Hindawi
Complexity
Volume 2021, Article ID 7321719, 10 pages
https://doi.org/10.1155/2021/7321719

Research Article

Ultrahigh-Dimensional Model and Optimization Algorithm for Resource Allocation in Large-Scale Intelligent D2D Communication System

Minxin Liang,[1] **Jiandong Liu**,[1] **Jinrui Tang**,[2] **and Ruoli Tang**[3]

[1]*Guangzhou Power Supply Bureau, Guangdong Power Grid Co., Ltd., Guangzhou, China*
[2]*School of Automation, Wuhan University of Technology, Wuhan, China*
[3]*School of Energy and Power Engineering, Wuhan University of Technology, Wuhan, China*

Correspondence should be addressed to Ruoli Tang; ruolitang@hotmail.com

Received 7 June 2021; Revised 19 July 2021; Accepted 27 July 2021; Published 4 August 2021

Academic Editor: Chen Wang

The optimal resource allocation in the large-scale intelligent device-to-device (D2D) communication system is of great importance for improving system spectrum efficiency and ensuring communication quality. In this study, the D2D resource allocation is modelled as an ultrahigh-dimensional optimization (UHDO) problem with thousands of binary dimensionalities. Then, for efficiently optimizing this UHDO problem, the coupling relationships among those dimensionalities are comprehensively analysed, and several efficient variable-grouping strategies are developed, i.e., cellular user grouping (CU-grouping), D2D pair grouping (DP-grouping), and random grouping (R-grouping). In addition, a novel evolutionary algorithm called the cooperatively coevolving particle swarm optimization with variable-grouping (VGCC-PSO) is developed, in which a novel mutation operation is introduced for ensuring fast satisfaction of constraints. Finally, the proposed UHDO-based allocation model and VGCC-PSO algorithm as well as the grouping and mutation strategies are verified by a comprehensive set of case studies. Simulation results show that the developed VGCC-PSO algorithm performs the best in optimizing the UHDO model with up to 6000 dimensionalities. According to our study, the proposed methodology can effectively overcome the "curse of dimensionality" and optimally allocate the resources with high accuracy and robustness.

1. Introduction

Due to the fast development of cellular communication networks, the complexity of net structure and user number explosively increases in recent years. As a result, the device-to-device (D2D) communication technology is developed and plays an increasingly important role in the modern 5G cellular networks [1, 2]. However, due to the fast growing cellular users and high requirement for quality of service (QoS), the lack of spectrum resource becomes one of the main reasons which severely restricts the development of modern communication network [3, 4].

In the D2D communication system, two types of user equipment nearby (namely, D2D-pair and DP) can directly communicate under the control of enhanced-Node B (eNB) [5]. However, the direct communication of DP always requires to reuse the physical resource blocks (PRBs) of the traditional cellular users (CUs). In order to obtain promising performance on spectrum efficiency and communication quality, the aforementioned PRB of CU should be optimally allocated to each DP. As a result, the resource allocation model and optimization algorithm are hot topics in the field of D2D communication in recent years [6–9]. For example, Li et al. developed a nonconvex mixed-integer nonlinear programming (MINLP) problem-based model to minimize the mobile power consumption to obtain efficient resource allocation solution and also ensured the QoS and high communication rate at the same time [10]. Su et al. proposed an approach to maximize the total D2D groups capacity by considering the requirement of QoS and energy causality constraints. Simulation results verified the effectiveness of their methodology [11]. In order to reduce the cross-tier interference in D2D communication, Khazali et al. proposed a fractional frequency reuse (FFR)-based spectrum partitioning scheme. In Khazali et al.'s study, they also modelled the spectral efficiency as an optimization problem, which can be effectively solved by employing iterative algorithms [12]. Mohamad et al. proposed a dynamic sectorization method in which eNB can vary the number of sectors dynamically and allocated the resource block to D2D users. According to their study, the signal-to-interference-noise-ratio (SINR) and the network overall performance were improved [13]. Amin et al. proposed a resource allocation algorithm based on the so-called Q-learning, in which the multiagent learners from multiple D2D users were created, and the system throughput was determined by the state-learning of Q value list. According to their study, the system throughput was effectively maximized by controlling the D2D users' power, and a fine QoS of cellular users was also ensured [14].

In this study, the resource allocation problem in an intelligent D2D communication system with large number of users is addressed. To be specific, by describing the communication constraints as penalty functions, the aforementioned resource allocation is modelled as a binary optimization problem with ultrahigh dimensionality, called the binary large-scale global optimization (BLSGO) problem in this study. Then, considering the consequent "curse of dimensionality," the coupling relationships among the thousands of dimensionalities are comprehensively analysed and some efficient variable-grouping strategies are developed, i.e., the cellular user grouping (CU-grouping), D2D pair grouping (DP-grouping), and random grouping (R-grouping). In addition, a novel swarm-intelligence-based algorithm, namely, cooperatively coevolving particle swarm optimization with variable-grouping (VGCC-PSO) is developed, in which an efficient mutation operation is also introduced for rapidly escaping the punishment of penalty function and speeding up the convergence process. Finally, the proposed model and optimization methodologies are comprehensively verified by case studies.

The contributions of this paper can be summarized as follows. Firstly, the BLSGO-based resource allocation model for the intelligent D2D communication system is established. Secondly, the variable-grouping strategies including the CU-grouping, DP-grouping, and R-grouping are developed. Finally, a novel VGCC-PSO algorithm is proposed and employed to optimize the aforementioned BLSGO-based model.

The rest of this paper is organized as follows. In Section 2, the ultrahigh dimensional resource allocation model is developed. The corresponding constraints and penalty functions as well as the encoding scheme for defining optimization vector are also discussed in this section. In Section 3, the variable-coupling relationships are comprehensively analysed, and the VGCC-PSO with different variable-grouping strategies and mutation operation is developed. Then, in Section 4, the effectiveness of the proposed variable-grouping strategies and mutation operation is tested. In Section 5, the proposed model and optimization methodologies are verified by a comprehensive set of case studies. Finally, this paper is concluded in Section 6.

2. Ultrahigh-Dimensional Resource Allocation Model

2.1. Resource Allocation in D2D Communication. In an intelligent D2D communication system, the allocation of PRB is of great importance for improving system spectrum efficiency and ensuring communication quality. In order to optimally allocate the CU resources to DP, an efficient offline model for evaluating the cost of each allocation solution is required [15].

For a cellular network of LTE-advance systems, assume the eNB locates at the center of a region, in which all the CUs and DPs are randomly distributed. Denote $C = \{CU_n | n = 1, 2, \ldots, N\}$ as the set of CU, and denote $D = \{DP_m | m = 1, 2, \ldots, M\}$ as the set of DP. The resource allocation principle employed in this study is defined as follows: on the one hand, the PRB of each CU should be reused by only one DP; on the other hand, each DP can reuse more than one CUs' PRB (but at least one). Schematic of the evaluated D2D communication system is illustrated as Figure 1.

In the D2D communication system, an efficient resource allocation solution is to maximize the system energy efficiency by allocating all the CUs' PRB to each DP while satisfying some constraints. The energy efficiency to be maximized can be formulized as follows:

$$\eta_e = \frac{\sum_{m=1}^{M} \sum_{n=1}^{N} x_{m,n} \cdot R_{m,n}}{\sum_{m=1}^{M} \sum_{n=1}^{N} x_{m,n} \cdot P_{m,n} + P_c}, \tag{1}$$

where η_e represents the system energy efficiency; $x_{m,n}$ is the binary variable, $x_{m,n} = 1$ denotes the PRB of CU_n which is reused by DP_m, $x_{m,n} = 0$ denotes the opposite, $R_{m,n}$, which is formulized as equation (2), represents the transmission speed of DP_m when reusing the PRB of CU_n, $P_{m,n}$ represents the transmission power of DP_m when reusing the PRB of CU_n; and P_c represents the circuit power consumption of DP_m.

$$R_{m,n} = \log_2\left(1 + \frac{P_{m,n} \cdot H_m}{P_n \cdot H_{n,m} + n_0}\right), \tag{2}$$

where H_m represents the channel gain from DP transmitter DT_m to DP receiver DR_m; P_n represents the transmission power of CU_n; $H_{m,n}$ represents the channel gain from DT_m to CU_n; and n_0 represents the channel noise power under the effect of white Gaussian noise.

According to reference [16], the maximization of energy efficiency η_e is equal to the minimization of the following equation:

$$f_{\min} = \sum_{m=1}^{M} \sum_{n=1}^{N} x_{m,n} \cdot \frac{H_{n,m} \cdot H_{m,n}}{H_m \cdot H_n}, \tag{3}$$

where H_n represents the channel gain from CU_n to eNB and $H_{n,m}$ represents the channel gain from CU_n to DR_m. The channel gains here (H_n, H_m, $H_{n,m}$, and $H_{m,n}$) are all calculated as $H = 10^{(-PL-SHD)/10}$, where PL represents the path

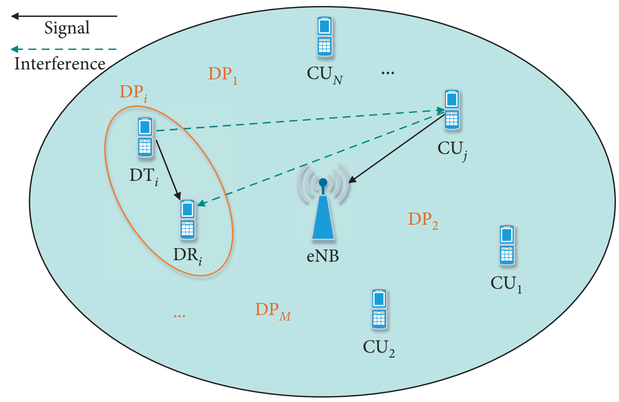

Figure 1: Schematic of the D2D communication system.

loss and SHD represents the lognormal fading between each transmitter and receiver.

As mentioned above, the PRB of each CU should be reused by only one DP and each DP should be allocated with one or more CUs' PRB. As a result, the overall allocation model can be formulized as the following constrained optimization problem:

$$\min_{x_{m,n}} f = \sum_{m=1}^{M}\sum_{n=1}^{N} x_{m,n}\cdot\frac{H_{n,m}\cdot H_{m,n}}{H_m\cdot H_n}$$
$$s.t.\begin{cases} x_{m,n}\in\{0,1\} \\ \sum_{m=1}^{M} x_{m,n}=1, & (n=1,2,\ldots,N) \\ \sum_{n=1}^{N} x_{m,n}\geq 1, & (m=1,2,\ldots,M). \end{cases} \tag{4}$$

2.2. Encoding Scheme. As shown in equation (4), the parameters to be optimized for obtaining optimal resource allocation are the $N\times M$ binary variables $x_{m,n}$ ($m=1,2,\ldots,M$; $n=1,2,\ldots,N$). In this study, the direct encoding scheme is employed, i.e., all the $N\times M$ binary variables $x_{m,n}$ are directly employed to combine the optimization vector $\vec{x}$, which is formulized as follows:

$$\vec{x}=\left(x_{1,1},x_{1,2},\ldots,x_{1,N},\ldots,x_{M,1},x_{M,2},\ldots,x_{M,N}\right). \tag{5}$$

Note that each $x_{m,n}$ ($m=1,2,\ldots,M$; $n=1,2,\ldots,N$) in equation (5) is a binary variable, which indicates whether CU_n is reused by DP_m. Obviously, dimensionality of the optimization vector $\vec{x}$ is equal to $N\times M$. This implies that the problem dimensionality (or complexity) will become extremely high when N and M are large. For example, assume that a D2D communication system contains 100 CU (i.e., $N=100$) and 20 DP (i.e., $M=20$). Then, dimensionality of the model will become $N\times M=2000$. Obviously, complexity of this 2000-dimensional problem is extremely high because of the "curse of dimensionality." As a result, an effective optimization algorithm is required to solve this BLSGO problem.

Note that in this study, the continuous evolutionary algorithm, namely, VGCC-PSO is developed and employed to optimize the variables listed in equation (5). As a result, all the binary variables $x_{m,n}$ are bounded within the interval [0, 100]. The encoding scheme is defined as follows: for the variable $x_{m,n}$, encode $x_{m,n}$ to 0 when it belongs to [0, 50) in VGCC-PSO; otherwise, when $x_{m,n}$ belongs to [50, 100] in VGCC-PSO, encode it to 1.

2.3. Ultrahigh-Dimensional Model for D2D Resource Allocation. In order to optimize the variables in equation (5) using swarm-intelligence-based algorithms, the constraints listed in equation (4) are transformed into penalty function in our model. That is to say, the constrained problem shown in equation (4) is transformed into an unconstrained problem by defining the following penalty function:

$$f_p=\lambda\cdot(N_1+N_2), \tag{6}$$

where λ represents the penalty factor which is used to control the penalty intensity; N_1 denotes the number of CU which does not satisfy the second constraint in equation (4), i.e., $\sum_{m=1}^{M}x_{m,n}=1$, ($n=1,2,\ldots,N$); and N_2 denotes the number of DP which does not satisfy the third constraint in equation (4), i.e., $\sum_{n=1}^{N}x_{m,n}\geq 1$, ($m=1,2,\ldots,M$). Note that for a certain solution $\vec{x}$, the values of N_1 and N_2 can be calculated by decoding each dimensionality of $\vec{x}$.

By introducing the penalty function, the overall resource allocation model can be formulized as

$$\min_{x_{m,n}} f = \sum_{m=1}^{M}\sum_{n=1}^{N} x_{m,n}\cdot\frac{H_{n,m}\cdot H_{m,n}}{H_m\cdot H_n}+\lambda\cdot(N_1+N_2). \tag{7}$$

3. Optimization Methodology

In the field of numerical optimization, different kinds of optimization methodologies are developed and employed in solving real-world engineering problems, e.g., the linear programming methods [17], neural network methods [18], evolutionary algorithms [19], and so on. In this study, the cooperatively coevolving algorithms are developed for solving the aforementioned UHDO-based resource allocation model.

3.1. Cooperatively Coevolving. The cooperatively coevolving (CC) is a general algorithm framework proposed for solving the high-dimensional optimization problem [20–22]. In basic CC, the D-dimensional problem is decomposed into several subproblems based on the philosophy of "divide and conquer." Each of these low-dimensional subproblems is solved by a certain algorithm in turn. Then, a D-dimensional individual, namely, context vector is defined to connect these subproblems and ensure the coevolving process. The CC framework has been integrated with different evolutionary algorithms and obtained promising performance on solving high-dimensional problems [20, 23, 24]. Principle of the basic CC framework can be illustrated as the following steps:

(1) For a D-dimensional problem P, initialize the D-dimensional population with N_P individuals. Then, decompose the original problem P into K subproblems SP_i ($i = 1, 2, \ldots, K$), i.e., $P = [SP_1, SP_2, \ldots, SP_K]$. Note that the dimensionality of each subproblem SP_i is equal to D/K. For a D-dimensional individual x, $x = (x^1, x^2, \ldots, x^K)$, where x^i represents the corresponding variables that belong to the ith subproblem.

(2) Define the context vector as the current global best individual y. Then, the ith subproblem in CC is defined as

$$\min f^i(x, y), \quad x \in R^S, \tag{8}$$

where $f^i(x, y) = f(y^1, \ldots, y^{i-1}, x, y^{i+1}, \ldots, y^K)$ and R^S represents the solution space. Start an evolution circle, in which all the subproblems are optimized with a certain algorithm. The context vector y is updated in every iteration.

(3) Proceed another cycle if the stopping criteria are not satisfied; otherwise, stop the cooperative coevolution.

Note that, in CC framework, in order to decrease the complexity of high-dimensional problem, the original problem is decomposed into several less difficult subproblems to be solved separately. According to reference [25], the basic CC framework is effective only if any two subproblems have no interaction. In another word, the variable-grouping strategy (means the subordinate relationship between variables and subproblems) significantly affects the performance of CC.

3.2. Variable-Grouping Strategy. In order to effectively optimize the ultrahigh-dimensional problem using CC, the coupled (or called nonseparable) variables should be grouped into the same subproblem and coevolved for enough iterations [25]. With regard to the resource allocation model as listed in equation (4), all the optimization variables $x_{m,n}$ ($m = 1, 2, \ldots, M$; $n = 1, 2, \ldots, N$) are grouped using the following strategies.

3.2.1. Random Grouping (R-Grouping). In R-grouping, all the variables are randomly disorganized and grouped into different subproblems. To be specific, flow of R-grouping mechanism is as the following steps:

(i) Firstly, orders of the entire $D = N \times M$ dimensionalities in the original model are randomly disorganized.

(ii) Secondly, these disorganized dimensionalities are decomposed into $K = D/s$ sub-problems. Obviously, each subproblem has s dimensionalities, where the group size s is randomly generated within a predefined set S.

(iii) Finally, the group size s is dynamically changed during the coevolving process as the following principle: for each coevolving iteration, randomly selected a new s in S if the global optimum is not updated; otherwise, keep the current s value unchanged.

Schematic of the R-grouping mechanism is illustrated in Figure 2.

3.2.2. Cellular User Grouping (CU-Grouping). As discussed in Section 2.2, each optimization variable represents the reusing relationship between a certain CU_n and a certain DP_m. In CU-grouping, the variables reflecting the relationships between one certain CU_n and every DP are grouped into a subproblem and are employed to coevolve for enough iterations. To be specific, the variables for CU_1, i.e., $x_{1,1}, x_{2,1}, \ldots, x_{M,1}$, are regarded as the first subproblem, then the variables for CU_2, i.e., $x_{1,2}, x_{2,2}, \ldots, x_{M,2}$, are regarded as the second subproblem, and so on. Note that in CU-grouping, as each subproblem (or called group) has M dimensionalities, i.e., $s = M$, the number of subproblems K is equal to $D/s = N$.

Schematic of the CU-grouping mechanism is illustrated in Figure 3.

3.2.3. D2D Pair Grouping (DP-Grouping). Similarly, in DP-grouping, the variables reflecting the relationships between every CU_n and one certain DP are grouped into a subproblem. To be specific, the variables for DP_1, i.e., $x_{1,1}, x_{1,2}, \ldots, x_{1,N}$, are regarded as the first subproblem, then the variables for DP_2, i.e., $x_{2,1}, x_{2,2}, \ldots, x_{2,N}$, are regarded as the second subproblem, and so on. Note that in DP-grouping, as each subproblem has N dimensionalities, i.e., $s = N$, the number of subproblems K is equal to $D/s = M$.

Schematic of the DP-grouping mechanism is illustrated in Figure 4.

3.3. Mutation Operation. According to the encoding scheme developed in Section 2.2, it can be easily concluded that the binary variable $x_{m,n}$ is not related to its specific value within the solution space but is directly decided by whether it is greater than the boundary 50. As a result, the encoding scheme will significantly increase the solution space and complicate the original model. In order to overcome this problem, a novel mutation operation is developed and imposed on all the context vectors of VGCC-PSO.

As discussed in Section 2, the PRB of each CU should be reused by only one DP, and each DP can reuse more than one CUs' PRB (but at least one). That is to say, in a feasible solution, there is at most one variable in $x_{1,n}, x_{2,n}, \ldots, x_{M,n}$ ($n = 1, 2, \ldots, N$) which is greater than 0 at each time (denoted as Constraint I). In addition, there is at least one variable in $x_{m,1}, x_{m,2}, \ldots, x_{m,N}$ ($m = 1, 2, \ldots, M$) which is greater than 0 at each time (denoted as Constraint II). As Constraints I and II are closely related to the entire variables, most of the solutions in solution space will be infeasible because of these constraints. In order to reduce the model complexity caused by these so many infeasible solutions, the feasible solutions satisfying Constraint I and Constraint II are directly

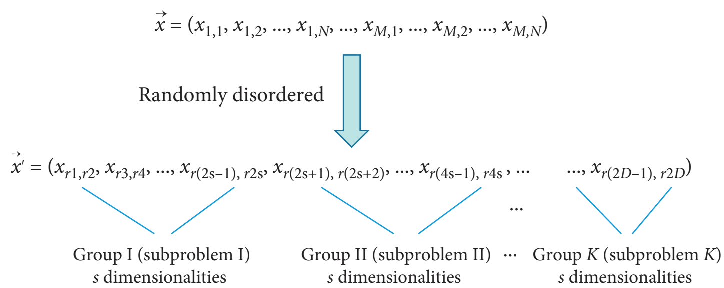

Figure 2: Schematic of R-grouping.

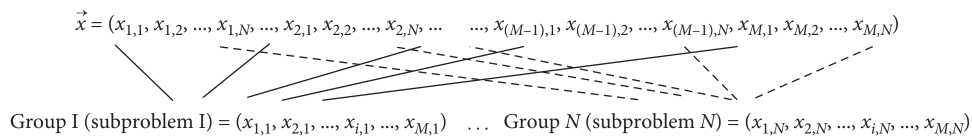

Figure 3: Schematic of CU-grouping.

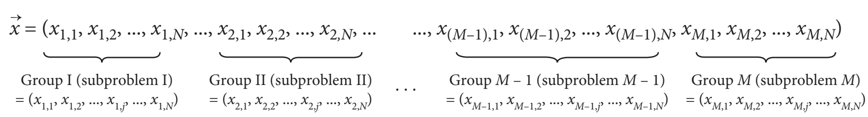

Figure 4: Schematic of DP-grouping.

employed as the context vector and inserted into VGCC-PSO population. The proposed mutation operation for context vector is illustrated as the following steps:

Step 1. Define parameters P_{m1} and P_{m2} satisfying $P_{m1} \le P_{m2}$ and $P_{m1}, P_{m2} \in [0,1]$ to control the mutation probabilities.

Step 2. In each iteration, for each of the context vectors in VGCC-PSO, say the ith context vector in the tth iteration $CV_i(t)$, randomly generate a mutation variable $P_i(t)$ with the interval [0, 1]. Then, mutate $CV_i(t)$ according to the following principles:

(i) If $P_i(t) < P_{m1}$, keep $CV_i(t)$ unchanged

(ii) If $P_{m1} \le P_i(t) < P_{m2}$, each of the components $[x_{1,n}, x_{2,n}, \ldots, x_{M,n}]$ $(n = 1, 2, \ldots, N)$ is randomly mutated to $[r_0, r_0, \ldots, r_0, r_1]$, $[r_0, \ldots, r_0, r_1, r_0]$, $\ldots$, $[r_0, r_1, r_0, \ldots, r_0]$ and $[r_1, r_0, r_0, \ldots, r_0]$, in which each r_0 is randomly generated within [0, 50) and each r_1 is randomly generated within [50, 100]

(iii) Otherwise (i.e., $P_i(t) \ge P_{m2}$), check each of the components $[x_{m,1}, x_{m,2}, \ldots, x_{m,N}]$ $(m = 1, 2, \ldots, M)$ if all the variables are lower than 50, i.e., $x_{m,1}, x_{m,2}, \ldots, x_{m,N}$ are encoded to 0, then randomly set one variable (e.g., $x_{m,n}$) to r_1

Step 3. Denote the mutated context vector $CV_i(t)$ as $CV_{i\text{-mut}}(t)$. Update $CV_i(t)$ using $CV_{i\text{-mut}}(t)$ if better.

Note that the proposed mutation mechanism is only imposed on the context vectors rather than the entire individuals in current population. The reason is that, on the one hand, the mutated context vectors can better guide the other individuals to rapidly satisfy the constraints and thus significantly reduce the scope of solution space. On the other hand, the population diversity will be not destroyed in mutation process.

3.4. VGCC-PSO Algorithm

3.4. VGCC-PSO Algorithm. In this study, a novel evolutionary algorithm, namely, VGCC-PSO is developed for optimizing the BLSGO-based allocation model. In VGCC-PSO, the aforementioned variable-grouping strategies and mutation operation are integrated for overcoming the ultrahigh dimensionality characteristic of the model.

In VGCC-PSO, the basic CC framework described in Section 3.1 is imposed on the PSO algorithm. Then, the R-grouping, CU-grouping, and DP-grouping mechanisms are randomly selected in each iteration as the following steps:

Step 1. Set the selection probabilities P_R (for R-grouping), P_{CU} (for CU-grouping), and P_{DP} (for DP-grouping), satisfying

$$\begin{cases} P_R, P_{\mathrm{CU}}, P_{\mathrm{DP}} \in [0,1], \\ P_R + P_{\mathrm{CU}} + P_{\mathrm{DP}} = 1. \end{cases} \tag{9}$$

Step 2. In each iteration, randomly generate a variable $P_g \in [0,1]$. Then, select a grouping strategy according to the following equation:

$$\begin{cases} \text{select } R\text{-grouping}, & \text{if } \quad 0 \le p_g < P_R, \\ \text{select CU-grouping}, & \text{if } \quad P_R \le p_g < P_R + P_{\mathrm{CU}}, \\ \text{select DP-grouping}, & \text{if } \quad P_R + P_{\mathrm{CU}} \le p_g \le 1. \end{cases} \tag{10}$$

In addition, in VGCC-PSO, the mutation operation described in Section 3.3 is imposed on each of the context vectors in each iteration. Pseudo code of VGCC-PSO is given in Algorithm 1.

4. Verification for Variable-Grouping Strategies and Mutation Operation

In this section, efficiency of the proposed variable-grouping strategies and mutation operation is verified by simulation experiments. In the following simulation, the numbers of CU and DP are set to 80 and 20, respectively. The location of each CU, DT, and DR is randomly generated within a hexagon region with the radius of 700 m. As suggested in reference [5], the communication model and parameters employed in the following simulation are chosen in accordance with 3GPP LTE regulation for the OFDMA system. In addition, the path loss model is defined as follows:

$$\begin{cases} \text{eNB-UE: PL} = 33.65 + 23.47\ \log\ 10(d[m]), \\ \text{UE-UE: PL} = 36.67 + 19.54\ \log\ 10(d[m]). \end{cases} \tag{11}$$

According to the encoding scheme described in Section 2.2, the model dimensionality D in this case is equal to $N \times M = 1600$. In this section, the VGCC-PSO algorithm is employed for optimizing this 1600-dimensional problem. In order to verify effectiveness of the proposed variable-grouping strategy and mutation operation, the basic PSO without CC framework, variable-grouping strategy, and mutation operation (denoted as PSO), the CC-based PSO (i.e., without variable-grouping strategy and mutation operation, denoted as CCPSO), the CC-based PSO only integrated with mutation operation (i.e., without variable-grouping strategy, denoted as $\text{CCPSO}_{\text{mut}}$), and the CC-based PSO only integrated with variable-grouping strategy (i.e., without mutation operation, denoted as CCPSO_{vg}) are employed for comparison.

For all the compared algorithms, the dynamic group size S in R-grouping is set as $S = \{10, 20, 50, 100, 200\}$. According to our numerical experiments, the selection probabilities for variable-grouping strategies P_R, P_{CU}, and P_{DP} are suggested to be set as follows: $P_R = 0.4$, $P_{\text{CU}} = 0.3$, and $P_{\text{DP}} = 0.3$. The penalty factor λ in equation (6) is set to 10000. The probabilities in mutation operation P_{m1} and P_{m2} are set to 0.3 and 0.6, respectively. The maximum number of fitness evaluations ($FE_{\max}$) is set to 1×10^6. The population size is set to 50, and the number of context vectors is set to 5. Results of the simulation experiments are compared in Figure 5 and Table 1.

According to the simulation results, the proposed VGCC-PSO algorithm performs the best and obtains the minimum fitness function value of 12.7027. Compared with the CC-based algorithms, the basic PSO without CC framework fails to optimize the 1600-dimensional problem and obtains the worst performance of 631.2110, which is significantly larger than its competitors. This implies that by decomposing the original problem into several low-dimensional subproblems, the CC framework is very efficient on overcoming the ultrahigh dimensional characteristic.

By integrating the CC framework, the result obtained by CCPSO is significantly better than that of PSO but worse than the best performer VGCC-PSO. Obviously, the gap between CCPSO and VGCC-PSO shows the efficacy of the developed variable-grouping strategies and mutation operation. To be specific, by integrating the variable-grouping strategies, the CCPSO_{vg} obtains the final result of 17.4469, which significantly outperforms 49.3261 obtained by CCPSO. Rationale behind the achievement is that by integrating the CU-grouping and DP-grouping strategies, the coupled variables are given higher probability to be grouped into the same subproblem and coevolved for enough iterations.

By integrating the mutation operation, $\text{CCPSO}_{\text{mut}}$ obtains the final result of 27.9705, which outperforms 49.3261 obtained by CCPSO. In addition, according to the convergence graph shown in Figure 5, the mutation operation can help the algorithm to fast satisfy the constraints and avoid the punishment brought by penalty function. As discussed above, the developed variable-grouping strategies and mutation operation are efficient on improving the performance of the evolutionary algorithm on solving ultrahigh dimensional problem. To be specific, the variable-grouping strategies can improve the global exploration ability and optimization accuracy, while the mutation operation can significantly accelerate the convergence or satisfaction speed of constraints.

5. Simulation Experiments and Analysis

In this section, the performance of VGCC-PSO is empirically evaluated on a comprehensive set of case studies. Parameters setting of VGCC-PSO is the same with Section 4. In addition, some state-of-the-art evolutionary algorithms are employed for comparison, including the CPSO-S_{K} [26], CPSO-$\text{S}_{\text{K-rg-aw}}$ [27], CCPSO2 [28], and CCDE [29]. Parameter settings of these algorithms are following their original studies. The detailed model parameters for each case are listed in Table 2.

Simulation results of the case studies are listed in Table 3, in which the best performance is set in bold. The convergence graphs for each case are plotted in Figure 6.

As shown in Table 3, the proposed VGCC-PSO obtains the best performance for all the cases. To be specific, for the low-dimensional models (i.e., Cases 1 and 2), the outperformance of VGCC-PSO is not significant compared with that of CCDE, CCPSO2, and CPSO-$\text{S}_{\text{K-rg-aw}}$. However, when scale of the D2D communication system becomes large (i.e., the numbers of CU and DP increase to several decades and the model dimensionality increases to more than 1000 in Cases 3 to 6), VGCC-PSO can obtain its efficiency and significantly outperforms the competitors because of the integration of variable-grouping mechanism and mutation operation. For example, in Cases 3 and 4, VGCC-PSO obtains the final results of 18.8794 and 13.1455 for the 1200-dimensional and 2000-dimensional problems, respectively. However, the results obtained by other algorithms are 35.0793 and 23.2162 for CCDE, 30.0329 and 27.0283 for CCPSO2, and 130.2828 and 115.9234 for CPSO-

Algorithm: VGCC-PSO
Initialize a D-dimensional population with N_P particles. Initialize p context vectors with the best p particles.
repeat
Randomly generate a variable P_g, then select a variable-grouping strategy using equation (10).
Decompose the original optimization vector into K subproblems according to the selected variable-grouping strategy. Denote the jth subproblem as P_j.
for *each subproblem* P_j **do**
Coevolve the corresponding dimensionalities of P_j using the CC-based PSO as discussed in our previous work [22].
end
Update the personal best of each particle, and update the context vectors according to reference [22].
for *each context vector* CV_i **do**
Mutate CV_i to $CV_{i\text{-mut}}$ according to the principles developed in Section 3.3.
if $f(CV_{i\text{-mut}}) < f(CV_i)$ **then**
Update CV_i using $CV_{i\text{-}mut}$.
end
Update the global best with the best context vector.
until the stopping criteria are satisfied

Algorithm 1: Pseudo code of VGCC-PSO.

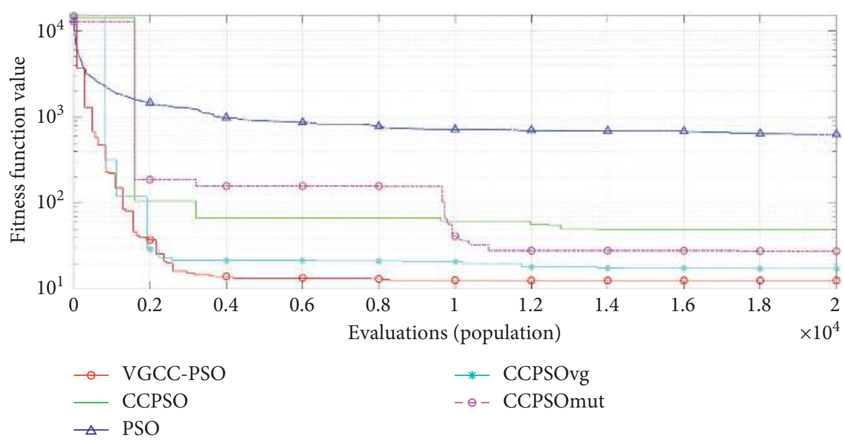

Figure 5: Convergence graphs for optimizing the 1600-dimensional model.

Table 1: Optimization results of the compared algorithms.

Algorithm	Optimization result
VGCC-PSO	12.7027
CCPSO	49.3261
PSO	631.2110
$CCPSO_{vg}$	17.4469
$CCPSO_{mut}$	27.9705

Table 2: Parameter settings of resource allocation models.

Case number	Number of CU	Number of DP	Model dimensionality	Dynamic group size in R-grouping
Case 1	30	8	240	{5, 10, 12, 20, 40}
Case 2	50	10	500	{5, 10, 20, 25, 50}
Case 3	60	20	1200	{10, 20, 50, 100, 200}
Case 4	80	25	2000	{20, 50, 100, 200, 400}
Case 5	100	40	4000	{20, 50, 100, 200, 500}
Case 6	120	50	6000	{50, 100, 200, 600, 1000}

Table 3: Simulation results for Case 1 to 6.

Algorithm	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
VGCC-PSO	**10.5182**	**10.0771**	**18.8794**	**13.1455**	**30.0673**	**48.7768**
CCDE	22.9087	21.6069	35.0793	23.2162	42.0547	87.0291
CCPSO2	24.2608	34.4517	30.0329	27.0283	96.0441	77.4215
CPSO-S_K	146.3635	264.6194	613.8953	431.4242	2098.5629	1602.9015
CPSO-$S_{K\text{-rg-aw}}$	24.1810	62.8635	130.2828	115.9234	315.2044	321.8840

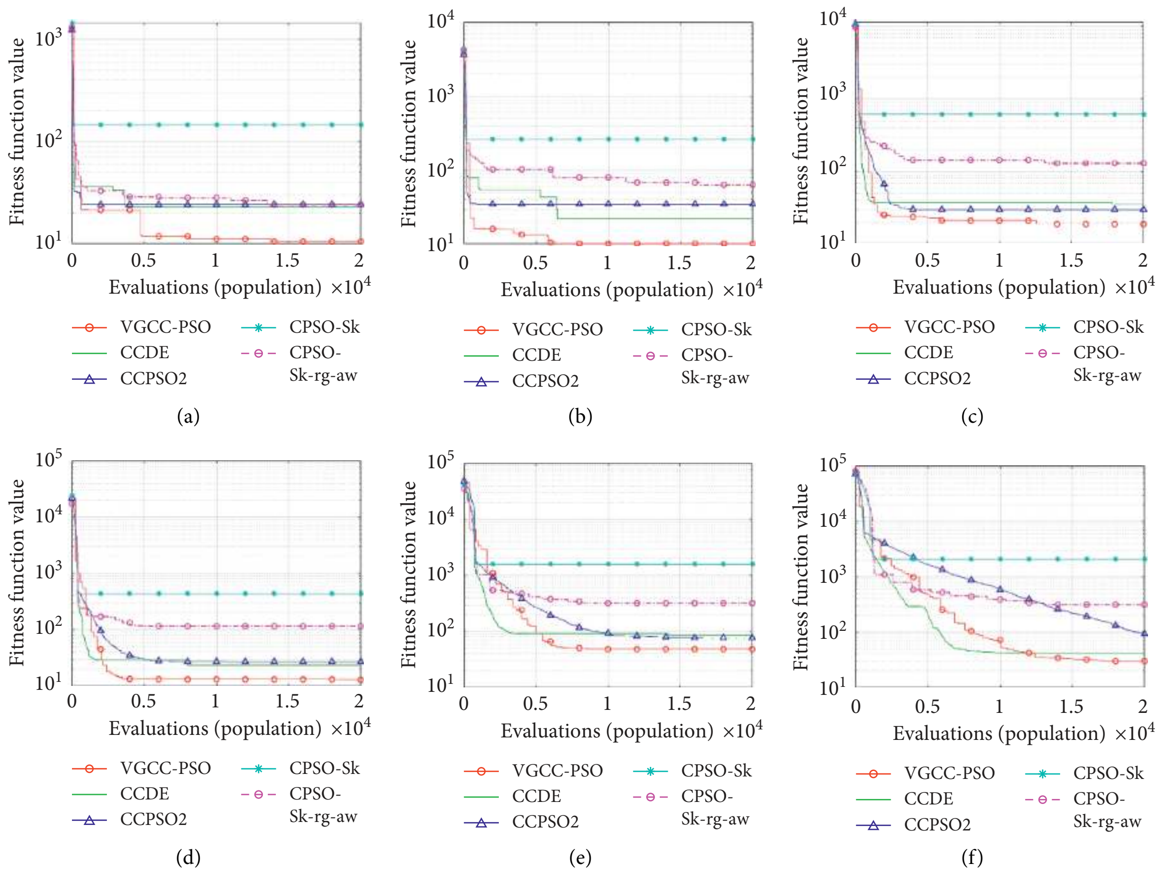

Figure 6: Convergence graphs for Case 1 to 6: (a) Case 1; (b) Case 2; (c) Case 3; (d) Case 4; (e) Case 5; (f) Case 6.

$S_{K\text{-rg-aw}}$. Note that the results obtained by CPSO-S_K for Cases 3 and 4 are 613.8953 and 431.4242, which implies that CPSO-S_K losses its efficacy and fails to optimize these ultrahigh dimensional problems.

In Cases 5 and 6, the model dimensionality increases to 4000 and 6000, and VGCC-PSO is still able to effectively optimize the model and obtains the final results of 30.0673 and 48.7768, which significantly outperforms 42.0547 and 87.0291 by CCDE, 96.0441 and 77.4215 by CCPSO2, 315.2044 and 321.8840 by CPSO-$S_{K\text{-rg-aw}}$, and 2098.5629 and 1602.9015 by CPSO-S_K. Note that the final results listed in Table 3 are all lower than the penalty factor λ which is set to 10000 in the simulations. This indicates that because of the application of CC framework, all the algorithms can satisfy the constraints and avoid punishment for each of the ultrahigh-dimensional cases.

6. Conclusion

In this study, the ultrahigh dimensional model for resource allocation in a large-scale intelligent D2D communication system is established, and a novel optimization methodology, namely, VGCC-PSO is also developed for optimizing the BLSGO-based model.

For a large-scale D2D communication system with N CUs and M DPs, by defining the binary encoding scheme and penalty function, the resource allocation problem is modelled as an unconstrained optimization problem with ultrahigh dimensionalities of $N \times M$. In order to effectively optimize the ultrahigh dimensional model, the CC framework is applied to decompose the original problem and coevolve each subproblem according to the philosophy of "divide and conquer."

For further improving the optimization performance, some efficient variable-grouping strategies like the R-grouping, CU-grouping, and DP-grouping are developed to rearrange and co-optimize the large number of optimization variables. In addition, a novel mutation operation is also developed to accelerate the convergence speed. Simulation results show the effectiveness of these algorithm mechanisms; the integration of variable-grouping strategies can improve global exploration ability and final optimization accuracy, while the mutation operation can significantly accelerate the satisfaction of constraints.

Finally, by integrating the CC framework, variable-grouping strategies, and mutation operation, the proposed VGCC-PSO algorithm is empirically evaluated on a comprehensive set of case studies, and some state-of-the-art algorithms are also employed for comparison. Simulation results show that VGCC-PSO performs the best in optimizing the ultrahigh-dimensional model with up to 6000 dimensionalities. In a word, the proposed methodology can effectively overcome the "curse of dimensionality" and optimally allocate the resources in the large-scale intelligent D2D communication system with high accuracy and robustness.

Data Availability

The prior studies and data are cited at relevant places within the text as references [17–19, 21, 22, 25].

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the Science and Technology Project of China Southern Power Grid Co., Ltd (GZHKJXM20190097).

References

[1] I. Loannou, V. Vassiliou, C. Christophorou, and A. Pitsillides, "Distributed aritificial intelligence solution for D2D communication in 5G networks," *IEEE Systems Journal*, vol. 14, no. 3, pp. 4232–4241, 2020.

[2] W. K. Lai, C.-S. Shieh, F.-S. Chou, C.-Y. Hsu, and M.-H. Shen, "Handover management for D2D communication in 5G networks," *Applied Sciences*, vol. 10, no. 12, p. 4409, 2020.

[3] M. Hayati, H. Kalbkhani, and M. G. Shayesteh, "Energy-efficient relay selection and power allocation for multi-source multicast network-coded D2D communications," *AEU—International Journal of Electronics and Communications*, vol. 128, Article ID 153522, 2021.

[4] Y. P. Llerena and P. R. L. Gondim, "Social-aware spectrum sharing for D2D communication by artificial bee colony optimization," *Computer Networks*, vol. 183, Article ID 107581, 2020.

[5] F. Jiang, B. Wang, C. Sun, Y. Liu, and R. Wang, "Mode selection and resource allocation for device-to-device communications in 5G cellular networks," *China Communications*, vol. 13, no. 6, pp. 32–47, 2016.

[6] S. Jayakumar and S. Nandakumar, "A review on resource allocation techniques in D2D communication for 5G and B5G technology," *Peer-to-Peer Networking and Applications*, vol. 14, no. 1, pp. 243–269, 2020.

[7] Y. Yang, L. Feng, C. Zhang, Q. Ou, and W. Li, "Resource allocation for virtual reality content sharing based on 5G D2D multicast communication," *EURASIP Journal on Wireless Communications and Networking*, vol. 2020, no. 1, p. 112, 2020.

[8] G. Hou and L. Chen, "D2D communication mode selection and resource allocation in 5G wireless networks," *Computer Communications*, vol. 155, pp. 244–251, 2020.

[9] M. Liu and L. Zhang, "Graph colour-based resource allocation for relay-assisted D2D underlay communications," *IET Communications*, vol. 14, no. 16, pp. 2701–2708, 2020.

[10] R. Li, P. Hong, K. Xue, M. Zhang, and T. Yang, "Energy-efficient resource allocation for high-rate underlay D2D communications with statistical CSI: a one-to-many strategy," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 4, pp. 4006–4018, 2020.

[11] N. Su, Q. Zhu, and Y. Wang, "Resource allocation algorithm for NOMA-enhanced D2D communications with energy harvesting," *Mobile Information Systems*, vol. 2020, Article ID 4062487, 11 pages, 2020.

[12] A. Khazali, S. Sobhi-Givi, H. Kalbkhani, and M. G. Shayesteh, "Energy-spectral efficient resource allocation and power control in heterogeneous networks with D2D communication," *Wireless Networks*, vol. 26, no. 1, pp. 253–267, 2020.

[13] N. M. V. Mohamad, P. Ambastha, S. Gautam, R. Jain, H. Subramaniyam, and L. Muthukaruppan, "Dynamic sectorization and parallel processing for device-to-device (D2D) resource allocation in 5G and B5G cellular network," *Peer-to-Peer Networking and Applications*, vol. 14, no. 1, pp. 296–304, 2020.

[14] A. Amin, X.-H. Liu, I. Khan, P. Uthansaku, M. Forsat, and S. Sajad Mirjavadi, "A robust resource allocation scheme for device-to-device communications based on Q-learning," *Computers, Materials & Continua*, vol. 65, no. 2, pp. 1487–1505, 2020.

[15] J. Dai, J. Liu, Y. Shi, S. Zhang, and J. Ma, "Analytical modeling of resource allocation in D2D overlaying multihop multichannel uplink cellular networks," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 8, pp. 6633–6644, 2017.

[16] X. W. Li and W. K. Liu, "Particle swarm optimization based energy efficiency maximizing strategy in device-to-device (D2D) communications," *Telecommunication Engineering*, vol. 57, no. 10, pp. 1171–1176, 2017.

[17] R. Tang, Z. Wu, and X. Li, "Optimal operation of photovoltaic/battery/diesel/cold-ironing hybrid energy system for maritime application," *Energy*, vol. 162, pp. 697–714, 2018.

[18] R. Tang, Q. Lin, J. Zhou et al., "Suppression strategy of short-term and long-term environmental disturbances for maritime photovoltaic system," *Applied Energy*, vol. 259, Article ID 114183, 2020.

[19] R. Tang, X. Li, and J. Lai, "A novel optimal energy-management strategy for a maritime hybrid energy system based on large-scale global optimization," *Applied Energy*, vol. 228, pp. 254–264, 2018.

[20] R. S. Lan, Y. Zhu, H. M. Lu, Z. L. Tang, Z. B. Liu, and X. N. Luo, "Large-scale optimisation via cooperatively coevolving competition swarm optimiser," *Enterprise Information Systems*, vol. 14, no. 9-10, pp. 1439–1456, 2020.

[21] R.-l. Tang and X. Li, “Adaptive multi-context cooperatively coevolving in differential evolution,” *Applied Intelligence*, vol. 48, no. 9, pp. 2719–2729, 2018.

[22] R. L. Tang, Z. Wu, and Y. J. Fang, “Adaptive multi-context cooperatively coevolving particle swarm optimization for large-scale problems,” *Soft Computing*, vol. 21, no. 6, pp. 4735–4754, 2017.

[23] F.-S. Hsieh and Y.-H. Guo, “A discrete cooperatively coevolving particle swarm optimization algorithm for combinatorial double auctions,” *Applied Intelligence*, vol. 49, no. 11, pp. 3845–3863, 2019.

[24] S. M. J. A. Tabatabaee and H. Zamiri-Jafarian, “Prototype filter design for FBMC systems via evolutionary PSO algorithm in highly doubly dispersive channels,” *Transactions on Emerging Telecommunications Technologies*, vol. 28, no. 4, p. e3048, 2017.

[25] R. Tang, Q. An, F. Xu et al., “Optimal operation of hybrid energy system for intelligent ship: an ultrahigh-dimensional model and control method,” *Energy*, vol. 211, Article ID 119077, 2020.

[26] F. vandenBergh and A. P. Engelbrecht, “A cooperative approach to particle swarm optimization,” *IEEE Transactions on Evolutionary Computation*, vol. 8, no. 3, pp. 225–239, 2004.

[27] X. D. Li and X. Yao, “Tackling high dimensional nonseparable optimization problems by cooperatively coevolving particle swarms,” in *Proceedings of the IEEE Congress on Evolutionary Computation*, vol. 1–5, pp. 1546–1553, Trondheim, Norway, May 2009.

[28] X. D. Li and X. Yao, “Cooperatively coevolving particle swarms for large scale optimization,” *IEEE Transactions on Evolutionary Computation*, vol. 16, no. 2, pp. 210–224, 2012.

[29] C. H. Chen and W. H. Chen, “Cooperatively coevolving differential evolution for compensatory neural fuzzy networks,” in *Proceedings of the International Conference on Fuzzy Theory and Its Applications*, pp. 264–267, Taipei, Taiwan, December 2013.