Large-Scale Binary Matrix Optimization for Multimicrogrids Network Structure Design

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Abstract—The multimicrogrid network structure design problem (MNSDP) represents a binary matrix optimization challenge, targeting the minimization of the cumulative length of power supply circuits within a multimicrogrid system, subject to specific constraints. The optimization of this problem is pivotal for augmenting the stability and resilience of power systems, particularly in remote locales harnessing renewable energy sources. Given its inherent large-scale, sparse, and multimodal nature, the pursuit of the global optimal solution for MNSDP is inherently complex. In this research, we introduce a sophisticated mathematical model of the MNSDP, accommodating three distinct node types, each having disparate reliability prerequisites. We further unveil a benchmark test suite based on real-world scenarios, dubbed MNSDP-LIB. To further our innovations, we present the large-scale binary matrix-based differential evolution (LBMDE) algorithm. This novel algorithm adopts a binary-matrix-centric DE operator with an enhanced feasibility-centric environmental selection strategy. Empirical experiments accentuate the proficiency of LBMDE in addressing large-scale binary matrix optimization challenges. When juxtaposed with extant evolutionary algorithms and a renowned commercial solver, LBMDE demonstrates commendable competitiveness.

Index Terms—Binary matrix optimization, constrained differential evolution algorithm, multimicrogrid network structure design, renewable energy sources.

I. INTRODUCTION

The increasing emphasis on renewable energy has bolstered the relevance of microgrid technology [1]. This technology finds use across sectors, notably in manufacturing units and industrial domains. In locales without access to the central power grid, stand-alone microgrids [2] emerge as critical instruments for maintaining uninterrupted power system functions. Yet, renewable energy sources, impacted by unpredictable elements like severe weather or equipment malfunction, can disrupt this continuous operation, particularly in essential facilities.

Building a network of multiple microgrids can augment the resilience and stability of the system. In essence, each stand-alone microgrid behaves as an independent node under typical conditions [3]. Should a microgrid falter or be unable to cater to energy requisites, designated power circuits kick in to ensure continuity. Thus, there arises an imperative to design this microgrid power supply circuit network, termed as the multimicrogrid network structure design problem (MNSDP). MNSDP’s objective centers around curtailing the cumulative length of power circuits while adhering to set constraints [4].

Conventionally, solutions to MNSDP are conveyed via binary matrices. These matrices find their counterparts in real-world scenarios, observed in fields like network topology, power supply restructuring [1], and logistics fine-tuning [5]. This category of problems falls under the ambit of binary matrix optimization problems (BMOPs) [6]. The mathematical representation of a BMOP stands as

$$\min f(x)$$
$$s.t. \ g(x) \leq 0$$
$$h(x) = 0$$

$$x_{i,j} \in \{0, 1\}, i \in [1, m], j \in [1, n].$$ (1)

In the above formulation, $x$ denotes the binary decision variables, encapsulated within a decision vector that spans $mn$ variables. A solution, termed as $x_a$, reaches global optimality when, for every feasible solution $x_b$, $f(x_a) \leq f(x_b)$.

Over recent decades, evolutionary algorithms (EAs) have made headway in resolving multifaceted engineering conundrums [7], [8]. Notwithstanding their achievements, foundational EAs predominantly veer toward continuous optimization paradigms [9]. Pan et al.’s survey [10] underscores two main tactics for binary decision variables. One tactic treats these variables as real numbers, subsequently converting them using a rounding mechanism [11]. The other encompasses the creation of specialized operators, like the XOR operator [12], that engage directly with binary variables. These methods proficiently tackle simpler problems. However, as problem dimensions grow, leading to large-scale optimization problems (LSOPs) [13], the effectiveness of conventional EAs dwindles. This limitation stems from...
the broad decision landscape and operational inefficiencies of techniques like simulated binary crossover (SBX) and polynomial mutation (PM). To circumvent these challenges, numerous studies have birthed novel strategies, exemplified by Kong et al.'s binary harmony search algorithm simplified binary harmony search (SBHS) [14] for large-scale knapsack issues, and a fresh self-adapting binary differential evolution algorithm [15] which employs adaptive mechanisms.

However, the capabilities of extensive EAs in managing BMOPs remain largely unexplored. Solutions to MNSDPs often take the form of symmetric binary matrices. Without strategies tailored to this inherent matrix structure, conventional EAs might not yield the best results. Acknowledging this gap, we put forth a novel matrix-centric constrained differential evolution algorithm, fortified with sophisticated feasibility rules. In summary, this study’s primary contributions are as follows.

1) Introduction of a novel mathematical model for the MNSDP, incorporating three node types with varying reliability demands and restrictions. For the convenience of other researchers, a benchmark test suite (MNSDP-LIB) is proposed, which is inspired by real-world contexts, to assess the competency of EAs in tackling BMOPs.

2) Development of a unique matrix-based constrained algorithm large-scale binary matrix-based differential evolution LBMDE designed for large-scale BMOPs. This algorithm encapsulates a binary-matrix-centric DE operator coupled with an augmented feasibility rule-based environmental selection strategy.

3) Empirical evidence demonstrating the effectiveness and efficiency of LBME in addressing MNSDP-LIB and other BMOPs. This is juxtaposed against several contemporary EAs and a commercial solver, revealing LBME’s capacity to produce competitive solutions with reduced computational demands.

4) A notable contribution to advancing renewable energy and microgrid technologies by furnishing a pragmatic, robust methodology for devising optimal multimicrogrid network architectures, thereby bolstering system stability and resilience.

The structure of this article unfolds as follows: Section II provides a concise review of both MNSDPs and the EAs tailored for BMOPs. This is followed by Section III, where we delineate the proposed mathematical model for MNSDPs, and Section IV, detailing the LBMDE approach. Comprehensive experimental evaluations of the proposed model and algorithm are presented in Section V. We conclude the study and outline potential avenues for future research in Section VI.

II. PRELIMINARY WORKS

A. Network Structure Design Problems

Characterized as a quintessential power insurance network, the multimicrogrid network system (MMGNS) [16] is composed of multiple independently operating microgrids. For analytical clarity in this study, subsequent references to each microgrid will consider them as individual nodes, as depicted in Fig. 1.

The schematic in Fig. 1 portrays a single DC bus, four power sources (namely, wind power, photovoltaic, diesel generator, and battery system), and three loads within an autonomous microgrid system. Ordinarily, the cumulative power generation, denoted as DG, exceeds the power consumption (loads) in such a system, ensuring its stable operation. For clear depiction, green circles, orange boxes, and black circled lines symbolize the total power generation, total loads, and the DC bus, respectively. The blue circle, green square, and red triangle denote Type-I, Type-II, and Type-III nodes, which are elucidated further in subsequent sections.

Under standard operational conditions, each node in the MMGNS functions independently. However, in scenarios of power generation failure or if generation proves inadequate for load demands, the pre-established power supply circuits connected to the compromised node activate, drawing surplus power from neighboring nodes [17]. For the sake of simplicity in modeling, it is posited that upon DG failure at a node, associated circuits instantaneously connect to ensure energy continuity. Given the described characteristics, nodes in the MMGNS display distributed behavior under regular conditions and exhibit interconnectivity during malfunctioning phases. Consequently, discerning the optimal network structure becomes paramount to ensure the stable, cost-effective operation of an MMGNS, which is termed as the MNSDP.

Over the past decade, MNSDPs have garnered substantial academic interest [18]. In a pioneering effort in 2011, Erol-Kantarci et al. [19] introduced a reliable overlay topology design paradigm, aiming for enhanced utilization of renewable energy within the multimicrogrid framework. Striving for augmented reliability and economic efficiency of multimicrogrids, Che et al. [20] ventured into a probabilistic minimal cut-set-based iterative methodology to strategically plan microgrid interconnections, especially those harnessing variable renewable energy sources. Subsequently, a model for the optimal expansion planning of an energy hub, encompassing various energy systems, was presented [21]. In a pursuit of superior operational performance and robustness, a methodology integrating graph partitioning and integer programming was proposed [22]. Inspired by this endeavor, Cortes et al. [23] unveiled an iterative procedure capable of optimizing a loop-based microgrid structure within...
active distribution networks. In recent times, a trend has emerged wherein researchers are gravitating toward clustering methodologies for optimizing network structures [24]. While the significance of MNSDPs is well-acknowledged with considerable research contributions to bolster the efficacy of multimicrogrid systems, there remains an evident gap necessitating further exploration.

B. Evolutionary Algorithms

EAs stand out as potent and efficient instruments for tackling intricate, nonlinear challenges [25], [26]. Notably, a vast array of real-world engineering quandaries can be categorized as matrix optimization problems. Yet, a comprehensive academic discourse on such problems remains relatively scant. Certain problems can be intricately structured, necessitating multilayered encoding. To illustrate, in job-shop scheduling issues [27], both the sequence of processes and the affiliated machinery are distinctly encoded via a bifurcated layering system. Subsequent to this, Kang et al. [28] introduced a matrix-centric automated concept generation technique, incorporating ant colony optimization (ACO) to refine the conceptual solutions generated.

In the context of BMOPs, contemporary research over past decades predominantly zeroes in on augmenting the efficacy of extant EAs. Banitalebi et al. [15] unveiled a self-adaptive decades predominantly zeroes in on augmenting the efficacy of hybrid methodologies. Integrating these CHTs into pre-existing EAs has culminated in the creation of numerous state-of-the-art algorithms. Nonetheless, the design and development of algorithms specifically for large-scale constrained BMOPs remain a nascent field of inquiry.

III. MATHEMATICAL MODEL OF THE MNSDP

Conventionally, the stability of a system can be articulated through its failure probability [36]. Nevertheless, ascertaining the precise failure probability of an individual node poses significant challenges. In response, the $N - K$ methodology is invoked [37], signifying that a system comprising $N$ nodes (components) can endure the damage of $K$ nodes and still function adequately. The $N - K$ approach appraises system stability systematically, premised on the assumption that all nodes possess identical failure probabilities or are of equal significance. Yet, this premise does not consistently align with real-world MMGNS scenarios [3].

To more adeptly encapsulate varying node reliability requirements, this research designates to each node $i$, $i \in [1, N]$ a criterion $N - K_i$ reflective of its distinct circumstances. This means node $i$ remains operational even if $K_i$ nodes malfunction. Based on $K$ values, nodes can be classified into distinct categories. Specifically, in this investigation, values of $K=1$, 2, and 3 are associated with Type-I, Type-II, and Type-III nodes, respectively. A greater value of $K$ insinuates heightened node significance [38]. Fig. 2 elucidates various instances of topological adaptations induced by failures in microgrid nodes within an MMGNS.

A. Constraints for Type-I Nodes

In Section II-A, we elucidated the constraints pertinent to Type-I nodes. By the definition of $N - 1$, a Type-I node is mandated to function normally even if a single node in the system fails. This posits that in the gravest scenario, the DG of the current node is nullified. Consequently, neighboring nodes must compensate to sustain the load of the incapacitated node. Given a Type-I node $i$, the subsequent constraints are obligatory

$$S_i \geq L_i \forall i \in V_I$$

$$S_i = \sum_{j=1, j \neq i}^{n} (G_j - L_j)x_{ij}$$

Fig. 2. Illustrative representation of topological shifts due to microgrid node failure, wherein dotted lines indicate pre-established power circuits.
Herein, \( n \) represents the aggregate number of nodes, and \( V_I \) denotes the set of Type-I nodes. \( S_i \) signifies the cumulative energy support that neighboring nodes of node \( i \) can proffer. Further, \( L_i \) and \( G_i \) typify the load and power generation of node \( i \), respectively. The decision variable is represented as \( x_{ij} \), where \( x_{ij} = 1 \) indicates a connection between nodes \( i \) and \( j \).

### B. Constraints for Type-II Nodes

For Type-II nodes, the system must uphold normal functionality even with the failure of any two arbitrary nodes. Drawing parallels with Type-I nodes, the direst circumstance is envisaged when both the power supply of the current node and its adjacent node are compromised. Under such conditions, neighboring nodes must bear the loads of the two affected nodes. Thus, a Type-II node \( j \) is compelled to meet the ensuing constraints

\[
S_j + S_i - r_{ij} - s_j \geq L_j + L_i \quad \forall j \in V_{II} \quad \forall i \in V, \quad i \neq j
\]

\[
r_{ij} = x_{ij}(G_i - L_i + G_j - L_j)
\]

\[
s_{ij} = \sum_{k=1, k\neq i, j}^{n} x_{ik} x_{jk}(G_k - L_k).
\]

In this context, \( V_{II} \) constitutes the set of Type-II nodes. The terms \( r_{ij} \) and \( s_{ij} \) correspond to the shared energy supply between nodes \( i \) and \( j \) and the accumulated energy provision from their mutual neighbors, respectively.

### C. Constraints for Type-III Nodes

Relative to the resiliency criterion of \( N - 3 \), Type-III nodes must persevere even if the system loses three arbitrary nodes. Analogous to Type-II constraints, the harshest scenario ensues when the power supplies of the current node and two of its neighbors are obliterated. In this scenario, the load demands of these three nodes must be fulfilled by adjacent nodes. Hence, a Type-III node \( j \) should comply with the subsequent constraints

\[
S_j + S_i - r_{ji} - s_k + r_{kj} - s_{jk} + t_{ijk} \geq L_j + L_i + L_k
\]

\[
r_{ik} - s_k \geq L_i + L_j + L_k
\]

\[
\forall j \in V_{III} \quad \forall i, k \in V, \quad i \neq j \neq k
\]

\[
t_{ijk} = \sum_{l=1, l\neq i, j, k}^{n} x_{il} x_{lj} x_{lk}(G_l - L_l).
\]

Here, \( V_{III} \) symbolizes the set of Type-III nodes. The variable \( t_{ijk} \) encapsulates the collective power provision from common neighbors of nodes \( i, j, \) and \( k \).

### D. Objective Function

In this study, our primary objective was to ensure a stable system, adhering to the \( N - K \) requirement. As such, the stability and robustness of the system are inherently integrated into our mathematical model. In essence, any feasible solution derived from this model inherently represents a stable and robust network structure.

The primary goal of the MNSDP is to curtail the aggregate length of the pre-established power supply circuits. In this study, the Euclidean distance is employed. The MNSDP’s objective function can be delineated as

\[
Y = \min \frac{\sum_{i,j=1}^{n} x_{ij} D_{ij}}{2}
\]

where \( D_{ij} \) are distances between node \( i \) and node \( j \). \( x_{ij} = 1 \) means there is a preset power supply circuit between node \( i \) and node \( j \).

The decision variables of the MNSDP are characterized as a symmetrical binary matrix, categorized as a BMOP. Given that (6) and (8) incorporate product terms of Boolean variables, this model aligns with the mixed-integer nonlinear programming paradigm, amenable to resolution via commercial solver software [39]. It merits emphasis that this study’s scope is restricted to instances where \( K \in [1, 2, 3] \) for scholarly exploration. This method was validated through dialogues with seasoned engineers, who concurred that a \( K \) value of 3 suffices in illustrating a highly reliable system. Moreover, predicated on the model formulated herein, the MNSDP framework can be seamlessly extrapolated to more intricate scenarios.

### IV. Matrix-Based Constrained Differential Evolution Algorithm

Conventional EAs excel in handling low-dimensional problems. These algorithms often prioritize solutions with superior constraint violations and objective values. Consequently, numerous potential solutions, proximal to the optima, are discarded, leading to premature convergence to local optima. Furthermore, for large-scale BMOPs, prevalent EAs exhibit inefficiency. Hence, there is a pressing need for an efficient EA tailored for high-dimensional BMOPs.

Inspired by the underpinnings of DE algorithms and contemporary CHT, this study introduces an innovative differential evolution algorithm, LBMDE, tailored for BMOPs. LBMDE enhances the conventional DE by incorporating a binary matrix-centric operator, bolstering the search process. Additionally, to foster solution diversity and amplify the search capability of LBMDE, we have embedded an environmental selection strategy pivoted around an advanced feasibility rule. Subsequent subsections elucidate the specifics of LBMDE.

#### A. Framework

The LBMDE algorithmic framework is delineated in Algorithm 1. Notably, the inception phase employs a heuristic strategy to conceive high-caliber solutions (refer to line 1). This heuristic significantly expedites the convergence trajectory. Subsequently, an adapted DE operator is executed to spawn offspring, explicitly devised for BMOPs (see line 3). A mutation function is then invoked to ensure thorough exploration of the decision landscape (refer to line 5). Finally, an enhanced feasibility rule-steered environmental selection method is employed to augment solution diversity and proficiently navigate constraints. The intricacies of each phase are detailed in upcoming subsections.
For this reason, we propose a heuristic tailored for BMOPs, showcased in Algorithm 2. The solution is initialized with all decision variables set to one (see line 1). In subsequent iterations, connections between distinct nodes are randomly pruned (lines 4–8). If the emergent solution maintains feasibility, it is integrated as a more optimized solution. If not, a counter increments. When the counter surpasses a threshold, such as the node count $n$, we surmise the optimization has plateaued, designating the entire network structure as an optimized initial solution. The probability $p_i$ of selecting a neighboring node $i$ of node $j$ is given by

$$p_i = \frac{D_{ij}}{\sum_{k \in N_j} D_{jk}} \tag{10}$$

where $D_{ij}$ and $N_j$ are the distance between node $i$, $j$ and the neighbor nodes set of node $j$.

### C. Binary-Matrix-Based DE Operator

The DE algorithm is an esteemed optimization tool that has proven efficacy across diverse optimization challenges. Compared to other EAs, DE showcases superior attributes, such as its intuitive design, efficiency, inherent real coding, accessibility, local search capabilities, and rapid convergence. The DE algorithm manifests in multiple variants with tunable parameters tailored for different problems and contexts. Such variations are captured using the notation $DE/x/y/z$ [40], where $x$ signifies the vector subjected to mutation, $y$ denotes the count of difference vectors, and $z$ specifies the crossover strategy.

For the conventional DE algorithm, represented as $DE/rand/2/bin$, consider a population comprising $N$ solutions $x_i,G$, where $i = 1, 2, \ldots, N$ for generation $G$. The mutation operation is articulated as

$$v_{i,G+1} = x_{i,1,G} + F \cdot (x_{i,2,G} - x_{i,3,G}). \tag{11}$$

In this equation, indices $r1$, $r2$, and $r3$ are chosen at random, while $F \in [0, 2]$ is a scalar multiplier governing the amplification of the differential vector $(x_{i,2,G} - x_{i,3,G})$.

For the crossover functionality in DE, let $u_{ji,G}$ represent the $j$th decision variable of solution $x_i$ in generation $G$. The DE updating process is then defined by

$$u_{ji,G+1} = \begin{cases} v_{ji,G+1} & \text{if } (r(j) \leq CR) \text{ or } j = m(i) \\ u_{ji,G} & \text{if } (r(j) > CR) \text{ and } j \neq m(i). \end{cases} \tag{12}$$

Here, $CR \in [0, 1]$ represents the crossover factor. The term $m(i) \in \{1, 2, \ldots, D\}$, where $D$ symbolizes the quantity of decision variables, is a randomly selected index ensuring that $u_{ji,G+1}$ inherits at least one component from $v_{ji,G+1}$. Notably, $v_{i,G+1}$ can either be a random selection from the prevailing population or the optimal solution.

Conventional crossover and mutation operations entail random selection of specific gene points. While this approach exhibits efficacy in low-dimensional decision variable problems, its performance dwindles for large-scale challenges. To mitigate this inefficiency, we introduce a binary-matrix-based DE operator tailored for BMOPs. Specifically, the update of

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**Algorithm 1** General Framework of LBMDE

**Input:** Maximum generations $MaxGen$, population size $N$, problem parameters $P$

**Output:** Optimal solution $BestSol$

1. $Pop \leftarrow Initialization(N, P)$ /* Use heuristic method to initialize high-quality population. */
2. while $gen \leq MaxGen$
   3. $Off \leftarrow MatrixDE(Pop)$ /* Special DE to produce new solutions. */
   4. $Pop \leftarrow Mutation(Pop)$ /* Utilize a mutation strategy to help jump out of local optima. */
   5. $Pop \leftarrow EnvSel(Pop, Off, N)$ /* Improved feasible rule-based method to select solutions. */
3. $gen \leftarrow gen + 1$
4. $BestSol \leftarrow GetBestSol(Pop)$ /* Obtain the final optimal solution. */

**Algorithm 2** Heuristic Method

**Input:** Number of nodes $n$, distance between all nodes $D$

**Output:** High-quality solution $X$

1. $X \leftarrow GenerateMatrix(n)$ /* Set each decision variable in $X$ equals to 1 */
2. $count \leftarrow 0$
3. while $count < n$
   4. $X1 \leftarrow X$
   5. $p \leftarrow RandomPick(n)$ /* Randomly select a node */
   6. $remainP \leftarrow FindNeighbor(p)$
   7. $selP \leftarrow RouletteWheelSel(D(p, remainP))$ /* Randomly select a node according to Eq. (10) */
   8. $X1(p, selP) \leftarrow 0$
   9. if $isfeasible(X1)$ then
      10. $X \leftarrow X1$
      11. $count \leftarrow 0$
   12. else
      13. $count \leftarrow count + 1$ /* The counter is used to evaluate if $X$ can be improved or not */
14. end if
15. end while

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**B. General Initialization Method for BMOPs**

The BMOPs scrutinized herein are characterized by an immense number of decision variables. For a system encompassing $n$ nodes, the quantity of valid decision variables scales to $[(n^2 - n)/2]$. Moreover, given the objective of truncating the total extent of power supply circuits, a substantial portion of the decision variables ought to be set to zero. Thus, MNSDP epitomizes a quintessential large-scale sparse optimization challenge. This underscores the imperative for a heuristic strategy that can rapidly conceive high-quality solutions. Yet, achieving an equilibrium between solution diversity and quality presents a formidable challenge. A paucity of solution diversity can ensnare the search in local optima. This predicament is exacerbated in large-scale sparse scenarios, rendering escape from local optima via crossover or mutation exceedingly challenging.

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Fig. 3. Schematic representation of the introduced binary-matrix-based DE operator.

the $k$th decision variable in the $j$th row/column for generation $G$ adheres to

$$x_{jG+1}^{ik} = \begin{cases} 
  \text{best}^{ik}_{G+1} & \text{if } (r1(k) \leq F) \\
  u^{ik}_{G+1} & \text{if } (r1(k) > F \text{ and } r2(k) \leq CR) \\
  x_{jG}^{ik} & \text{otherwise.}
\end{cases} \quad (13)$$

In this equation, $\text{best}$ and $u$ signify the global optimal solution and a random solution, respectively. Meanwhile, $r1(k), r2(k) \in (0, 1)$ are random values.

The procedure for updating solutions is elucidated in Fig. 3. Specifically, the second row of decision variables, comprising five binary values in this instance, is chosen. Subsequently, four gene points from the random solution $u$ (as determined by $F$) and one from the optimal solution $\text{best}$ (as determined by $CR$) are selected to refine the current solution. This results in the gene of the $j$th row/column amalgamating components from the current, random, and optimal solutions.

In the crossover operation, multiple rows/columns are probabilistically chosen with a likelihood of $1/n$, in alignment with parameters advised for SBX and PM. Employing this innovative DE operator facilitates the acquisition of high-caliber gene fragments from diverse solutions. The designed DE operator is different from existing operators in two aspects: 1) the representation and 2) the update mechanism. The representation is based on a binary matrix instead of a binary vector, which can capture the network structure and connection information more naturally and intuitively. The update mechanism is based on rows or columns instead of gene points, which can retain the connection information and accelerate the search process.

D. Environmental Selection

In this research, the “feasible rules” method is utilized to handle constraints. Specifically, a solution $x_i$ is deemed superior to solution $x_j$ under any of the following circumstances.

1) $x_i$ is feasible, whereas $x_j$ is not.
2) Both $x_i$ and $x_j$ are feasible, yet the objective value of $x_i$ is superior to that of $x_j$.
3) Both $x_i$ and $x_j$ are infeasible, but the constraint violation of $x_i$ is less severe than that of $x_j$.

Through the adoption of these feasible rules, EAs prioritize solutions with minor constraint violations and enhanced objective values. Intriguingly, solutions with preferable objective values but heightened constraint violations might not be preserved. These solutions, however, could potentially be proximate to the true optima, given their diminished objective values. This could lead to algorithms becoming ensnared in local optima. Several studies have been undertaken to counteract this predicament. For instance, Wang et al. [41] advocated for the integration of objective function data into the feasibility rule. In essence, accommodating solutions with intensified constraint violations but superior objective values can notably amplify the efficacy of EAs.

Inspired by the aforementioned algorithms [42], [43], we introduce an enhanced feasible rule-driven environmental selection technique, as delineated in Algorithm 3. This strategy primarily aims to elevate the selection likelihood of an infeasible solution possessing a superior objective value. Broadly, two phases are involved. The initial phase revolves around choosing solutions with reduced constraint violations and optimal objective values, executed in accordance with fundamental feasible rules (refer to lines 3 and 4). The subsequent phase is centered on the identification of potentially optimal solutions. Initially, residual solutions are archived in $\text{Arc}$ (refer to lines 5 and 6). Throughout the iteration process, we arbitrarily select $\text{batchsize}$ solutions from the primary population, identifying the solution with the most pronounced constraint violation as $\text{worstsol}$.

Subsequently, the most proficient solution in the $\text{Arc}$ is juxtaposed against $\text{worstsol}$ based on their objective values. If the archived solution’s objective value outperforms the main population’s inferior solution, a replacement occurs (refer to lines 9–13). Through this methodology, solutions potentially closer to true optima are not prematurely excluded during

**Algorithm 3 Environmental Selection**

**Input:** Population $Pop$, offspring $Off$, population size $N$  
**Output:** Updated Population $Pop$

1: $[\text{PopCon}, \text{OffCon}] \leftarrow \text{GetCon}(Pop, Off)$ /* Retrieve constraint violations for all solutions */  
2: $[\text{PopObj}, OffObj] \leftarrow \text{GetObj}(Pop, Off)$ /* Obtain objective values for all solutions */  
3: $next \leftarrow \text{PopCon} > \text{OffCon}$  
4: $\text{Pop(next)} \leftarrow Off(next)$ /* Replace parent solution if offspring’s constraint violation is lower */  
5: $\text{remain} \leftarrow \text{PopCon} < \text{OffCon} \& \text{&} \text{PopObj} > \text{OffObj}$  
6: $\text{Arc} \leftarrow Off(\text{remain})$ /* Solutions with improved objective values but elevated constraint violations may harbor potential */  
7: for $i = 1 : N$/batchsize do  
8: $\text{pick} \leftarrow \text{rand}(N, \text{batchsize})$ /* Randomly choose batchsize solutions */  
9: $\text{worstsol} \leftarrow \text{max}(\text{GetCon}(\text{Pop}(\text{pick})))$  
10: $\text{bestsol} \leftarrow \text{min}(\text{GetCon}(\text{Arc}))$  
11: if $\text{GetObj}(\text{worstsol}) > \text{GetObj}(\text{bestsol})$ then  
12: $\text{Pop(worst)} \leftarrow \text{Arc(best)}$ /* Supplant the inferior solution with the superior alternative */  
13: end if  
14: end for
evolution, enhancing EA’s capability to navigate beyond local optima.

V. EXPERIMENT

A. Experimental Setting

1) Benchmark Problems: In this investigation, we introduce an innovative mathematical model for the MNSDPs. Since existing benchmark test suites are not tailored for this model, we developed the MNSDP library (MNSDP-LIB). This library is designed to be scalable and adaptable in difficulty to foster future research. Our test problem offers a pragmatic portrayal of the MNSDPs, integrating diverse scenarios one might encounter in real-life applications. Specifically, we introduce two pivotal control parameters: 1) the number of nodes \( n \) and 2) the ratio of energy generation to consumption \( r \). The procedure for generating MNSDP-LIB test instances includes the following.

1) Randomly selecting \( n \) points within a Cartesian coordinate system \((x, y \in [0, 10])\) to denote node positions.
2) Allocating a random real value to each node, signifying its energy generation.
3) Determining the energy consumption of nodes based on their energy generation and the parameter \( r \).
4) Randomly choosing from 1, 2, 3 to designate node types \( K \).

The constraint count largely hinges on Type-III nodes. Furthermore, a smaller \( r \) value results in more intricate network structures, as nodes with lower-\( r \) values necessitate more neighbors. Thus, these two parameters provide avenues for adjusting problem difficulty. Employing the outlined method, we generated 25 test instances, with specific parameters \( n \in \{10, 20, 50, 80, 100\} \) and \( r \in \{1.3, 1.4, 1.5, 1.6, 1.7\} \). It is crucial to note that selecting \( r < 1.3 \) might yield instances devoid of feasible solutions.

2) Competitor Algorithms: To substantiate the efficacy of LBMDE in handling large-scale BMOPs, we selected the following algorithms as benchmarks: SabDE [15], MGA [32], Jaya-based binary optimization algorithm (JayaX) [12], binary particle swarm optimization (BPSO) [34], and the novel binary gaining sharing knowledge-based optimization algorithm with population size reduction (PR-NBGSK) [44]. Each chosen algorithm epitomizes state-of-the-art EAs tailored for large-scale binary optimization, grounded in distinct operators. Among these, SabDE leverages the DE operator, MGA utilizes the GA operator, while JayaX and BPSO employ the XOR and PSO operators, respectively. PR-NBGSK stands out as a contemporary approach. It is worth highlighting that BPSO and PR-NBGSK utilize the rounding operation to transition decimal numbers to their closest binary counterparts. Additionally, the MNSDP mathematical model introduced in this research can be seamlessly converted to a MIP problem. Such a problem can be addressed by commercial solvers to discern the optimal solution. Hence, we employed IBM ILOG CPLEX as a baseline for a robust evaluation of the selected EAs.

For all algorithms, we set the population size as \( N = \min\{10 \times n, 500\} \), while the upper limit for generations, \( G \), is fixed at 50 \( \times n \), where \( n \) represents the node count. It is pertinent to mention that for algorithms not equipped to tackle constraint optimization problems, we adopted a rudimentary feasible rule-based methodology. For equitable comparisons, all algorithms are initialized via the method delineated in Section IV-B. The experiments were executed on a PC equipped with an Intel i9-9900X @ 3.50 GHz and 64 G RAM. To facilitate future research endeavors, the source codes for LBMDE and MNSDP-LIB are made publicly accessible. 

B. Result Analysis

1) Performance Comparison: This section offers a detailed comparison between the performance of LBMDE and the benchmarked algorithms using MNSDP-LIB. We evaluate 25 instances with different node counts. The results, including both the average and standard deviation of the objective values from 30 independent runs, are presented in Table I. Additionally, Fig. 6 presents the runtimes of all algorithms, grouped by the number of nodes.

It is essential to note that for CPLEX, the time required to obtain exact optimal results for problems with 80 nodes is excessively long, often between two to four days. As a result, we established an acceptable gap of 3%. This means the solution obtained is at most 3% worse than the optimal solution. For problems with 100 nodes, this tolerance is increased to 5%. The convergence trend of CPLEX over time can be seen in Fig. 4. It is evident that while the gap reduces significantly in the early phases (especially when the gap is \( \geq 10\% \)), the rate of improvement slows down in the later stages. Here, minor improvements in objective values come with considerable computational costs.

The data in Table I provides a clear comparison of average objective values. It is evident from the results that LBMDE surpasses other state-of-the-art EAs on the tested problems. Notably, LBMDE performs best in 22 out of the 25 benchmark problems. It should be highlighted that MGA performs optimally for MNSDP-LIB-10-1, MNSDP-LIB-10-2, and MNSDP-LIB-10-5. When compared to the baseline (the exact optimal solution determined through the MIP method), LBMDE’s solutions display significant competitiveness. For problems with a smaller scale (where \( n \leq 20 \)), LBMDE consistently produces high-quality and stable results. Specifically, the difference between LBMDE’s results and the true optimal solution is typically less than 1% for most test cases, with minimal variability. LBMDE maintains its

\[ \text{https://github.com/Wenhua-Li/LBMDEforMNSDP} \]
TABLE I

| Problems    | CPLEX | SabDE | MGA   | JayAX | BPSO | PR-NBGSK | LBME |
|-------------|-------|-------|-------|-------|------|----------|------|
| MNSDP-10-1  | 181.40| 184.98| 181.79| 181.79| 191.42| 188.36   | 185.30| 182.23|
| MNSDP-10-2  | 141.99| 147.10| 143.75| 143.75| 165.96| 160.34   | 152.81| 144.07|
| MNSDP-10-3  | 122.52| 125.48| 122.81| 122.81| 140.60| 139.74   | 131.48| 122.62|
| MNSDP-10-4  | 123.45| 126.56| 123.57| 123.57| 151.78| 141.76   | 132.77| 123.48|
| MNSDP-10-5  | 113.38| 114.99| 113.38| 113.38| 132.34| 124.95   | 118.84| 113.54|
| MNSDP-20-1  | 258.61| 292.03| 288.40| 288.40| 372.84| 343.16   | 303.86| 263.41|
| MNSDP-20-2  | 184.49| 208.25| 197.27| 197.27| 268.45| 241.89   | 217.47| 191.31|
| MNSDP-20-3  | 161.47| 179.44| 162.62| 162.62| 284.41| 221.67   | 191.74| 161.30|
| MNSDP-20-4  | 142.58| 161.87| 150.87| 150.87| 217.19| 189.93   | 167.42| 144.92|
| MNSDP-20-5  | 129.96| 142.19| 136.82| 136.82| 198.99| 179.32   | 155.15| 130.99|
| MNSDP-50-1  | 375.95| 491.06| 448.46| 448.46| 593.13| 628.38   | 508.50| 387.15|
| MNSDP-50-2  | 263.97| 350.76| 315.43| 315.43| 452.72| 438.01   | 352.04| 266.08|
| MNSDP-50-3  | 246.66| 337.44| 293.60| 293.60| 420.93| 455.58   | 353.11| 258.03|
| MNSDP-50-4  | 199.91| 293.66| 253.32| 253.32| 347.93| 378.88   | 441.27| 303.66|
| MNSDP-50-5  | 188.39| 285.84| 239.58| 239.58| 347.32| 456.76   | 423.86| 299.96|
| MNSDP-80-1  | 418.99| 757.72| 561.74| 561.74| 806.27| 2847.65  | 1642.61| 437.56|
| MNSDP-80-2  | 330.32| 613.34| 483.99| 483.99| 697.94| 897.23   | 622.89| 348.55|
| MNSDP-80-3  | 286.70| 526.79| 407.22| 407.22| 583.02| 702.73   | 524.10| 300.86|
| MNSDP-80-4  | 252.89| 513.43| 387.28| 387.28| 562.75| 2865.63  | 1556.55| 267.47|
| MNSDP-80-5  | 225.23| 488.66| 346.09| 346.09| 533.07| 2807.11  | 1523.23| 239.35|
| MNSDP-100-1 | 456.70| 918.83| 728.36| 728.36| 948.41| 993.24   | 751.10| 508.96|
| MNSDP-100-2 | 368.34| 762.68| 570.64| 570.64| 907.94| 5299.53  | 2814.63| 399.73|
| MNSDP-100-3 | 298.45| 671.63| 476.50| 476.50| 723.86| 5240.97  | 2782.26| 323.55|
| MNSDP-100-4 | 275.67| 666.16| 457.88| 457.88| 705.23| 5510.92  | 2903.48| 296.03|
| MNSDP-100-5 | 239.65| 603.79| 422.37| 422.37| 648.27| 5440.21  | 2852.43| 264.65|

effectiveness for larger-scale problems, surpassing the baseline in some instances, even when the baseline is set with a 3% gap for 80-node problems. LBMDE’s performance is notably consistent across varying problem sizes.

Further examination of Table I shows that, in addition to LBMDE, both MGA and SabDE perform admirably on smaller-scale problems. For problems with 10 and 20 nodes, which have decision variable totals of 45 and 190, respectively, these counts, though relatively small, enable the existing EAs to closely approximate the optimal solutions. However, when faced with problems that have a larger number of decision variables, their search efficiency decreases, especially in comparison to LBMDE. BPSO, in particular, underperforms. In the BPSO algorithm, real values are used for solution encoding. Further investigation suggests that the particle velocities in BPSO tend to approach zero. The problems in this study can be described as large-scale sparse optimization tasks, which often require most decision variables to be zero. In BPSO, the mechanism for updating particle velocity is intrinsically linked to particle position, leading to a decrease over the course of the evolutionary process. As a result, BPSO tends to converge quickly to local optima and becomes static thereafter. This behavior is similarly observed in PR-NBGSK, due to its similar approach of transitioning from real to binary decision variables.

Fig. 5 illustrates the optimal network structures determined by the evaluated algorithms for MNSDP-LIB-20-4 and MNSDP-LIB-80-2. It is important to emphasize that the results depicted are the ones most closely aligned with the mean objective values. For the 20-node problem, a significant portion of the algorithms deliver solutions of commendable quality. However, for MNSDP-LIB-80-2, only LBMDE and CPLEX manage to produce results of an outstanding standard. Given space limitations in this article, we have chosen not to detail all optimal network structures here. Nonetheless, an extensive examination is accessible online for those interested.

2) Computational Complexity: This section offers an empirical analysis comparing the computational complexities of EAs with the traditional MIP method. Specifically, the mean execution time for EAs is collated over 30 independent runs, while the execution time for MIP is taken from a single algorithmic run. Fig. 6 illustrates the mean execution times of all algorithms, grouped by different node counts.

Interestingly, when it comes to computational complexity, the existing EAs display remarkable consistency. Their runtimes are largely driven by function evaluation. To elaborate, JayaX stands out as the most efficient for small-scale problems. However, when handling larger problem scales, both MGA and JayaX deliver the most impressive runtimes. A detailed observation of Fig. 6 reveals that the MIP methodologies, as represented by CPLEX, experience an exponential increase in runtime as the node count grows (specifically, for problems with 80 nodes and 100 nodes, acceptable gaps are established at 3% and 5%, respectively).

For problems with 10 and 20 nodes, CPLEX showcases its computational efficiency. But as the node count increases, the runtime trend for EAs remains relatively linear and manageable. For larger problem sizes, the MIP approach becomes time-consuming, highlighting the effectiveness and suitability of EAs in such scenarios. In conclusion, while the runtime of all EAs correlates closely with the node count, CPLEX excels for smaller-scale problems. However, EAs demonstrate a clear advantage when addressing larger problem dimensions.

3) Analysis of MNSDP-LIB: In Section V-A1, we elaborated on the construction methodology behind MNSDP-LIB. To regulate the complexity of solving the test instances, we...
introduced the parameter $r$. This parameter denotes the ratio between energy generation and consumption.

Fig. 7 showcases the optimized power network structures for both MNSDP-LIB-20 and MNSDP-LIB-50 test instances across different values of $r$. It is observable that as $r$ increases, the resulting optimal network structure becomes progressively simplified. Specifically, the average number of neighboring nodes for the instances MNSDP-LIB-50-1 through MNSDP-LIB-50-5 are 4.56, 3.84, 3.32, 3, and 2.96, respectively. This suggests that, while ensuring system stability, nodes tend to establish connections with a reduced set of other nodes. Consequently, the intricacy of test instances can be modulated effectively by adjusting the parameter $r$.

C. Exploring the Impact of the Binary-Matrix-Based DE Operator

To delve deeper into the implications of our newly introduced DE operator, we designed several variations of the LBMDE algorithm, namely, LBMbDE, LBMbPSO, LBMbGA, LBMJayaX, and LBMbGSk. Specifically, LBMbDE is a variant derived from LBMDE but employs the standard DE operator, as depicted in (11). LBMbGA utilizes the SBX and PM operators, while both LBMbPSO and LBMJayaX are fashioned using the binary PSO operator and the JayaX operator, respectively. It is pivotal to note that all other parameters are kept consistent with those of LBMDE.

Table II presents the outcomes from various LBMDE variant algorithms when applied to the MNSDP-LIB test instances. Clearly, LBMDE outperforms its counterparts. In particular, both LBMbDE and LBMbGA yield high-quality solutions. When juxtaposed with SabDE and MGA,
these variants display pronounced strengths, especially when tackling extensive problems. As delineated in Section IV-D, we introduced an innovative environmental selection strategy optimized for constraints handling, enabling algorithms to achieve superior results. Conversely, LBMbPSO and LBMbGSK yield relatively suboptimal results. As elaborated earlier, the inherent updating mechanism of PSO is ill-suited for extensive sparse problems. This limitation prompts premature convergence and a consequent dearth in solution diversity within the decision space. Consequently, a reimagined strategy tailored for PSO is imperative to address such challenges.

Furthermore, Fig. 8 delineates the convergence trajectories of the algorithms for MNSDP-LIB-20-3 and MNSDP-LIB-50-3 instances. Evidently, for less complex problems, LBMbDE, LBMbGA, and LBMD are all pinpoint the optimal solution. Notably, LBMD exhibits a swifter convergence trajectory compared to LBMbDE and LBMbGA.

**Table II**

| Problems  | LBMbDE | LBMbGA | LBMJayaX | LBMbPSO | LBMbGSK | LBMD |
|----------|--------|--------|----------|---------|---------|------|
| MNSDP-10-2 | 183.14(1.02) | 182.01(0.72) | 185.50(3.10) | 192.96(7.02) | 187.60(5.33) | 182.23(0.85) |
| MNSDP-10-3 | 151.05(2.40) | 144.77(1.76) | 146.95(4.65) | 161.87(8.36) | 153.58(4.34) | 145.28(2.37) |
| MNSDP-10-4 | 123.64(0.86) | 122.52(0.90) | 128.41(3.92) | 137.43(7.18) | 130.32(3.46) | 123.22(0.95) |
| MNSDP-10-5 | 114.57(0.21) | 118.05(1.83) | 117.18(2.71) | 131.02(10.65) | 122.82(5.27) | 113.54(0.29) |
| MNSDP-20-1 | 265.21(3.11) | 271.69(4.76) | 318.94(8.09) | 345.09(17.60) | 304.83(7.86) | 264.56(4.38) |
| MNSDP-20-2 | 190.43(4.20) | 193.24(0.79) | 239.98(13.98) | 242.69(15.53) | 217.87(8.52) | 193.05(3.50) |
| MNSDP-20-3 | 161.98(1.06) | 161.47(0.00) | 219.89(16.22) | 224.91(19.84) | 193.36(9.82) | 161.80(0.81) |
| MNSDP-20-4 | 144.08(1.51) | 144.88(1.35) | 176.63(8.59) | 187.84(9.19) | 166.38(4.46) | 144.92(1.46) |
| MNSDP-20-5 | 130.91(0.80) | 130.21(0.50) | 172.15(10.43) | 191.11(8.13) | 161.05(4.19) | 130.99(0.63) |
| MNSDP-50-1 | 390.95(2.57) | 402.76(4.57) | 544.97(11.57) | 580.76(20.78) | 484.69(10.22) | 388.62(9.15) |
| MNSDP-50-2 | 268.90(4.24) | 272.95(4.27) | 413.50(14.08) | 433.95(17.78) | 350.80(8.15) | 266.80(0.74) |
| MNSDP-50-3 | 253.02(2.25) | 259.64(1.49) | 412.45(19.11) | 474.35(151.95) | 362.49(75.97) | 250.63(1.00) |
| MNSDP-50-4 | 205.38(1.58) | 212.50(5.54) | 343.82(21.65) | 736.22(62.73) | 469.94(31.54) | 203.66(0.52) |
| MNSDP-50-5 | 195.36(1.87) | 201.67(2.67) | 324.18(12.64) | 672.63(55.99) | 431.79(27.94) | 190.96(0.48) |
| MNSDP-80-1 | 498.52(11.80) | 510.44(13.58) | 839.45(29.32) | 3042.23(219.82) | 1739.90(109.50) | 437.56(2.65) |
| MNSDP-80-2 | 419.63(7.09) | 435.20(12.67) | 812.09(59.71) | 702.65(26.09) | 525.60(13.84) | 348.55(4.32) |
| MNSDP-80-3 | 361.93(14.93) | 374.32(8.58) | 616.07(39.08) | 2695.48(682.50) | 1498.17(341.74) | 300.86(1.44) |
| MNSDP-80-4 | 337.41(15.97) | 349.15(25.03) | 554.18(29.68) | 2921.81(216.07) | 1594.64(108.47) | 267.47(2.17) |
| MNSDP-80-5 | 306.38(12.37) | 321.00(14.70) | 521.32(71.40) | 2772.54(192.25) | 1505.95(95.74) | 239.35(1.49) |

LBMbPSO displays promising evolution during initial stages but seems predisposed to early entrapment in local optima. LBMJayaX's convergence is gradual yet consistent, updating predominantly at the granularity of individual decision
variables. Given the intricate interdependencies between decision variables in extensive problems, the JayaX operator is less efficacious. LBMbGSK’s performance strikes a median between LBMJayaX and LMBbGA.

Moreover, it is worth noting that LBMbGA is essentially a derivative of MGA, differing chiefly in their environmental selection paradigms. A direct comparison can be drawn using Tables I and II. The results underscore the superior efficacy of our feasibility-rule-centric environmental selection approach over MGA. This edge is primarily attributed to its adeptness at balancing feasibility with optimality, eschewing infeasible solutions, and preserving solution diversity.

In summation, the binary-matrix-based DE operator proposed herein holds significant promise in enhancing the search process, particularly when addressing large-scale optimization quandaries.

VI. CONCLUSION

Many real-world engineering challenges can be classified as BMOPs. Despite their prevalence in practical scenarios, there exists a noticeable dearth of research focusing on this particular category of problems. In the current investigation, we delved into the large-scale network structure design problem, representing it through a binary matrix encoding.

A common strategy among many EAs tailored for LSOPs is the partitioning of decision variables into distinct clusters, facilitating their independent optimization. Consequently, determining an effective grouping strategy is pivotal. Typically, this is anchored on the co-relation of the decision variables. In the context of large-scale BMOPs, decision variables sharing the same row or column are intuitively aggregated into a singular group. This grouping renders it logical to treat them collectively during crossover and mutation operations, which is the main motivation of LBMEDE. Empirical assessments conducted on MNSDP-LIB affirm the prowess of LBMEDE in addressing large-scale BMOPs. Notably, LBMEDE surpassed several contemporary algorithms in metrics of solution fidelity and computational efficiency. A salient feature of LBMEDE is its adaptability; it can be seamlessly tailored to diverse BMOPs by modulating the objective function and constraints.

This study has illuminated the potential of harnessing EAs for intricate and pragmatic engineering tasks that employ binary matrix decision variables. As a progression of this research, our future endeavors will be oriented toward augmenting the capabilities of LBMEDE through the integration of adaptive mechanisms and hybrid methodologies.

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