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Multiobjective optimization based on self-organizing Particle Swarm Optimization algorithm for massive MIMO 5G wireless network

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Summary

The development of future fifth-generation (5G) wireless networks (WNs) is an active research area worldwide. The 5G network grants significantly upgraded necessities contrasted with those in present wireless systems. Although massive MIMO (mMIMO) incorporation in WN empowers one to encounter 5G network technical necessities, it should handle different challenges to increase the performance. In this paper, a novel multiple objective self-organizing particle swarm optimizer (SOMPSO) is used to solve multiple objective functions such as user data rate, energy efficiency, spectral efficiency, and average area rate of 5G WN with mMIMO. Furthermore, a fuzzy decision maker is utilized to select a solution vector for getting the best compromising result. Our experimental outputs demonstrate that this SOMPSO is an efficient and promising method to solve multiple objective problems in 5G networks.

KEYWORDS

massive MIMO, multiple objective optimization, objective functions, self-organizing map, spectral efficiency

1 | INTRODUCTION

The information and communication technology (ICT) is creating a quick evolution toward fifth-generation (5G) wireless network (WN). They tried to assimilate nearly everything over the world into the Internet. The 5G networks can offer 20 GB/s of data rates, average data rates of above 100 Mbps, and connectivity for an enormous amount of Internet of things (IoT) tools per unit area.[1,2] The ultra-dense network's (UDNs) spectral efficiency and consumption of power can be improved by evolving methodologies like large-scale (LS) MIMO,[3] massive MIMO (mMIMO), mm-waves,[4] and densification approaches. The spectral and energy efficiency can be improved in multiple order with the help of a recently proposed mMIMO method. Thus, it is used in the 5G network to improve performance.[5]

The current fascinating sub-6-GHz physical-layer methodology is represented as mMIMO for future wireless access. In mMIMO, every base station (BS) consists of huge number of antennas, and it exploits channel reciprocity in time-division duplex.[6] The study on future 5G wireless systems tries to find a solution for many exceptional technical necessities and contests.[7,8] Different desires and objectives of mMIMO 5G network design should be considered to optimize the network structure efficiently by jointly bear in mind all the 5G objectives, which are a conflict to each other.[9] The challenges of 5G networks that aren't sufficiently specified in LTE-advanced systems should be addressed on the basis of current developments. They are higher data rate, higher energy efficiency, higher area rate, and higher spectral efficiency.[10]

The solution to one problem may degrade the solution to another problem. Therefore, the future network requires a network design trade-off. The multiple objective problems of 5G mMIMO system such as energy efficiency and spectral efficiency were solved by transforming the multiple objective problems into a single objective problem using weighted-sum method (WSM) because of the nonexistence of appropriate solution methods.[11,12] The selection of weighting parameter that is used to determine the trade-off between multiple objectives is a challenging problem. Thus, the best trade-off solution set can be acquired through multiple objective optimization (MOO) method without converting the problems into a single problem. The principal descriptions, features, and algorithmic implements of multiobjective optimization are surveyed in Bjornson et al.[13] It exposes the way of signal processing procedures for visualizing the intrinsic conflicts of 5G objectives to allow the network engineer for understanding the probable functioning points and for balancing the objectives efficiently.

Many Pareto optimal solutions for 5G mMIMO have been obtained by using the population method of multiple objective evolutionary algorithms (MOEAs) in a single simulation run.[6,14] It is very challenging to obtain the Pareto optimal front using MOEAs for MOO issues,[15,16] because every solution in the population rapidly turns out to be nondominated by concerning the leftovers. Only the density evaluator is used to identify the best individuals. Hence, it may discard good locally nondominated solutions based on convergence in certain circumstances by maintaining good solutions based on diversity, even though they are far-off from the optimal Pareto front (PF). The modest and rapid nondominated sorting MOEAs are NSGA-II,[17] MOPSO,[18] and NSGA-III.[19] The diversity of such approaches is lost to a certain level due to the rapid convergence. However, MOPSO is the simplest and robust approach.

Also, the existing MOO frameworks of mMIMO 5G network design do not consider the energy efficiency, spectral efficiency, average area rate, and average user rate together in one model without converting them into single problems; 5G mMIMO network needs to maximize these four objectives for allocating the resources efficiently, but these objectives are conflicting with one another. Hence, the optimal solution for all these objectives is difficult to obtain simultaneously. Thus, an efficient optimization algorithm is needed to find out the best trade-off between all objectives. While considering many objective conflicting problems, the behavior of the neighborhood leader of the MOO framework should be considered in the local search to obtain excellent Pareto optimal set by preserving the local topological properties, but the existing approaches failed to preserve the local topological properties. Thus, the performance of the MOPSO algorithm should be increased by including the neighborhood relations in the decision space. Thus, we combined MOPSO algorithm with self-organizing map (SOM) due to its neighborhood property. Also, we used an elite learning methodology to tackle the issue of diversity problems in the existing approaches. The main contributions of our proposed work are as follows:

- To develop an optimization framework for optimizing the downlink communication of a mMIMO network to find a trade-off between four conflicting objectives: average area rates, average user rates, spectral efficiency, and energy efficiency.
- To introduce a novel self-organizing particle swarm optimizer (SOMPSO) for determining nondominated solutions in one run without converting the problems into a single optimization problem as the traditional MOO approaches.
- To construct neighborhood relations in decision space, this will maintain the diversity of the solution by integrating SOM with the MOPSO algorithm. Here, SOM is used to determine the solution distribution of the present population by picking the neighborhood relations. It improves the distribution characteristics in both decision and objective space.
- To increase the diversity of the Pareto optimal sets, an elite learning methodology is used.

The structure of this paper is given as follows: Section 2 describes related works on MOOs for 5G WNs. Section 3 explains the system model for a 5G WN with mMIMO. The proposed optimization structure is provided in Section 4. The simulation outputs and analysis are discussed in Section 5. Section 6 concludes the paper and also provides future work.

2 | RELATED WORK

Several researchers focused on MOOs for different applications in 5G WNs. Some of them are listed below.

Osman et al.[20] presented a structure to optimize the energy efficiency and spectral efficiency of 5G and beyond 5G (B5G) nets. Here, the shared networks were defined using a multifarious service level agreement (SLA) context wherein various operator's restrictions were processed with utility profile and scalarization processes. The generalized fractional programming scheme was combined with the processes mentioned above to get Pareto optimal solutions. They focused to maximize the spectral efficiency as well as the global energy efficiency (GEE) and ensured the QoS and energy consumption restrictions. These optimization algorithms utilized a weight factor for converting the multiple objective problems into a single objective problem.

Bedeer[21] adopted a MOO processes for investigating the problems related with optimum link adaption for orthogonal frequency division multiplexing (OFDM)-based cognitive radio (CR) systems. They were formulated a nonconvex problem to maximize the throughput of the secondary user and to minimize the transmitting power by considering the constraints such as BER, co-channel interference and adjacent channel interference of the primary users and maximum allotted bits/subcarrier for the secondary user. Then, the nonconvex problem is converted into a convex problem using Karush–Khun–Tucker (KKT) conditions. This would increase the computational complexities. Thus, the algorithm proposed by Bedeer[21] was not suitable for nonconvex problems.

An optimization metric with a self-organizing characteristic could optimize the radio resource allocation process dynamically. López-Pérez et al.[22,23] represented the minimization problem of cell down link transmitting power as a self-organization rule to distribute radio resource allocations among the cells. This approach has been used for converging the distributed cellular network into resource reuse pattern efficiently. Also, the problems related with resource allocation process is solved by Bedeer et al.[24] by developing a MOO algorithm. They were determined the trade-off between energy efficiency and spectral efficiency by employing the weighted sum approach. Hao et al.[25] also used weighted sum approach to determine the trade-off between energy efficiency and spectral efficiency in mMIMO HetNets, but it is very difficult to select an optimal weight for balancing the conflicting objectives. Thus, an alternative solution for this issue is suggested in the proposed work based on MOEAs.

Goudos et al.[9] introduced to use MOEAs for optimizing the multiple objective problems in 5G WNs. They were considered the energy efficiency, user rate, and area rate as the conflicting issues in the 5G network. They utilized standard NSGA-II and SMPSO[26] algorithm to find a solution for the aforementioned conflicting objectives. The multiple objective problems related to edge device location in ultra-dense 5G systems were investigated by Chantre and da Fonseca.[27] to provide stable broadcasting facilities. They mainly concentrated on edge device positioning issues and developed an algorithm for solving these issues to guarantee the 5G NFV-based small cells security. MOO problems (MOOP) were formed to address the contradictory objectives to get lower service response time, higher reliability, wide coverage, and lower service cost.

Nowadays, the researchers used a different version of PSO to find the solution for different problems due to its simpler design construction. Liu et al.[28] used a PSO algorithm for finding the routing solution for XGRouter, but it can't be used for finding a discrete solution for a certain application. Thus, Guo et al.[29] proposed a discrete particle swarm optimization (DPSO) for allocating real-time fault tolerant task in the wireless sensor network. Also, a local search strategy was integrated with DPSO in Guo et al.[30] for solving the multiple objective circuit portioning issue. Liu et al.[31] used PSO for the construction of multiple layer obstacle avoiding X-structure Steiner minimal tree, but there might be a loss of diversity due to the rapid convergence of PSO algorithm. Also, it could easily get into local optima in high-dimensional space.

Two commonly used MOEAs such as MOPSO and NSGA-II were utilized for solving the multiple objective problems in 5G WNs. Recently, Yi et al.[19] analyzed the effectiveness of different crossover operators in NSGA-III for LS optimization problem, but it requires external guidance mechanism for maintaining the diversity between the solutions. The NSG-II could create duplicate individuals, and therefore, the dimension of variables was increased, which causes the difficulty of searching isolated points. Also, the crowding distance did not operate in the decision space. Because of the rapid convergence of MOPSO algorithm, the diversity was reduced. The proposed scheme tried to eliminate the constraints presented in the aforementioned state-of-the-art approaches.

3 | SYSTEM MODEL AND PROBLEM FORMULATION

Assume a mMIMO downlink network with one BS and N users. Figure 1 shows the mMIMO network model with M BS antenna and N users.

Assume a cellular network that consists of K number of square cells and area of each cell is considered as $A_{\text{cell}} = a_{\max}^2$. The distance between the users within each cell is uniform ($\alpha_{\min}$). There is a single BS with M antennas

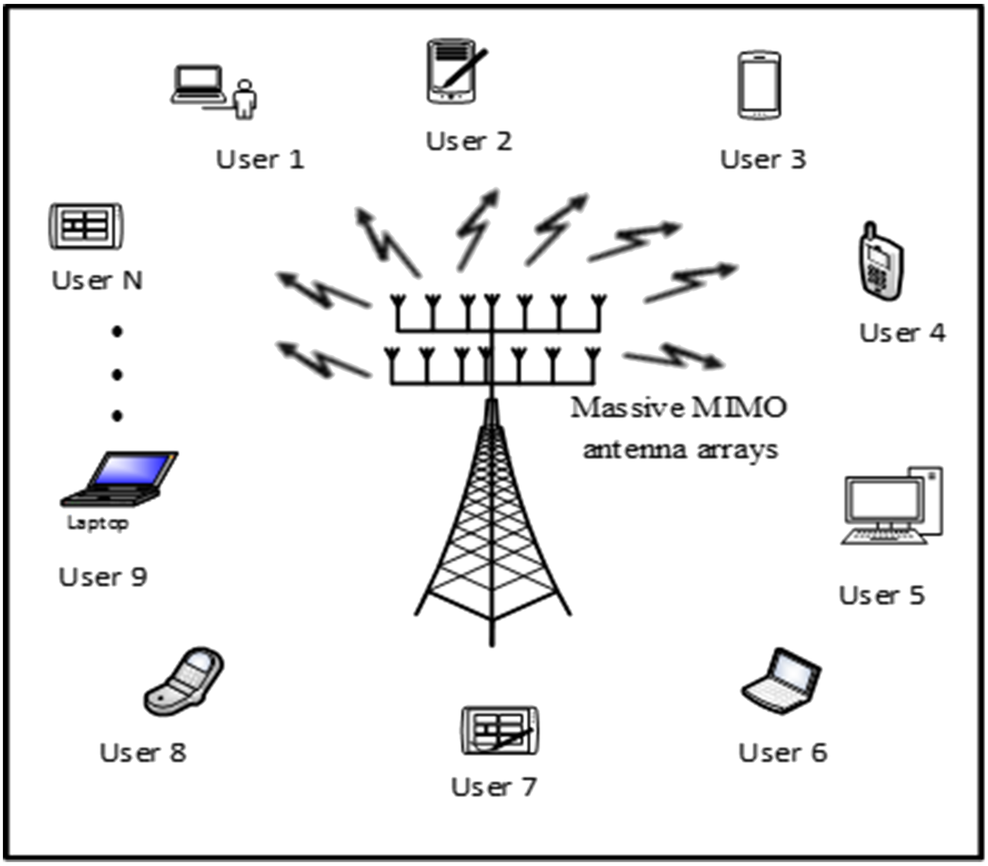

FIGURE 1 Massive MIMO network model

and N users in each cell. The optimization/resource variables of mMIMO system are M, N, and the transmitting power P_t for each cell. The optimization variable constraints are given as follows[13]:

$$\mathbf{x} = \left\{ [N\ M\ P_t]^T : \begin{array}{c} 1 \le N \le \frac{M}{2} \\ 2 \le M \le M_{\max} \\ 0 \le P_t \le M P_t^{\max} \end{array} \right\}, \tag{1}$$

where $M_{\max}$ represents the largest amount of antenna allowed or possible at every BS, $P_t^{\max}$ denotes the maximal power discharged at each BS antenna. Here, the amount of BS antennas is high when compared to a number of active users and it can be guaranteed by the limit $N \le \frac{M}{2}$.

The definition of total power consumption and average user rate of each cell is given in subsequent lines. Here, an accurate CSI has been acquired by each BS for their users. This is the assumption made by us for simplifying the definition. In order to avoid intracellular interference, zero-forcing precoding is performed. It forms a beam, and the power allocation is adapted for guaranteeing a similar rate to each user. Here, the average user rate is defined by assuming intercell interference as noise, and a suitable channel is known to every user.

$$F_1(\mathbf{x}) = R_{\text{avg}} = \omega \left(1 - \frac{N}{\omega_c t_c}\right) \log_2 \left(1 + \frac{\frac{P_t}{N}(M-N)}{P_n^2 \Psi_1 + P_t \Psi_2}\right), \tag{2}$$

where ω and ω_c represent transmitting bandwidth and bandwidth of coherence respectively, t_c represents coherence time, P_n^2 represents average noise power, Ψ_1 denotes inverse channel loss, and ψ_2 is intercell interference strength. The term $1-\frac{N}{\omega_c t_c}$ explains about required overhead to acquire channel, $\frac{P_t}{N}$ denotes average transmitting power of a user, $M-N$ denotes efficient array gain, and $P_n^2\Psi_1+P_t\Psi_2$ denotes average degradation due to interference and noise. The definition for total power consumption of each cell is expressed as follows:

$$P_{\text{total}}(\mathbf{x})=\frac{P_t}{\eta}+MP_c^M+NP_c^N+\frac{C_{\text{pre}}}{\eta_c}+P_s, \tag{3}$$

where η denotes BS's power amplifier efficiency, P_c^M represents hardware power consumption at transmitting antenna, P_c^N describes the hardware power at each user, and P_s represents static hardware power, and η_c is a typical computational efficiency. In addition, C_{pre} is the floating-point processes needed for the computation of zero-forcing precoding per second, and it is expressed as:

$$C_{\text{pre}}=3N^2M\frac{\omega}{\omega_c t_c}. \tag{4}$$

Energy efficiency denotes the ratio of the number of transferred bits to the total power consumption. Spectral efficiency defines the rate of sustained data transmission per unit of bandwidth. The expression for average area rate, energy efficiency, and spectral efficiency are defined using the equation mentioned above and are given as follows:

$$F_2(\mathbf{x})=\frac{N}{A_{\text{cell}}}F_1(\mathbf{x}) \quad bps/km^2, \tag{5}$$

$$F_3(\mathbf{x})=\frac{NF_1(\mathbf{x})}{P_{\text{total}}(\mathbf{x})} \quad b/J, \tag{6}$$

$$F_4(\mathbf{x})=\frac{F_1(\mathbf{x})}{\omega} \quad bps/Hz. \tag{7}$$

The optimization parameters are $\mathbf{x}=[N\ M\ P_t]^T$. $F_1(\mathbf{x})$ represents an objective function for average user rate, $F_2(\mathbf{x})$ denotes the objective function for average area rate, $F_3(\mathbf{x})$ describes the objective function for energy efficiency, and $F_4(\mathbf{x})$ is the objective function for spectral efficiency. Generally, the objective functions conflicting with one another in MOOP and single solution sets are produced by considering trade-off conflicts among the objectives. The MOOP to maximize objectives described above concurrently can be stated as follows:

$$\begin{aligned}&\max F(\mathbf{x})=[F_1(\mathbf{x}),F_2(\mathbf{x}),F_3(\mathbf{x}),F_4(\mathbf{x})],\\&\textit{subject to}\quad (1)\end{aligned} \tag{8}$$

where $F(\mathbf{x})$ denotes the objective function vector. The objective space and search space are denoted as $\mathbf{Y}$ and $\mathbf{S}$ correspondingly. Hence, the map $F:\mathbf{S}\to\mathbf{Y}$ for every vector $\mathbf{x}\in\mathbf{S}$ resembling a vector $\bar{\mathbf{y}}=F(\mathbf{x})\in\mathbf{Y}$. The problems mentioned in Equation 8 can be optimized using SOMPSO.

4 | PROPOSED OPTIMIZATION FRAMEWORK

The balancing of four opposing objectives like average user rate, average area rate, energy efficiency, and spectral efficiency is required for optimizing the downlink data transfer in mMIMO network. Figure 2 illustrates the pipeline structure to optimize the multiple objectives of 5G mMIMO using SOMPSO.

Here, the objective functions of 5G mMIMO networks are solved by using SOMPSO. It is the hybridization of SOM and MOPSO algorithm. Initially, the dissemination structure for the population is determined using the SOM network, and the neighbors in the decision space are constructed. Then, the bests are chosen from the consequent neighbors. In the meantime, the elite learning approach is embraced for preventing the premature convergence of MOPSO. Subsequently, the external archive (EA) is revised utilizing a nondominated sorting algorithm with specific crowding

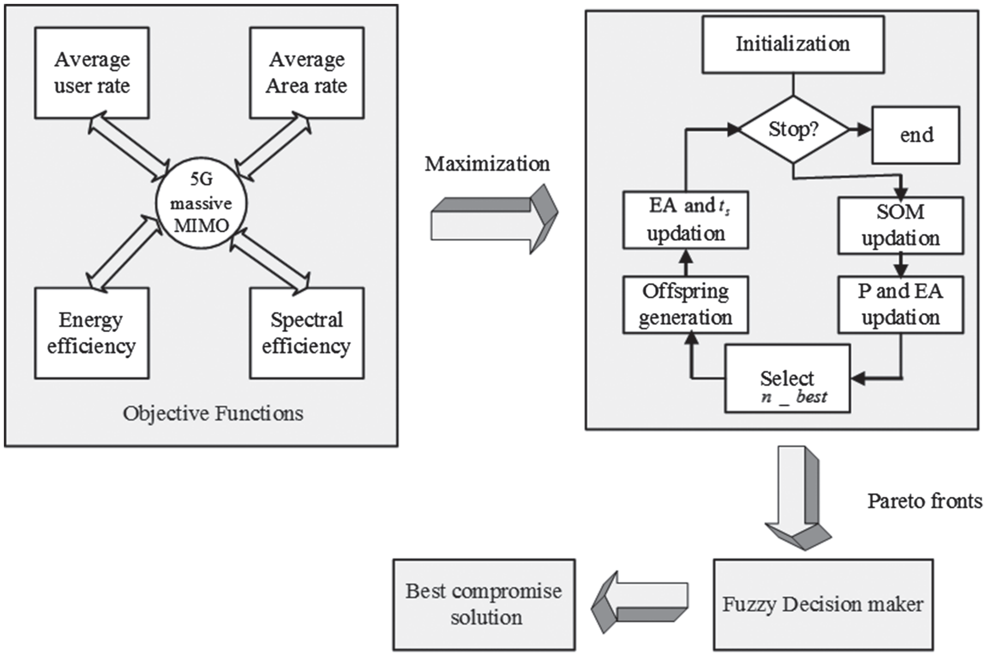

FIGURE 2 The proposed pipeline structure for optimizing multiple objectives of 5G massive MIMO

distance. The analogous solutions are mapped into similar neighborhoods using a self-organizing algorithm. This SOMPSO provides multiple Pareto optimal results. Then, the decision is made using fuzzy logic for obtaining the best compromising result.

4.1 | Self-organizing multiple objective PSO algorithm

The MOOP provided in Equation 8 is difficult to solve because it consists of multiple objectives and also they are convex. Thus, the complication of the conventional optimization algorithms is increased for finding the PF or nondominated solution set. Also, these problems may consume more solution for the similar points in **Y**. When solving MOOP, the functioning of leaders of the neighborhood is significant in local search. To this end, in this paper, the SOMPSO algorithm is utilized for finding multiple nondominated results through a single run.

MOPSO algorithm is a global optimization evolutionary algorithm, which imitates the procedure of bird's movement. The search individuals in the search space of MOPSO are known as particles. Every particle in the population is characterized by two parameters such as velocity and position. Every particle in MOPSO defines a possible solution. Consider a swarm with P particles whose search space is m-dimensional hyperspace. $\mathbf{x}_k$ and $\mathbf{s}_k$ represent the position and velocity vector of particle k, respectively. In order to maintain the diversity of the solution, MOPSO uses the neighborhood optimal solution as a replacement for the global optimal solution in conventional PSO. The location and velocity are updated using the subsequent expressions:

$$\mathbf{s}_k(n+1) = \hat{\omega} * \mathbf{s}_k(n) + a_1 r_1 \left(\mathbf{x}_k^{p\_best} - \mathbf{x}_k(n)\right) + a_2 r_2 \left(\mathbf{x}_k^{n\_best} - \mathbf{x}_k(n)\right), \tag{9}$$

$$\mathbf{x}_k(n+1) = \mathbf{x}_k(n) + \mathbf{s}_k(n+1), \tag{10}$$

where n represent iteration, $\hat{\omega}$ is inertia weight, a_1 and a_2 are acceleration constant, r_1 and r_2 represent random values between 0 and 1, *p_best* denotes the personal best, and *n_best* denotes the ith particle's best neighborhood location. The selection of *n_best* is a challenging problem. Here, SOM is used for constructing a neighborhood of each particle and to select *n_best*.

There are two space in SOM network, namely, input space and latent space. An external information can be received by the input layer, and this information is transmitted to the latent space to perform an “observation” process. The dimension of the input space is considered as m. The latent space consists of P neurons as same as the population size of MOPSO that every neuron $\nu = 1.2. ...P$ in the latent space is characterized by a location $\mathbf{z}^{\nu} = ({z_1}^{\nu}, {z_2}^{\nu})$ and weight $\hat{\boldsymbol{\omega}}^{\nu} = ({\hat{\omega}_1}^{\nu}, {\hat{\omega}_2}^{\nu})$. The location of each particle acquired through every iteration of MOPSO algorithm is projected to the initial weight of each neuron in SOM. The non-dominated results obtained from MOPSO are used as training set $\mathbf{T_s}$ in order to update SOM model. Analogous solutions are clustered into similar neighbors using SOM. *n_best* is selected using nondominated scd-sorting technique[32] from neighbors. The chosen *n_best* guides the particles to move toward the best position.

The functioning of SOM to select *n_best* is split into two phases, namely, SOM update and *n_best* selection. In the updating phase, initially, the weights of every neuron $\hat{\boldsymbol{\omega}}^{\nu}$ are initialized. After that, the learning rate and radius are calculated using

$$\varepsilon = \varepsilon_0 * \left(1 - \frac{n}{n_{\max}}\right) \text{ and } r = r_0 * \left(1 - \frac{n}{n_{\max}}\right), \tag{11}$$

where n and $n_{\max}$ represents current and maximum iteration respectively. The best neuron of randomly selected particle $\mathbf{x} \in \mathbf{T_s}$ and its neighboring neurons in the latent space can be calculated using the following expression:

$$\nu' = \arg \min_{1 \le \nu \le D} \|\mathbf{x} - \hat{\boldsymbol{\omega}}^{\nu}\|_2, \tag{12}$$

$$\mathbf{V} = \left\{ \nu | 1 \le \nu \le D \Lambda \left\| \mathbf{z}^{\nu} - \mathbf{z}^{\nu'} \right\|_2 < r \right\}. \tag{13}$$

The weights of every neuron can be updated using

$$\hat{\boldsymbol{\omega}}^{\nu}_{n+1} = \hat{\boldsymbol{\omega}}^{\nu}_{n} + \varepsilon(n) * \exp\left(\left\| \mathbf{z}^{\nu} - \mathbf{z}^{\nu'} \right\|_2 \right) \left(\mathbf{x} - \hat{\boldsymbol{\omega}}^{\nu}_{n} \right). \tag{14}$$

In the *n_best* selection phase, the test particles $\mathbf{x}_i \in \mathbf{P}$ are mapped to updated SOM latent space for the determination of best neuron using Equation 12. The particles in the EA $\mathbf{x}_i \in \mathbf{EA}$ are mapped to updated SOM latent space to determine *n_best* using nondominated scd-sorting algorithm. The population diversity of MOPSO can also be increased by creating offspring using elite learning policy. The capability of global searching can be enhanced using a mutation operation in the best position. Also, the algorithm can move out from the local optimum position using this operation.

$$\mathbf{x}_i = n\_best_i + Gaussian\ \left(0, \sigma^2\right) \times (l_i - u_i) \quad \text{if rand} < \sigma, \tag{15}$$

where l_i and u_i represent ith dimension's lower and upper limits. The term $Gaussian(0, \sigma^2)$ represents a Gaussian dissemination with a mean value of 0 mean and a standard deviation of σ. When the iteration is increased, σ will be reduced. The higher σ defines the locations that consist of a higher deviation range based on the Gaussian dissemination. It is used for global searching during the initial period. Later on, the range of deviation becomes lower, and it is used for local searching. EA can be updated by adopting a nondominated scd-sorting algorithm, and diversity can also be kept in objective as well as decision space using this method. In the nondominated scd-sorting algorithm, the particles are initially sorted based on dominance relations using this algorithm. After that, the crowd distance is computed in the decision as well as objective space. The higher preference is given to the particles which have larger crowding distance. The steps for SOMPSO is given in Table 1.

The pareto optimal solution set is obtained using this SOMPSO. This solution set is obtained by balancing the objectives provided in Equations 8 and aiming at maximizing the average user rates, average area rates, energy efficiency, and spectral efficiency respectively. These Pareto optimal results are given to the fuzzy decision maker for obtaining the best compromising result.

TABLE 1 Algorithm for SOMPSO

Step 1: Initialize population $\mathbf{P} = \{\mathbf{x}^1, \mathbf{x}^2, \ldots \mathbf{x}^P\}$, $\mathbf{S} = \{\mathbf{s}^1, \mathbf{s}^2, \ldots \mathbf{s}^P\}$, $\mathbf{EA} = \mathbf{P}$ $\hat{\boldsymbol{\omega}}^1, \hat{\boldsymbol{\omega}}^2, \ldots \hat{\boldsymbol{\omega}}^M = \mathbf{P}$, $\mathbf{T_s} = \mathbf{P}$, Rate of learning $\varepsilon_0$and radius of learning r_0.
Step 2: Evaluate objective functions using Equations 2, 5, 6, and 7
Step 3: Check the constraints given in Equation 1
Step 4: Choose *n_best* using SOM learning procedure based on Equations 11–14
Step 6: Update position and velocity using Equations 9 and 10
Step 7: Create offspring using elite learning equation 15
Step 8: Update **EA** and $\mathbf{T_s}$
$\mathbf{EA_{tmp}} = \mathbf{EA}(n) \cup \mathbf{P}(n+1)$
$\mathbf{EA}(n+1)$ = nondominated particle in $\mathbf{EA_{tmp}}$
$\mathbf{T_s} = \mathbf{EA}(n+1) \backslash \mathbf{EA}(n)$
Step 9: Stop if a stopping condition is fulfilled, or else go to Step 3.

4.2 | Fuzzy decision maker

A nondominated result set is provided by SOMPSO, and these solutions create the PF. Every objective may contain fuzziness because of the vagueness while making judgment using a decision maker. The fuzziness level can be described using a membership function. If the midpoint of the PF contains enormous solutions, then the results are giving nearly equivalent weightage for every objective are hard to differentiate. Thus, a compromised result can be determined using a fuzzy method. The corresponding solutions of every objective are seen by the fuzzy approach to assigning a fuzzy variable. This approach is particularly used to determine a compromised result when solutions are very nearer to one another.[33] The following expression defines the membership function for ith objective of jth solution in the PF:

$$m_i^j = \begin{cases} 1 & \text{if } y_{\mathbf{i}} \geq y_i^{\max} \\ \dfrac{y_i^{\max} - y_i}{y_i^{\max} - y_i^{\min}} & \text{if } y_i^{\min} < y_i < y_i^{\max}, \\ o & \text{if } y_i \leq y_i^{\min} \end{cases} \tag{16}$$

where m_i^j denotes the ability of jth nondominated result for satisfying the ith objective. y_i represents the value of ith objective function, $y_i^{\max}$ and $y_i^{\min}$ represent maximum and minimum value of ith objective function. The ability of a jth nondominated solution to satisfy entire objectives is denoted by the sum of membership values of entire objectives. Every nondominated solution attained regarding all nondominated results is given as

$$m^j = \frac{\sum_{i=1}^{M_{\text{obj}}} m_i^j}{\sum_{j=1}^{N_{\text{par}}} \sum_{i=1}^{M_{\text{obj}}} m_i^j}, \tag{17}$$

where M_{obj} represents the number of objectives, N_{par} denotes the number of nondominated results in the PF. The decision maker accepts the result with highest m^j as a compromised result.

5 | SIMULATION RESULTS AND ANALYSIS

The trade-off between the conflicting objectives in 5G with mMIMO is shown in this section. In the following subsections, evaluation environment and parameterization are described. Also, the quality indicators (QIs) given in[34] are used to analyze the performance of SOMPSO for optimizing the multiple objectives of 5G WNs with mMIMO. The performance analysis of the proposed multiobjective optimization of 5G mMIMO using the SOMPSO method is described and compared with the commonly used NSGA-II, NSGA-III, and SMPSO methods.

5.1 | Evaluation environment and parameterization

The multiobjective optimization based on self-organizing PSO algorithm for mMIMO 5G WN is run on MATLAB R2018a. Here, we considered 16 cells from a 5G cellular network. The size of every square cell is 250 × 250 m. The bandwidth and the average noise power is $\omega = 10$ MHz and $P_n^2 = 10^{-13}$ W, respectively. In every cell, N users are distributed uniformly, and the distance between every user is considered as 35 m. Based on LTE 3GPP and IEEE 802.11 standard, the values of Ψ_1 and Ψ_2 are 1.72×10^9 and 0.54, respectively. The number of channel is selected using $\omega_c = 200$ kHz and $t_c =$ ms. Also, the power amplifier's efficiency is $\eta = 0.31$. The simulation parameters of total power consumption per cell are $P_c^M = 1$ W, $P_c^N = 0.3$ W, $P_s = 10$ W, and $\eta_c = 12.8$ Gflops/W. All the parameters of the system model are summarized in Table 2.

Table 3 gives the parameter settings for SOMPSO. For SOMPSO, the parameters are $a_1 = a_2 = 2.05$ and $\hat{\omega} = 0.7298$. The SOM consists of the topological structure of 1 × 100. The learning rate is set to 0.7. When the iteration is increased, σ value used in elite learning will reduced to 0.05 from 0.2 linearly. The size of population P and EA are 100 and 100, respectively. Each experimentation is conducted twenty five times separately.

5.2 | Quality indicators

A QI is used for mapping a real value to every nondominated solution set. A unary indicator is defined as follows: $Q : \mathbf{\Omega} \rightarrow \mathbf{R}$. It maps every nondominated solution set to the real number sets. Here, we are using three unary QIs like the hyper volume indicator, the unary epsilon indicator, and the R2 and R3 indicators. The priority data for every indicator is not equal. When all the indicators are used together, we can obtain more information than utilizing a single indicator.

The hyper volume indicator is a set measurement utilized in multiobjective optimization algorithm for evaluating the search algorithm's effectiveness. It is also used for guiding the search. The hyper volume indicator Q_{HV} determines the hyper volume of the parts of objective space that are not strongly dominated using a Pareto set approximation set $\mathbf{A}$. The Hyper volume change of a reference set $Q_{HV}(\mathbf{A})$ for a provided set $\mathbf{A}$ can be given as

TABLE 2 Parameter settings for system model

Parameter	Value	Parameter	Value
$M_{\max}$	500	$P_t^{\max}$	20 W
ω	10 MHz	ω_c	200 KHz
P_n^2	10^{-13} W	t_c	5 ms
Ψ_1	1.72×10^9	η	0.31
Ψ_2	0.540	P_c^M	0.5 W
P_c^N	0.3 W	$\alpha_{\min}$	35 m
P_s	10 W	$\alpha_{\max}$	250 m
η_c	12.8 Gflops/W	K	16

TABLE 3 Parameter settings for SOMPSO

Parameter	Value
Population size P	100
Size of EA	100
Number of iteration	250
Acceleration constants a_1,a_2	2.05
Inertia weight $\hat{\omega}$	0.7298
Learning Rate ε_0	0.7
radius of learning r_0	50

$$Q_{HV}(\mathbf{A}) = Q_{HV}(\mathbf{R_f}) - Q_{HV}(\mathbf{A}), \tag{18}$$

where the reference set is denoted as $\mathbf{R_f}$ and is acquired through the union estimates of the Pareto set determined using every valued algorithms.

The binary ε indicator $Q_\varepsilon(\mathbf{A_1}, \mathbf{A_2})$ is used to define unary ε indicator Q_ε. According to its definition, $Q_\varepsilon(\mathbf{A_1}, \mathbf{A_2})$ delivers the maximal aspect, and it is used to multiply every point in $\mathbf{A_2}$ in which the resultant Pareto set approximation is dominated inefficiently by $\mathbf{A}_1$,

$$Q_\varepsilon(\mathbf{A_1}, \mathbf{A_2}) = \inf_{\varepsilon \in R}\{\forall \mathbf{y_2} \in \mathbf{A}_2\ \exists \mathbf{y_1} \in \mathbf{A_1} : \mathbf{y_1} \leq_\varepsilon \mathbf{y_2}\}. \tag{19}$$

In the above expression, the ε-dominance relationship $\preccurlyeq\varepsilon$ for $\mathbf{y_1}$,$\mathbf{y_2}$ vectors of the objective space is expressed as

$$\mathbf{y_1} \leq_\varepsilon \mathbf{y_2} \leftrightarrow \mathbf{y_{i,1}} \leq \varepsilon \mathbf{y_{i,2}},\ \forall \mathrm{i} \in 1, \ldots.., \mathrm{M_{obj}}. \tag{20}$$

The unary ε indicator $Q_{\varepsilon 1}(\mathbf{A})$ of a provided Pareto set approximation $\mathbf{A}$ can be described as$Q_{\varepsilon 1}(\mathbf{A}) = Q_\varepsilon(\mathbf{A}, \mathbf{R_f})$.

The approximation sets are compared using R_2 indicator based on utility function (UF) sets. UF is used to map the objective space set $\mathbf{Y}$ to the real number set $\mathbf{R}$, that is,$UF : \mathbf{Y} \to \mathbf{R}$. This indicator can be written as

$$Q_{R2}(\mathbf{A}) = \frac{\sum_{\lambda \in \delta} UF^*\left(\bar{\boldsymbol{\lambda}}, \mathbf{A}\right) - UF^*\left(\bar{\boldsymbol{\lambda}}, \mathbf{R_f}\right)}{|\delta|}. \tag{21}$$

The UF reaches the extreme level (UF^*) with weight vector $\bar{\boldsymbol{\lambda}}$ on a nondominated solution set $\mathbf{A}$, that is, $UF^*\left(\bar{\boldsymbol{\lambda}}, \mathbf{A}\right) = \max_{\mathbf{y} \in A} UF(\mathbf{y})$; here, $\boldsymbol{\delta}$ represents a normalized weight vector set, and it can be defined as:

$$\boldsymbol{\delta} = \left\{\bar{\boldsymbol{\lambda}} \in \mathbf{R}^{M_{\mathrm{obj}}} \middle| \boldsymbol{\lambda}_i \geq 0, i = 1, 2, \ldots\ldots M_{\mathrm{obj}} \Lambda \sum_{i=1}^{M_{\mathrm{obj}}} \boldsymbol{\lambda}_i = 1\right\}. \tag{22}$$

5.3 | Performance analysis

The efficiency of the developed approach for approximate computing nondominated results of the PFs is estimated and discussed in this section. In this work, the parameters such as number of BS antenna, number of users, and transmitting power are considered as optimization parameter to determine the best trade-off between the objectives of 5G mMIMO network such as average rate per user, average area rate, energy efficiency, and spectral efficiency. Hence, the impacts of a number of BS antenna with a constant number of users on the performances of 5G mMIMO network are analyzed initially. After that, the optimal solutions that together meet the optimization constraints are determined through Pareto analysis. The impact of number of BS antenna with respect to a constant number of users on 5G mMIMO network is shown in Figure 3.

The influence of a number of BS antennas on energy efficiency of 5G mMIMO network is shown in Figure 3A. If the total number of users is constant, then the energy efficiency will increase with the number of BS antennas, but the energy efficiency is not increased with the number of BS antennas after reaching certain point because of the restriction of the total number of users in the network. Furthermore, if the system contains more number of users when the number of antennas goes beyond certain value, the energy efficiency will be improved. The spectral efficiency is drawn for number of BS antennas in Figure 3B by maintaining a constant number of users in each cell. Here, when the numbers of BS antennas are increased, the spectral efficiency will increase abruptly at the starting points, and then they will become saturated. Thus, the spectral efficiency attains its maximum value with less number of BS antennas and users. At the starting points, the number of antenna with more number of user (k = 40) gives poor spectral efficiency than less number of user. This is because of less number of BS antennas will not give required beam-forming and

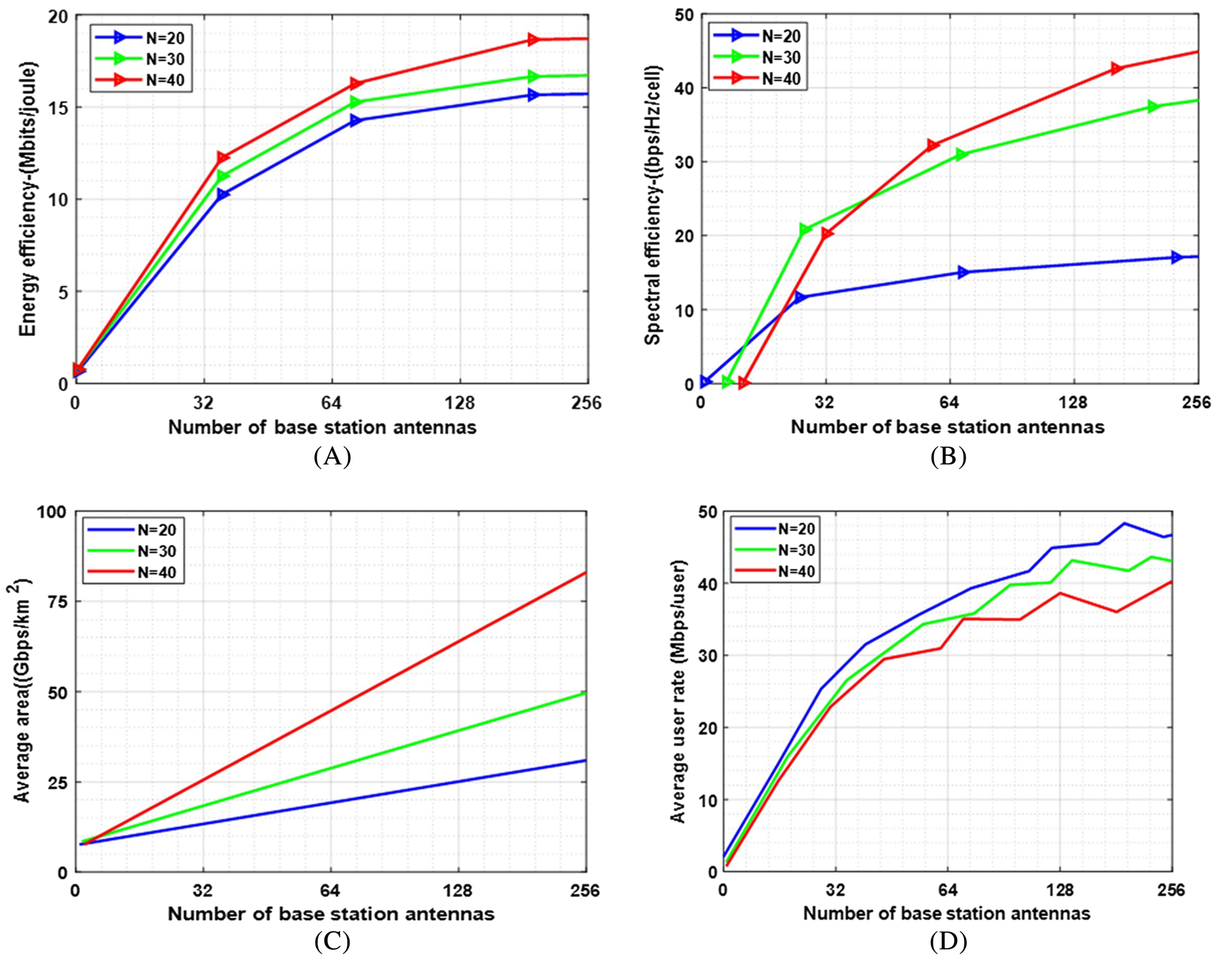

FIGURE 3 Impact of number of base station antenna on 5G mMIMO network performances: (A) energy efficiency, (B) spectral efficiency, (C) average area rate, and (d) average user rate

spatial diversity for more number of users. The average area rate is analyzed by varying the number of BS antennas with ZF processing method in Figure 3C. This figure shows that the transmission rate per unit area is linearly increased with number of transmitting antenna, but the performance of the average area rate will be reduced while increasing the radius of the area. Figure 3D shows the impact of number of BS antenna on average user rate. From this figure, we can understand that the data rate per user will be increased when the number of antenna array at the BS is increased. However, the user rate will be reduced when the number of users in a cell is increased.

This analysis shows that the optimal performance of 5G mMIMO can be obtained only it retains a good trade-off between all the above objectives. Also, the optimal values of energy efficiency, spectral efficiency, average area rate, and average user rate can be determined with the usage of optimal number of BS antennas and users. In order to find the trade-off between the multiple objective problems, the PFs should be analyzed. In this work, approximate PFs are acquired once the optimization framework reaches 250 iterations. Also, the set of outputs obtained using the proposed approach are illustrated. Figure 3A–E depicts the nondominated solutions obtained using SOMPSO algorithm, and it is compared with different MOEA algorithms such as NSGA-II,[17] NSGA-III,[19] and SMPSO.[26]

Figure 4A illustrates the trade-off between the average area rate and the average user rate. The result shows that the average area rate is decreased with the increase in the average user rate. Figure 4B shows that the compromise results for the average user rate and energy efficiency. These two objectives are conflicting with one another because if one needs to increase the user rate means, he should make radical sacrifices in the energy efficiency. One more trade-off is shown in Figure 4C, wherein the energy efficiency and average area rate are related. In this graph, both the objectives are linearly increased until the energy efficiency reaches its maximum value, but further improvement in area rate may loss some energy efficiency. Likewise, Figure 4D–F illustrates the trade-off of spectral efficiency with energy efficiency, average area rate, and average user rate. The method NSGA-II and NSGA-III dominates in Figure 4B–D when

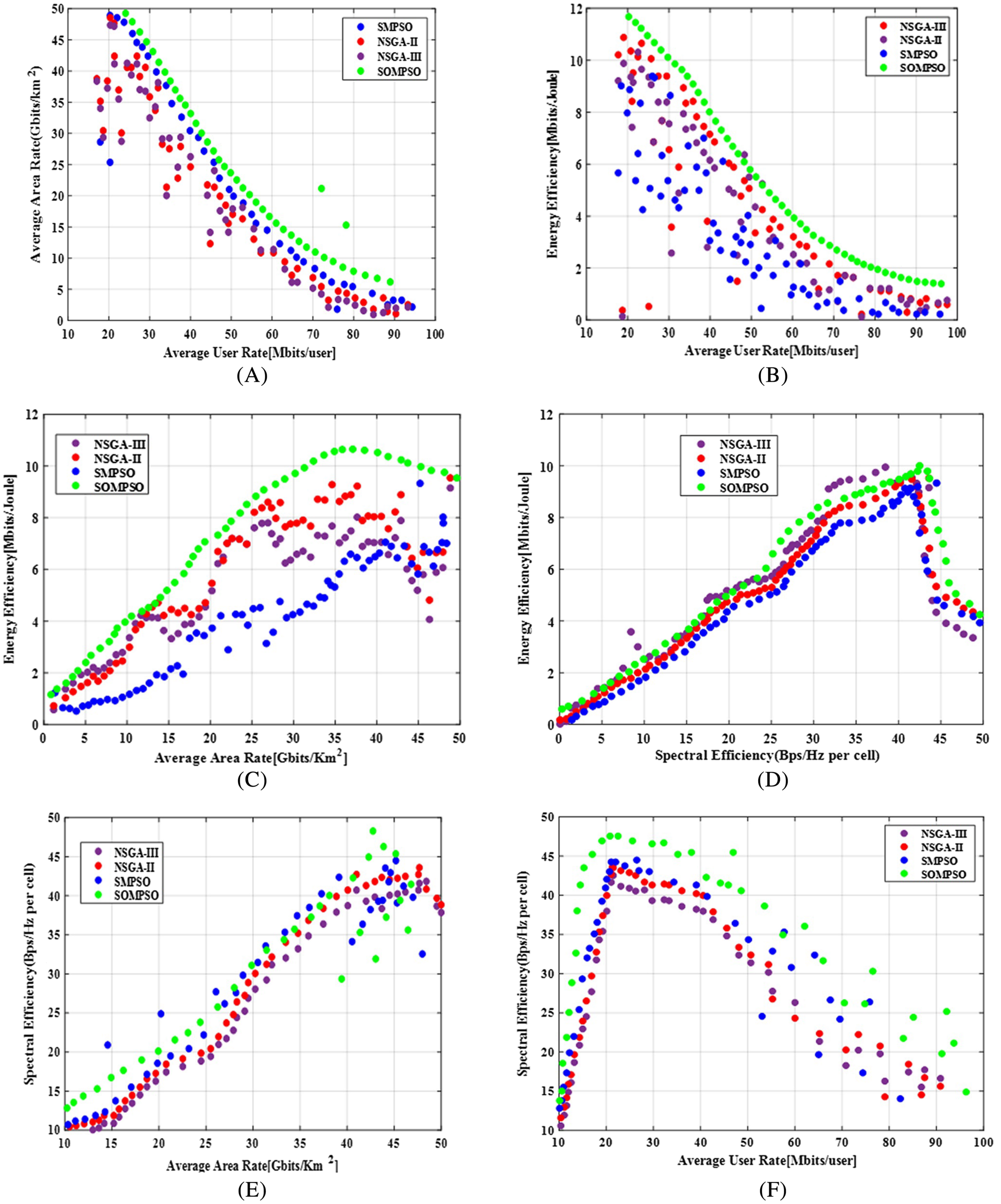

FIGURE 4 Trade-off attained using SOMPSO: (A) average user rate versus average area rate, (B) average user rate versus energy efficiency, (C) Average area rate versus energy efficiency, (D) spectral efficiency versus energy efficiency, (E) average area rate versus spectral efficiency, and (F) average user rate versus spectral efficiency

compared to SMPSO. However, SMPSO dominates NSGA-II and NSGA-III in Figure 4A. The SOMPSO algorithm dominates in all trade-off when compared to NSGS-II, NSGA-III, and SMPSO methods.

Table 4 holds the performance indicators values; the computational time is obtained in a single run by the SOMPSO algorithm and is compared with other MOEAS such as NSGA-II,[17] NSGA-III,[19] and SMPSO[26] algorithms. For all indicators, a good Pareto set approximation is shown by the smaller values. NSGA-II and NSGA-III give good results in terms of quality, but SMPSO provides good outputs based on time complexity. However, the SOMPSO algorithm gives better results based on both quality and time complexity. To end, the best solution determined for all objective function using SOMPSO algorithm is shown in Table 5. These results are compared with the baseline method provided in Yi et al.[19] for balancing conflicting metrics in 5G systems. This analysis shows that the performance of the proposed method is much better than the baseline method, which uses scalarization and visualization process to find best trade-off. Also, the results acquired using SOMPSO are better when compared to all other MOEA algorithms.

Furthermore, the worst case computational complexity of the proposed model is dominated by the fitness evaluation, nondominated sorting process, and archive update process. For updating the achieve, it have the complexity of $O(kn(\log n))$ where k represents number of objectives M_{obj}, m represents population size, and n represents archive size. It requires $k(m+n)$ comparisons to check a nondominance of a particle within $(m+n)$ particles. Thus, the worst case computational complexity of the nondominated sorting process is $O(k(m+n)^2)$. Since $(m \approx n)$, the computational complexity of archive update becomes less than that of nondominated sorting process. Thus, the complete complexity of the proposed model becomes $O(km^2)$, but the complexity of the NSGA-II and NSGA-III depends on a number of generation n_g because it is a function of chromosome length n_c. Hence, the computational complexity of NSGA-II is $O(n_g km^2)$. The concepts of NSGA-III are as same as NSGA-II excluding the selection concept. NSGA-III used reference points for applying the selection pressure that has been lacked in nondominated Pareto method. Thus, the computational complexity of NSGA-III is $O[\max(n_g m^2 \log^{k-2} m, n_g km^2)]$. Instead, the complexity of SMPSO is $O(k(m+n)^2)$. Thus, the computational complexity of the proposed model is better than SMPSO, NSGA-II, and NSGA-III algorithms. Thus, the execution time of the proposed model is reduced as given in Table 4.

In this paper, we have presented a self-organizing PSO-based multiobjective optimization framework for solving the multiple objective problems in the 5G mMIMO network. To the best of our knowledge, there is no existing literature are available to optimize energy efficiency, spectral efficiency, average area rate, and average user rate together in one model without converting them into single problems. These four objectives should be maximized and are the basic to allocate the resources in 5G mMIMO network since all the objectives of resource allocation in 5G network are conflicting with each other. Thus, it is difficult to find optimal solution for all objectives simultaneously. Thus, an efficient optimization algorithm is needed to find out the best trade-off between all objectives. The proposed model has determined the best trade-off among all objectives. Thus, it can be applied for optimal resource allocation in 5G mMIMO network. Also, the objectives of resource allocation include both maximization of efficiencies and minimization of processing time and cost. This work only considers the maximization problem. In future, we will consider both maximization and minimization problem for efficient resource allocation. Some of the work reviewed in the literature section utilizes the SMPSO, NSGA-III, and NSGA-II algorithm for optimizing different objectives of 5G networks based on their application. Thus, we compared our proposed work with those algorithms to prove the effectiveness of the proposed work. The experiment results showed that the proposed method can decrease computational complexity while generating the best compromising results.

TABLE 4 Quality Indicators of the nondominated solutions

Quality indicators	SMPSO[26]	NSGA-II[17]	NSGA-III[19]	SOMPSO
$Q_{\overline{HV}}$	$3.99e^{-2}$	$1.85e^{-2}$	$1.52e^{-2}$	$1.35e^{-2}$
Q_{ε}	$1.05e^{-1}$	$5.83e^{-2}$	$3.49e^{-2}$	$1.5e^{-2}$
Q_{R2}	$7.63e^{-3}$	$2.52e^{-3}$	$2.39e^{-3}$	$1.98e^{-3}$
Computation time (sec)	32.16	230.74	154.76	30.59

TABLE 5 Comparison of best compromise solutions

Methods	F_1 (Mbps/user)	F_2 (Gbps/km^2)	F_3 (Mbits/J)	F_4 (bps/Hz)
Baseline[13]	20.400	46.832	11.100	39.758
NSGA-II[17]	21.293	47.686	9.522	40.452
NSGA-III[19]	23.597	47.982	9.425	44.498
SMPSO[26]	26.487	45.190	9.331	43.253
SOMPSO	28.822	49.251	10.521	45.305

6 | CONCLUSION

In this paper, the mMIMO 5G system is examined to form a Pareto optimal set based MOOP. Every objective is optimized concurrently using the SOMPSO algorithm on the basis of a dominance relationship without transferring them into a single problem. For optimizing objectives concurrently, this algorithm keeps an elite archive and the members of the archive are used for leading the swarm to search the best nondominated solutions dynamically. In the decision space, the multiple solutions are positioned, and the PF in the objective space is distributed in a better way. Hence, a wide solution spread can be obtained using this algorithm. The experimental outputs illustrate that the SOMPSO algorithm gives good PF quality and it is quicker for multiple objective problems of the mMIMO 5G system. We will expand this work in the future to allocate the resources by considering all maximization and minimization problems.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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