained optimization because of their approaches and because the local optima are not the intended goal. Generally, a subset of unconstrained optimization is useful for the Constrained optimization methods [16, 17]. In this paper, the proposed methods are Particle Swarm Optimization and Neural Network for solving the Constrained Optimization problem. Using Particle Swarm Optimization (PSO) algorithm, the constraint optimization has been achieved by designing the genuine Objective function and applying the required upper and lower bounds on each of the Particles and after that, the selection of the desired Global bests are considered as the Optimized Solutions [18]. In [19], Neural networks are extraordinarily intelligent and intuitive. To solve any problem, we need to train the network to perform the specific task, and hence to solve nonlinear non-convex optimization problems, we need to train the neural networks [20]. Different approaches and methods have been proposed by researchers. The first method which revolutionizes all analysis were classical methods. The most popular and prevalent algorithm to train the neural networks is error back propagation [21]. It has a specialty of minimizing an error function using the steepest descent algorithm. All algorithms have their own pros and cons and so as with the error back propagation, usually its implementation is quite easy but it comes with a price, i.e. convergence problem etc. It has all the disadvantages in optimization algorithms of Newtown based, which inherits slow convergence rate and trapping in local minima [20, 21]. Over the years Researchers have proposed different supervised learning methods such as the Step net. The tilling algorithms cascade-correlation algorithm and the scaled conjugate algorithm in order to mitigate deficiencies and to enhance its applicability, global optimization methods ate another available alternative for Newtown based methods and to learn the deepest of the structure of the neural network. Along with the learning techniques for ANN discussed in the above sentences, we have another widely used and flaw-

**Algorithm 1** Algorithm for PSO

Inputs: Generated channel coefficients ($h_1, h_2, h_3$), transmitted power (P) and noise power ($\sigma^2$)
1. **Costfunction** $= \frac{\mathbf{1}}{\mathbf{C_3(1)}} + \frac{\mathbf{1}}{\mathbf{C_2(2)}} + \frac{\mathbf{1}}{\mathbf{C_1(3)}}$, considering $a_1, a_2, a_3$ as variable or particle
2. Define parameters: number of dimension variables = n, number of iterations = it, number of particles = N, inertia coefficient = W, personal acceleration coefficient = $C_1$, global acceleration coefficient = $C_2$
3. Initialize: particle position(normalize), particle velocity, personal best position, personal best cost, global best cost
4. for j = 1:it
for k = 1:N
particle velocity = W × (particle velocity) + $C_1$ × (particle best position-particle position) + $C_2$ × (global best position-particle position)
particle position = particle position+particle velocity
particle cost = cost function (particle position)
if $a_1 < a_2 < a_3$
if particle cost < particle best cost
particle best position = particle position
particle best cost = particle cost
if particle best cost < global best cost
global best = particle best
end
end
end
end
Outputs: global best positions ($a_1, a_2, a_3$)

less methods to train the Neural networks with optimized structure, are the quotient gradient system (QGS), genetic algorithms and stimulated annealing [19, 22–26]. Results achieved through neural networks are in convergence with standard results and performance parameters using classical error back propagation algorithm for the defined constrained optimization problem. Hence, the training of neural networks used here is error back propagation.

### *4.2 Problem Formulation*

The requirement is to obtain the optimal values for $a_1$, $a_2$, $a_3$ such that $C_1(1) + C_2(2) + C_3(3)$ is maximized, with constraints $C_3(1) > R_1$, $C_2(2) > R_2$, $C_1(3) > R_3$. Also $a_1 + a_2 + a_3 = 1$. It is noted that the order in which the data are detected is from strong signal to the weak signal (1, 2, 3), i.e. $|h_1| \geq |h_2| \geq |h_3|$. In this paper, we propose to use Particle Swarm Optimization (PSO) to optimize the power allocation ratio $a_1$, $a_2$ and $a_3$ such that it maximizes the total channel capacity in the downlink. PSO is the optimization algorithm inspired by the natural behaviour of the birds on identifying the path to the destination. The position of the bird is the possible solution that minimizes or converges the cost function and the distance of the position of the bird from the destination is the corresponding functional value. This is the analogy used in PSO algorithm. The steps involved in the PSO based optimization for given channel coefficients (refer algorithm in Sect. 4.1). Thus, for the given $|h_1|$, $|h_2|$, $|h_3|$, the corresponding values $a_1$, $a_2$ and $a_3$ are obtained using the proposed PSO based methodology. The experiments are repeated for various combinations of $h_1$, $h_2$, $h_3$ and the corresponding optimal fractional constants $a_1$, $a_2$ and $a_3$ obtained using PSO are collected. Further in the second part (refer Fig. 1b), Back propagation Network is used to construct the relationship between the $h_1$, $h_2$ and $h_3$ as the input and the corresponding values $a_1$ $a_2$ and $a_3$ as the target values.

## 5 Experiments and Results

Experiments are performed by generating 200 instances of channel coefficients $h_1$, $h_2$ and $h_3$ (with variances 0.9, 0.5, 0.1, respectively) and the corresponding optimal fractional weights $a_1$, $a_2$ and $a_3$ that maximize the total channel capacity, satisfying the constraints are obtained using Particle Swarm Optimization. Figures 2, 5 and 6 illustrate how the maximization of the total channel capacity is achieved and also showing the good convergence plot for defined objective function using Particle Swarm Optimization. 50% of the collected instances are used as the training data to construct the Back propagation Network to predict the optimal fractional constants $a_1$, $a_2$ and $a_3$. Figure 3 shows the designed back propagation neural network having

100 instances of each channel coefficient $h_1$, $h_2$ and $h_3$ are the 3 inputs and their corresponding optimal fractional weights $a_1$, $a_2$ and $a_3$ are the targets taken from PSO. Figure 4 describing the training performance of the constructed Network. Convergence plot concludes that it is fast at the training stage. Figure 7 is concluding the relationship between targets and actual Outputs and we got almost 99% regression values which means the actual outputs are completely converging to the targets. Figure 8a shows the magnitude plots of the channel coefficients corresponding to the three users. Figure 8b shows the optimal fractional constants $a_1$, $a_2$ and $a_3$ obtained using PSO and the values predicted using the trained constructed Neural Network. Also, the Table 1 shows the generated values of channel Coefficients and Tables 2 and 3 are the optimum values of Power Allocation Ratios by PSO and ANN respectively. Tables 4 and 5 are demonstrating the values of achieved Individual Rates and Sum Rates of the 3 users by PSO and ANN respectively. The results thus obtained act as the proof of concept and reveal the importance of proposed technique.

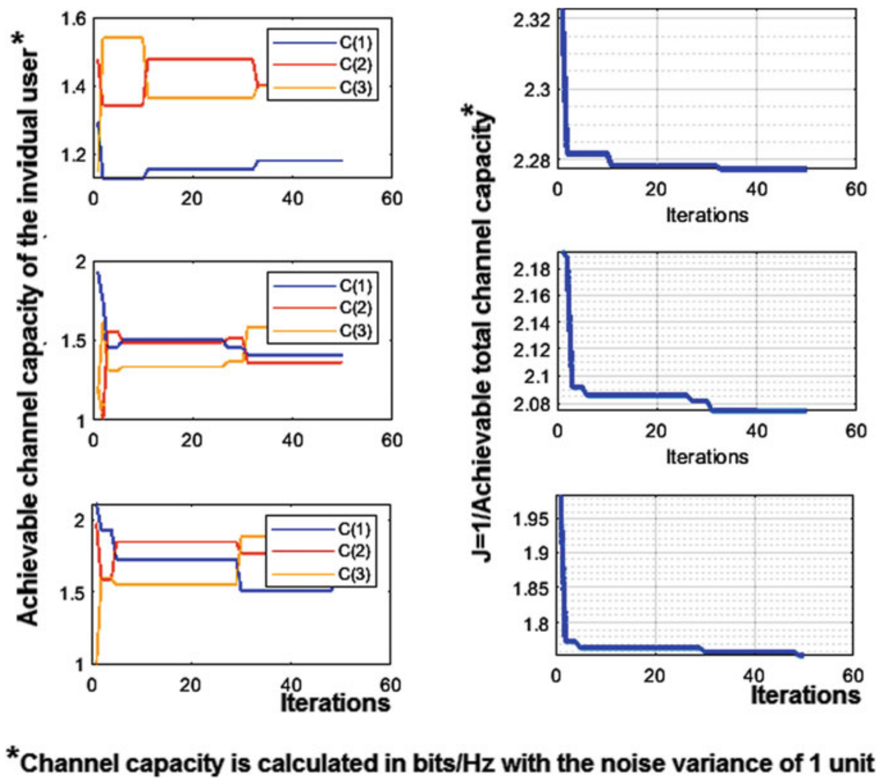


**Fig. 2** Illustrations on the performance of the PSO on achieving the maximum channel capacity for the individual users in the downlink scenario (Part 1)

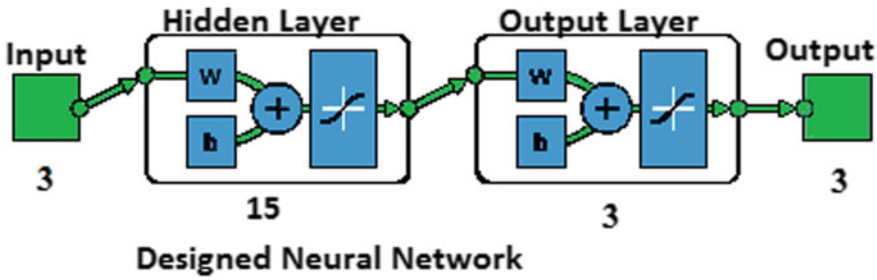


**Fig. 3** Designed neural network for channel coefficients as the inputs and Power allocation ratios as the targets and having 15 neurons in the hidden layer

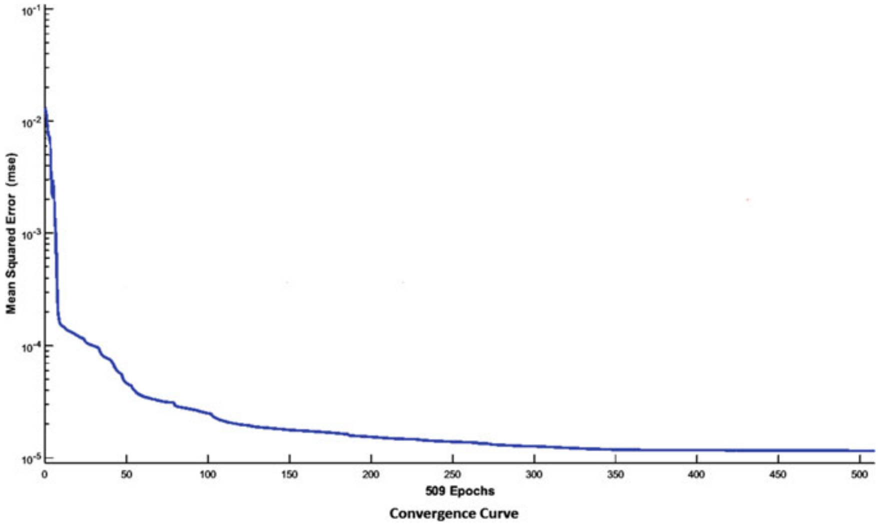


**Fig. 4** Performance plot of ANN showing convergence of MSE

**Table 1** Generated channel coefficient

| $h_1(0.9)$ | $h_2(0.5)$ | $h_3(0.1)$ |
|---|---|---|
| 1.65 | 0.56 | 0.03 |
| 0.60 | 0.20 | 0.05 |
| 1.11 | 0.69 | 0.09 |
| 1.47 | 0.21 | 0.001 |
| 0.78 | 0.20 | 0.06 |
| 0.35 | 0.28 | 0.06 |
| 1.32 | 0.48 | 0.19 |
| 0.94 | 0.09 | 0.06 |
| 2.24 | 0.85 | 0.09 |
| 1.42 | 0.25 | 0.14 |

For $P = 1000$ units and $\sigma^2 = 1$ units

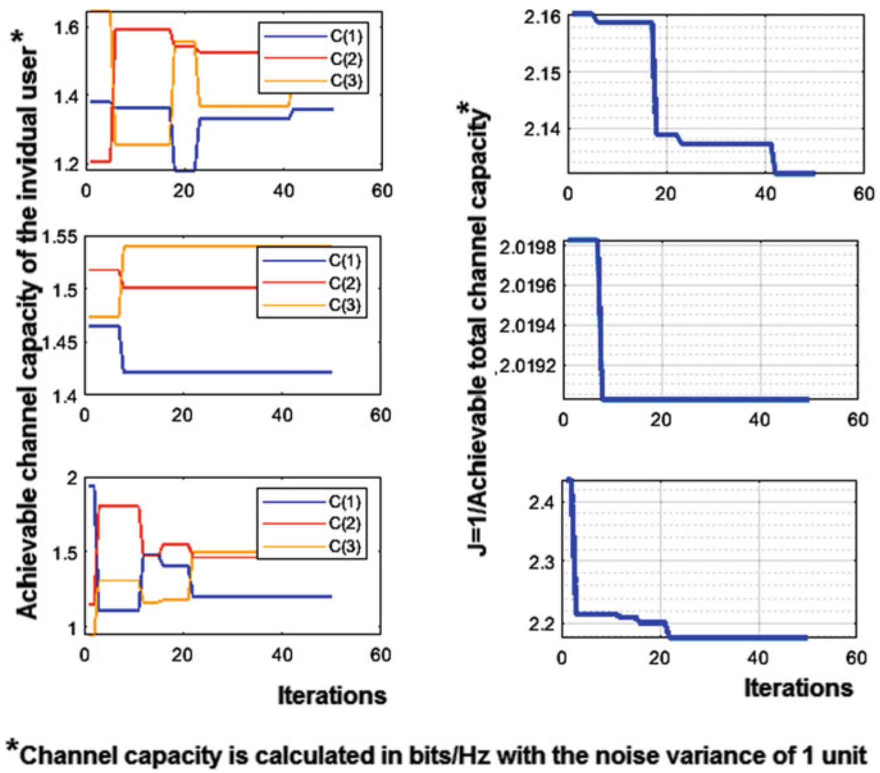


**Fig. 5** Illustrations on the performance of the PSO on achieving the maximum channel capacity for the individual users achieved in the downlink scenario (Part 2)

**Table 2** Optimum power allocation ratios by PSO

| $a_1$ | $a_2$ | $a_3$ |
|---|---|---|
| 0.0314 | 0.1731 | 0.7953 |
| 0.0464 | 0.2167 | 0.7368 |
| 0.0382 | 0.1734 | 0.7883 |
| 0.0140 | 0.0928 | 0.8930 |
| 0.0485 | 0.2208 | 0.7305 |
| 0.0616 | 0.2055 | 0.7328 |
| 0.0386 | 0.2167 | 0.7446 |
| 0.0224 | 0.1748 | 0.8006 |
| 0.0364 | 0.2370 | 0.7265 |
| 0.0430 | 0.2430 | 0.7139 |

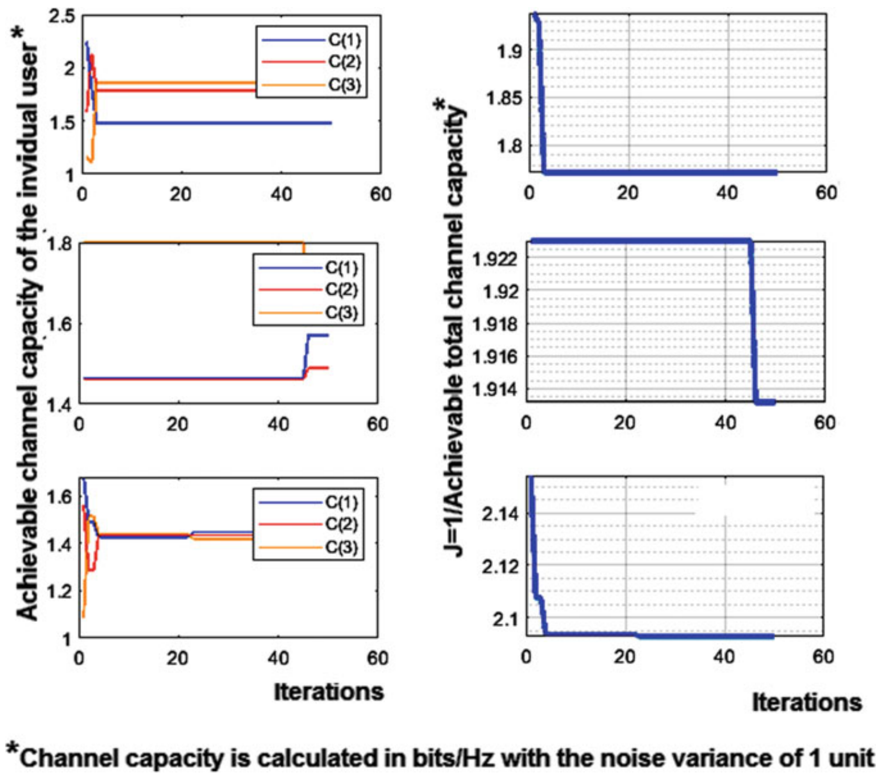


**Fig. 6** Illustrations on the performance of the PSO on achieving the maximum channel capacity for the individual users achieved in the downlink scenario (Part 3)

**Table 3** Optimum power allocation ratios by ANN

| $a_1$ | $a_2$ | $a_3$ |
|---|---|---|
| 0.0207 | 0.1428 | 0.8408 |
| 0.0518 | 0.2289 | 0.7188 |
| 0.0344 | 0.1810 | 0.7806 |
| 0.0195 | 0.1582 | 0.8327 |
| 0.0473 | 0.2366 | 0.7188 |
| 0.0683 | 0.2213 | 0.7101 |
| 0.0336 | 0.1825 | 0.7873 |
| 0.0195 | 0.1775 | 0.8021 |
| 0.0345 | 0.2310 | 0.7260 |
| 0.0451 | 0.2405 | 0.7105 |

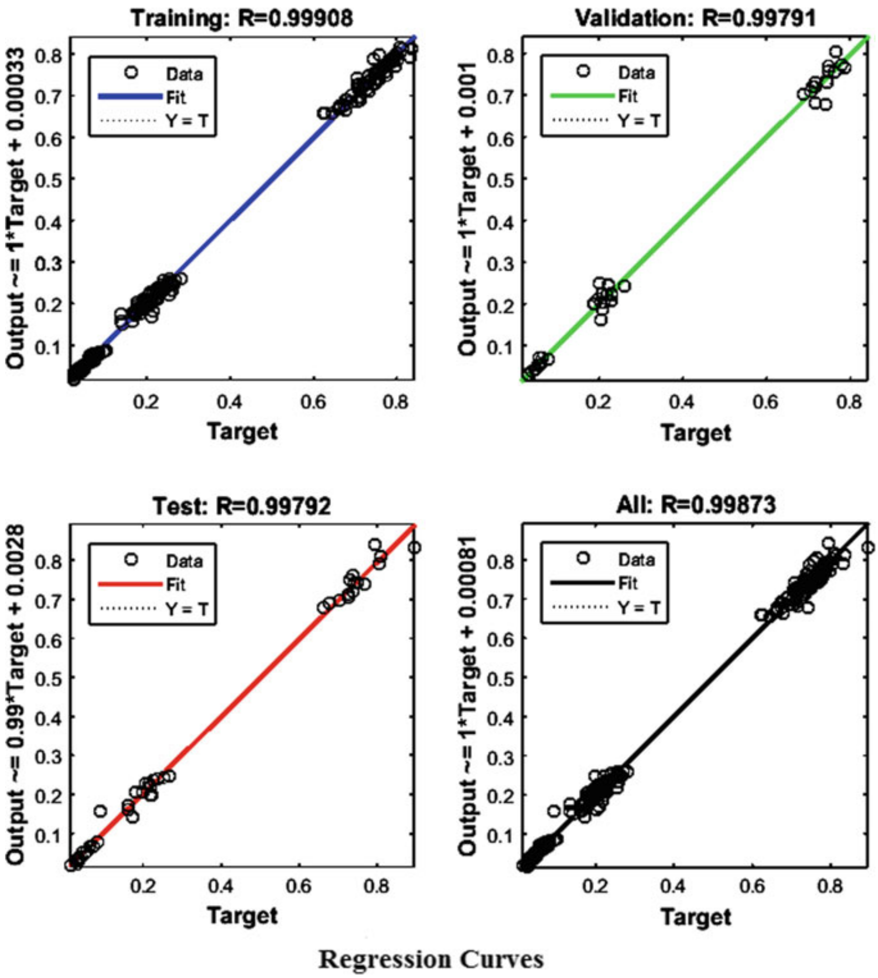


**Fig. 7** Plot for regression curves of ANN showing target and output relationship

## 6 Conclusion

The PSO based power allocation for the individual users of the NOMA downlink is demonstrated. Also, it is proposed to use the constructed Neural Network to obtain the power allocation as per one obtained using the proposed PSO based techniques. The experimental results reveal the importance of the proposed technique. The proposed technique can be extended to an uplink scenario as well as with various noise power and with an increasing number of users. In this paper, power allocation has been done for only 3 users, so the PSO algorithm having three dimensional (3D) search space has implemented for power allocation to the individual users such that the total

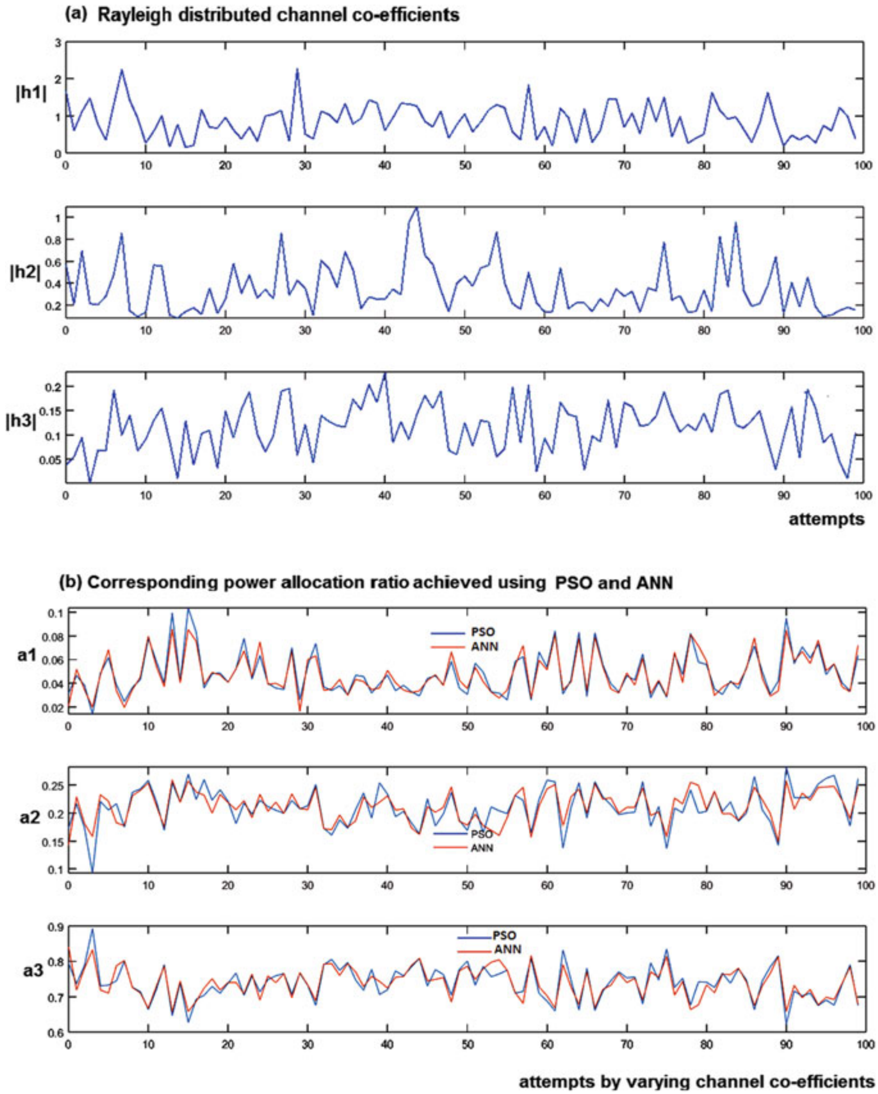


**Fig. 8** **a** Outcome of the Rayleigh distributed channel coefficients $h1$, $h2$ and $h3$ with variances 0.9, 0.5 and 0.1, respectively, **b** corresponding power allocation ratio achieved using PSO and ANN

**Table 4** Achievable rates using PSO

| $C_3(1)$ | $C_2(2)$ | $C_1(3)$ | Sum rate |
|---|---|---|---|
| 6.43 | 2.58 | 0.6821 | 9.69 |
| 4.156 | 2.0121 | 1.078 | 7.23 |
| 5.5994 | 2.40672 | 1.74533 | 9.73 |
| 4.9847 | 1.8197 | 1.00 | 7.79 |
| 4.93 | 2.00 | 1.22 | 8.15 |
| 3.113 | 1.912 | 1.22 | 6.24 |
| 6.0974 | 2.596 | 1.86040 | 10.54 |
| 6.9580 | 2.957 | 1.7988 | 11.69 |
| 6.224 | 2.465 | 1.6957 | 10.37 |
| 5.290 | 1.29 | 1.1823 | 7.76 |

**Table 5** Achievable rates using ANN

| $C_3(1)$ | $C_2(2)$ | $C_1(3)$ | Sum rate |
|---|---|---|---|
| 5.84 | 2.83 | 0.72 | 9.39 |
| 4.27 | 2.01 | 1.10 | 7.38 |
| 5.42 | 2.56 | 1.72 | 9.72 |
| 5.39 | 2.24 | 0.001199 | 7.63 |
| 4.88 | 2.09 | 1.18 | 8.15 |
| 3.22 | 1.89 | 1.17 | 6.28 |
| 5.87 | 2.54 | 2.08 | 10.49 |
| 6.56 | 3.17 | 1.81 | 11.56 |
| 6.14 | 2.47 | 1.71 | 10.32 |
| 5.44 | 1.27 | 1.17 | 7.88 |

sum rate will be maximized. And also, because of low dimensional error surface for the problem, the achieved results were in good agreement for Neural Network using error back propagation. But if we increase it for more number of users, for that we have to implement the PSO algorithm with higher dimensions that is according to the number of users and also increase in the number of users will give rise in dimensions of error surface for the problem hence for training the Neural Network, different alternatives methods can be used to achieve better results.

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