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Configuration Optimization of Mobile Photovoltaic-Diesel-Storage Microgrid System Based on CPS-MOEA

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Abstract: This paper presents a two-step approach for optimizing the configuration of a mobile photovoltaic-diesel-storage microgrid system. Initially, we developed a planning configuration model to ensure a balance between the mobility of components and a sustainable power supply. Then, we introduced a method that merges optimization and decision-making. The first phase identifies Pareto optimal solutions (POSs) with a favorable distribution by using a multi-objective evolutionary algorithm with classification-based preselection (CPS-MOEA). In the second phase, we utilize the fuzzy C-means algorithm (FCM) and the grey relational projection (GRP) method for comprehensive decision-making. This aims to select the most suitable and compromise solution from the POSs, closely aligning with the decision-maker's preferences. Beyond addressing the optimal planning and configuration issue, the experimental results show that the method surpasses other widely used multi-objective optimization algorithms, including the Preference Inspired Co-evolution Algorithm (PICEA-g), the Multi-Objective Particle Swarm Optimization Algorithm (MOPSO), and the third stage of Generalized Differential Evolution (GDE3).

Keywords: mobile microgrid system; multi-objective optimization; integrated decision-making; CPS-MOEA

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1. Introduction

As fossil fuels are increasingly consumed on a global scale, there is growing attention to the development and utilization of renewable energy sources. Consequently, microgrid systems incorporating renewable energy have begun to receive extensive research. A hybrid energy system refers to a microgrid system that incorporates both traditional fossil fuels and renewable energy sources. However, due to the characteristics of renewable energy, such as intermittency and instability, renewable energy sources often have varying outputs depending on the weather, season, time of day, and other factors. A combination of RE technologies yielded fewer emissions than one kind alone [1]. As a result, the generation of power in a hybrid energy system is somewhat random and unpredictable, making it a challenging aspect of research. The increasing capacity for renewable generation has strongly increased the level of uncertainty in the system, making the Unit Commitment model a large-scale, non-convex, uncertain program [2]. By modeling the uncertainty of renewable power generation with probabilistic constraints, a practical multi-objective optimal scheduling model of grid-connected MGs is proposed for minimizing the operating costs and improving the user experience based on chance-constrained programming (CCP) [3]. To address the uncertainty problem, researchers [4] have presented AIROBE, a data-driven system that uses machine-learning-based predictions of energy supply and demand as input to calculate robust energy exchange schedules using a multiband robust optimization approach to protect from deviations.

Current studies on hybrid energy microgrids primarily focus on single-objective functions such as cost reduction and extended power supply duration. Huang Jingyao has proposed an energy management optimization model that takes into account the mobile energy storage characteristics of electric vehicles. The objective function of the model is to minimize the expected total operating cost [5]. Considering the integration of electric vehicles in the traditional microgrid model, the microgrid system has been studied by various researchers [6]. A multi-objective function, including the operating cost of the microgrid and the charging and discharging cost for electric vehicle users, was established. A wind–solar–hydrogen multi-energy complementary microgrid optimization method has been proposed to address the economic cost optimization problem in the context of multi-energy complementary microgrids, taking into account the demand-side response [7].

Many experts and scholars have utilized different models and algorithms to improve the optimization scheduling and energy control of microgrids. A coordinated and balanced control strategy for the emergency fuel-storage auxiliary power unit in the emergency microgrid is proposed in the literature [8]. During power outages, energy storage and diesel generators are used as the main power sources to provide emergency power supply. The literature [9] presents quasi-oppositional differential evolution to solve the reactive power dispatch problem of a power system. However, research on the flexibility and sustainable power supply of mobile microgrids is still in its infancy; therefore, the study of mobile hybrid energy microgrid systems is of significant theoretical and practical importance.

Recently, research on hybrid energy systems (HESs) has become a hot topic. Researchers [10] have studied the use of an Integrated Energy System (IES) and the application of Hydrogen Compressed Natural Gas (HCNG) and Power to Gas (P2G) equipment in IESs. An optimal scheduling mode was proposed in the literature [11] for minimizing the operating costs of an isolated microgrid (MG) by using chance-constrained programming by modeling the uncertainty of spinning reserves provided by energy storage with probabilistic constraints. Researchers have [12] proposed methods for multi-objective optimal design of hybrid renewable energy systems (HRES) in both isolated-island and grid-connected modes. Researchers have also [13] presented and evaluated three energy management systems (EMSs) based on Particle Swarm Optimization (PSO) for long-term operation optimization of a grid-connected hybrid system. In order to reduce the curtailment of renewable energy resources through improving the operational flexibility, an optimal scheduling model based on chance-constrained programming (CCP) was proposed for a small-scale integrated energy system (IES) with CHP units, thermal power units, renewable generations and representative auxiliary equipment [14]. A generic optimal planning model was proposed in the literature [15] to assess the economic and environmental benefits of the capacity allocation of the grid-connected integrated energy system considering both price-based demand response and incentive-based demand response, respectively. The literature [16] has established a compact model of cogeneration systems by taking nonlinear energy conversion and heat transfer constraints of combined heat and power units into account.

The configuration optimization problem of microgrids is a complex constrained nonlinear optimization problem. The multi-objective evolutionary algorithm performs well when faced with these problems. Li Wenhua first reviewed the related works about multimodal multi-objective problems (MMOPs) in the literature [17], then chose 15 state-of-the-art algorithms that utilize different diversity-maintaining techniques and compared their performance on different types of the existing test suites. Later, Li Wenhua proposed an evolutionary algorithm with a hierarchy ranking method (HREA) to find both the global and the local PFs based on the decision-maker's preference [18], then presented a novel multimodal multi-objective coevolutionary algorithm (CoMMEA) to better produce both global and local PSs, and simultaneously to improve the convergence performance in dealing with high-dimension MMOPs [19]. Researchers [20] have proposed a reference vector-guided EA for multi-objective optimization. In the proposed algorithm, a scalarization approach, termed angle-penalized distance, is adopted to balance the convergence and diversity of the solutions in the high-dimensional objective space. Researchers [21] have also proposed a new concept for solving multi-objective optimization problems: PICEAs. In the algorithms, a family of preferences were coevolved with candidate solutions. A decomposition-based EMO algorithm called the multi-objective evolutionary algorithm based on the decomposition LWS (MOEA/D-LWS) was proposed in the literature [22]. In the literature [23], a GD indicator-based evolutionary algorithm is proposed to solve multi-objective optimization problems. Refs. [24,25] have utilized a pre-existing multi-objective evolutionary algorithm, specifically the Pareto sorting multi-objective evolutionary algorithm with classification-based preselection (CPS-MOEA).

This study introduces a scientific configuration approach that employs advanced optimization methods and algorithms to plan and configure a mobile photovoltaic-diesel-storage microgrid system. The main challenge in optimal planning and configuration lies in balancing the system's weight with minimizing power supply deficiency rates. This balance is crucial for preserving maneuverability and reliability while maximizing the system's potential. This process is recognized as a large-scale nonlinear mixed-integer programming problem, along with equality and inequality constraints. Taking into account the system's planning and configuration challenges, this research applies CPS-MOEA to the unique context of the mobile photovoltaic-diesel-storage microgrid system, addressing the specific combination of constraints and objectives.

This paper first constructs a hybrid microgrid system incorporating a photovoltaic-storage-diesel generator. The system's weight and power supply deficiency rate are considered as objective functions, which are optimized to achieve a balance between the system weight and sustainable power in the microgrid. Then, the multi-objective evolutionary algorithm with classification-based preselection (CPS-MOEA) is employed to solve the optimization problem and its performance is compared with other algorithms. Finally, a comprehensive decision-making process is conducted using the fuzzy C-means clustering (FCM) and grey relational projection algorithm (GRP).

The main contributions of this paper are as follows: a model is constructed for the mobile hybrid microgrid that accurately reflects the real-world situation. The microgrid considers renewable energy sources, energy storage systems, and diesel generators as backup power sources. To address the configuration optimization problem of the mobile microgrid system, we utilized a two-step approach. The first step focuses on the mobile microgrid system using a multi-objective evolutionary algorithm with classification based on preselection. This step takes into account the system's mobility and stability to obtain a series of Pareto optimal solutions. The experimental results demonstrate the effectiveness of CPS-MOEA in managing the complexities of the system's planning and configuration, highlighting a significant contribution to the field. The second step builds upon the first by considering decision-makers' preferences. It applies fuzzy C-means clustering to the Pareto optimal solutions obtained in the first step and ultimately selects the best compromise solution that best aligns with decision-makers' preferences using grey relational projection.

The rest of this work is structured as follows:

Section 2 presents the mathematical modeling of the components of the mobile photovoltaic-storage-diesel microgrid system. Section 3 presents the construction of the optimization model. Section 4 introduces the CPS-MOEA, FCM, and GRP. Section 5 analyzes the experimental results. Finally, Section 6 concludes the paper.

2. Mathematical Model of the Mobile Photovoltaic-Diesel-Storage Microgrid System

The mobile photovoltaic-diesel-storage microgrid system (MPDSMS) consists of a variety of renewable energy generations in addition to conventional power generation and storage. The energy sources considered in this work include photovoltaic power generation, diesel generators, primary batteries, and secondary batteries. The photovoltaic generator energy storage system is based on integrating small-scale generators with corresponding AC/DC conversion devices.

This system operates by supplying freshly generated electricity to the load for immediate use, and then recharging the battery pack with any surplus energy once the load's consumption is complete. To ensure quick power restoration, the diesel generator activates only when the energy from the battery pack combined with the electricity produced by the new energy generation component is insufficient to meet the load's requirements. Employing a diesel engine as a backup power supply can significantly enhance the power supply's overall efficiency and stability. The structure of the mobile microgrid system is shown in Figure 1.

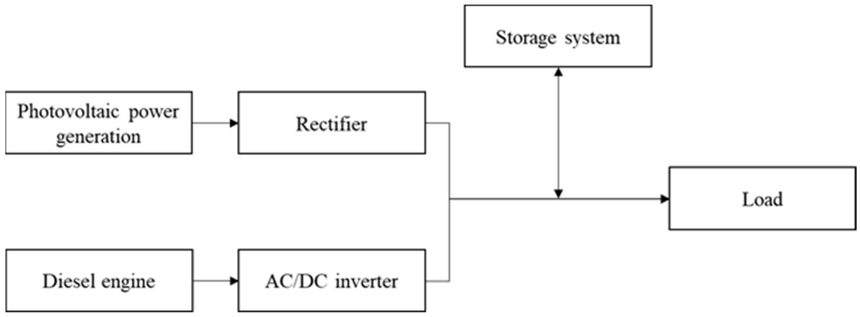

Figure 1. Mobile microgrid structure.

2.1. Photovoltaic Power Generation Unit Model

Photovoltaic power generation does not utilize fuel, emit any substances including greenhouse gases and other waste gases, pollute the air, or produce noise, making it environmentally friendly. Simultaneously, photovoltaic panels utilize solar radiation for power generation, allowing for the maximum utilization of energy, and solar energy is inexhaustible. However, photovoltaic power generation also has certain shortcomings. Its efficiency is highly dependent on weather and seasons and exhibits intermittency and instability to some extent. Consequently, photovoltaic power generation is typically suitable for use as an auxiliary power supply method.

To calculate the power output P_{PV} of a photovoltaic panel, several factors must be considered, including weather-related factors like light intensity, environmental temperature, and the panel's conversion efficiency, as well as installation-specific factors such as the panel's position and its inclination angle. The formula to calculate P_{PV} typically incorporates these variables to accurately estimate the power generation capacity under varying conditions.

Generally, the power output of a photovoltaic panel can be expressed as follows:

$$P_{PV} = A \cdot G \cdot \eta \cdot cos(\theta) \quad (1)$$

where A is the area of the photovoltaic panel (in square meters), G is the solar irradiance on the panel (in watts per square meter) and η is the conversion efficiency of the panel (as a decimal). θ is the angle between the solar radiation and the panel.

2.2. Battery Pack

The energy storage system consists of primary and secondary batteries. Its presence enhances the flexibility of the mobile photovoltaic-storage-diesel microgrid system. When the sunlight is adequate and the load demand is satisfied, excess electricity generated by the photovoltaic will be stored in the energy storage system. When the photovoltaic is unavailable, it can continue to supply power to the load, maximizing energy utilization efficiency.

The battery pack mainly includes non-rechargeable primary batteries and rechargeable secondary batteries. According to the literature, most battery models consider the variable state of charge. The state of charge of a battery pack is based on the relationship between the power generation and load consumption. It should be maintained within the minimum and maximum range given by the battery manufacturer to ensure the safety of the battery pack during use.

When the power generation in the system exceeds the demand of the task load, the excess produced energy can be stored in the battery pack to minimize the waste of power generation. The charging process of the battery can be described by the following formula:

$$SOC_{t+1} = SOC_t + \frac{Energy\ Input}{Battery\ Capacity} \times 100\% \tag{2}$$

In some cases, such as when the task requires silence and the generator with loud noise must not be turned on, or when the weather conditions are poor and the photovoltaic panel power generation is low, and the power generation cannot meet the task load, the battery pack discharges to meet the load and ensure the completion of the task. The discharging process of the battery can be described by the following equation:

$$SOC_{t+1} = SOC_t - \frac{Energy\ Output}{Battery\ Capacity} \times 100\% \tag{3}$$

where SOC_t is the state of charge at t, and the state of charge of a battery pack is based on the relationship between power generation and load consumption, and the state of charge should be maintained within the minimum and maximum range given by the battery manufacturer to ensure the safety of the battery pack during use. *Energy Input* is the amount of energy fed into the battery, and *Energy Output* is the amount of energy powered to the load, and *Battery Capacity* is the total energy capacity of the battery.

2.3. Diesel Generator

The addition of generators to the mobile photovoltaic-diesel-storage microgrid system improves the reliability of the entire system in terms of power generation. The output power of a diesel generator, which can be critical in scenarios where new energy generation schemes are constrained by unfavorable conditions such as weather and wind, can be represented by the following formula:

$$P_{gen} = \eta \cdot P_{rated} \tag{4}$$

where η is the generation efficiency, and P_{rated} is the rated generating power. When the new energy generation scheme cannot function normally, and the remaining battery pack cannot support the task load, the diesel generator can switch to a stable power supply mode. The operational status of the diesel generator can be defined as follows:

$$\begin{cases} \mathrm{OS} = 1 & P_{load} > P_{PV} + P_{battery} \\ \mathrm{OS} = 0 & otherwise \end{cases} \tag{5}$$

where *OS* is the Operational Status. In this model, the diesel generator is activated (Operational Status = 1) when the combined power from the photovoltaic system and the battery pack is insufficient to meet the task demand.

3. Optimization Model

Researchers often focus on cost and power supply stability in the optimization of microgrid configurations, while neglecting mobility. Mobility is a crucial metric for emergency response teams. Teams with high mobility requirements are unable to carry an excessive amount of energy, while the stability of power supply necessitates carrying an adequate number of power sources to ensure continuous and stable supply. Clearly, the mobility index conflicts with the power supply stability index. The problem that is addressed in this paper involves obtaining microgrid configuration solutions using a multi-objective evolutionary algorithm with classification based on preselection. We select solutions that achieve a compromise between mobility and stability indices, which effectively balance mobility and power supply stability.

3.1. Objective Functions

In this work, there are two objective functions: weight of the system and loss of power supply probability (LPSP).

3.1.1. LPSP

LPSP is defined as the probability that the system's output is insufficient to meet the load requirements. The value range is a closed interval of around [0, 1]. The values of 0 and 1 indicate that the load can always be satisfied and the load cannot be satisfied, respectively. Satisfying the load as much as possible is a necessary condition for highly reliable systems. The goal of this work is to always satisfy the load, which requires optimization to achieve a certain level. When the total power generation of the photovoltaic power generation and battery packs still cannot meet the load demand during this period, the time step is recorded as the time of insufficient supply.

$$LPSP = \frac{\sum_{t=1}^{T} t[(P_{new} + P_{bat}) < P_{load}]}{T} \tag{6}$$

$$P_{new} = \sum N_{pv} \times P_{pv} \tag{7}$$

$$P_{bat} = \sum N_{bat1} \times P_{bat1} + \sum N_{bat2} \times P_{bat2} \tag{8}$$

where T is the total duration of the task, given by the model input. P_{new} is the total output power of photovoltaic generation, and P_{bat} is the total output power of the battery pack, and P_{pv} is the output power of a single photovoltaic panel, and P_{bat1}, P_{bat2} are the output powers of primary and secondary batteries. It can be seen that for a good mobile photovoltaic-diesel-storage microgrid system, while ensuring that other aspects meet the requirements, the value of *LPSP* should be minimized as much as possible to improve the reliability of the system and ensure the completion of the tasks.

3.1.2. Weight

For a good mobile photovoltaic-diesel-storage microgrid system, especially in special operations teams, ensuring its flexibility is extremely important. Lightweight and sufficient electricity have always been a pair of conflicting variables: if we want to ensure a sufficient supply of electricity, the number of batteries and power generation components cannot be reduced, which will inevitably increase the burden of the system. Therefore, the weight of the system should be considered in the evaluation index. It is also necessary to find a plan to achieve the maximum balance between the total weight of carried components and the continuous power supply. The definition of this indicator is shown in the following formula:

$$Weight_{total} = \sum N_{pv} \times Wei_{pv} + \sum N_{bat1} \times Wei_{bat1} + \sum N_{bat2} \times Wei_{bat2} + \sum N_{dg} \times Wei_{dg} \tag{9}$$

where N_{pv}, N_{bat1}, N_{bat2}, N_{dg} are the number of photovoltaic panels, primary batteries, secondary batteries, and barrel diesel, while Wei_{pv}, Wei_{bat1}, Wei_{bat2}, Wei_{dg} are the unit weights of photovoltaic panels, primary batteries, secondary batteries, and barrel diesel.

3.2. Decision Variables

Based on the structure of the mobile photovoltaic-diesel-storage microgrid system described earlier, it can be determined that the decision variable for the optimization problem in this work is the number of the various types of energy carried.

$$N = [N_{pv}, N_{bat1}, N_{bat2}, N_{dg}] \tag{10}$$

3.3. Mathematical Expression of Optimization Model

The optimization problem of the mobile photovoltaic-diesel-storage microgrid system can be described using symbols as follows:

(1) Objective function:

$$Min\ Z(N) = (LPSP(N), Weight_{total}(N)) \tag{11}$$

(2) Constraint conditions:

$$\left(N_{pv}, N_{bat1}, N_{bat2}, N_{dg}\right) > 0 \quad (12)$$

$$SOC_{min} \leq SOC \leq SOC_{max} \quad (13)$$

$$0.1P_{bat2\_min} < P_{bat2} < P_{bat2\_max} \quad (14)$$

where Z represents the objective function; $LPSP$ and $Weight_{total}$ refer to the power outage rate and weight, respectively; the decision variable $[N_{PV}, N_{bat1}, N_{bat2}, N_{dg}]$ denotes the number of photovoltaic panels, primary batteries, secondary batteries and barrel diesel carried in the scheme.

Formulas (13) and (14) are constraints for primary and secondary batteries. The optimization goal of a battery is to discard it as much as possible after exhausting its battery capacity. Thus, its state of charge constraint should be within $[SOC_{min}, SOC_{max}]$, a closed interval on both sides. For secondary batteries to optimize their service life, their charging and discharging depth should be limited. To simplify the model, its use must be stopped when the power level is reduced to 10% of the maximum output.

4. Two-Step Approach

In the optimization problem of the mobile photovoltaic-energy storage-diesel micro-grid system in this paper, two steps are required to solve the problem [26]. The first step is to use the CPS-MOEA (multi-objective evolutionary algorithm with classification-based preselection) to obtain the optimal Pareto front. The second step is to use the FCM (fuzzy C-means clustering) and GRP (grey relational projection) algorithms for comprehensive decision-making to facilitate commanders to make more scientific and reasonable choices based on their personal preferences. This is shown in Figure 2.

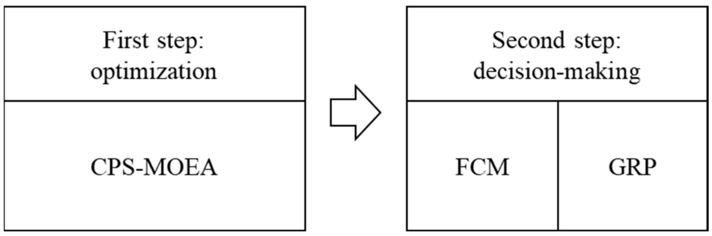

Figure 2. Two-step approach.

4.1. First Step: CPS-MOEA

The multi-objective evolutionary algorithm with classification based on preselection is expressed as CPS-MOEA in this work. The selection process in the multi-objective evolutionary algorithm can be regarded as a classification problem.

The CPS-MOEA follows the idea of marking some solutions as positive sample points, expecting that they are non-dominated, while marking other solutions as negative sample points. With these sample points, a classifier can be trained and used to classify the newly generated candidate offspring solutions. The simulated process flow diagram of its implementation is shown in Figure 3.

To implement classification-based preselection (CPS), two external populations were introduced, namely, P_+ and P_-: P_+, which consist of "good" solutions each labeled with +1, are hoped to be non-dominated and have been discovered so far, while P_- contains "bad" solutions, each labeled with -1. The selection process, denoted as $Q = NDS(P, N)$, is based on a non-dominated sorting scheme, referring to the classic multi-objective evolutionary algorithm- NSGA-II.

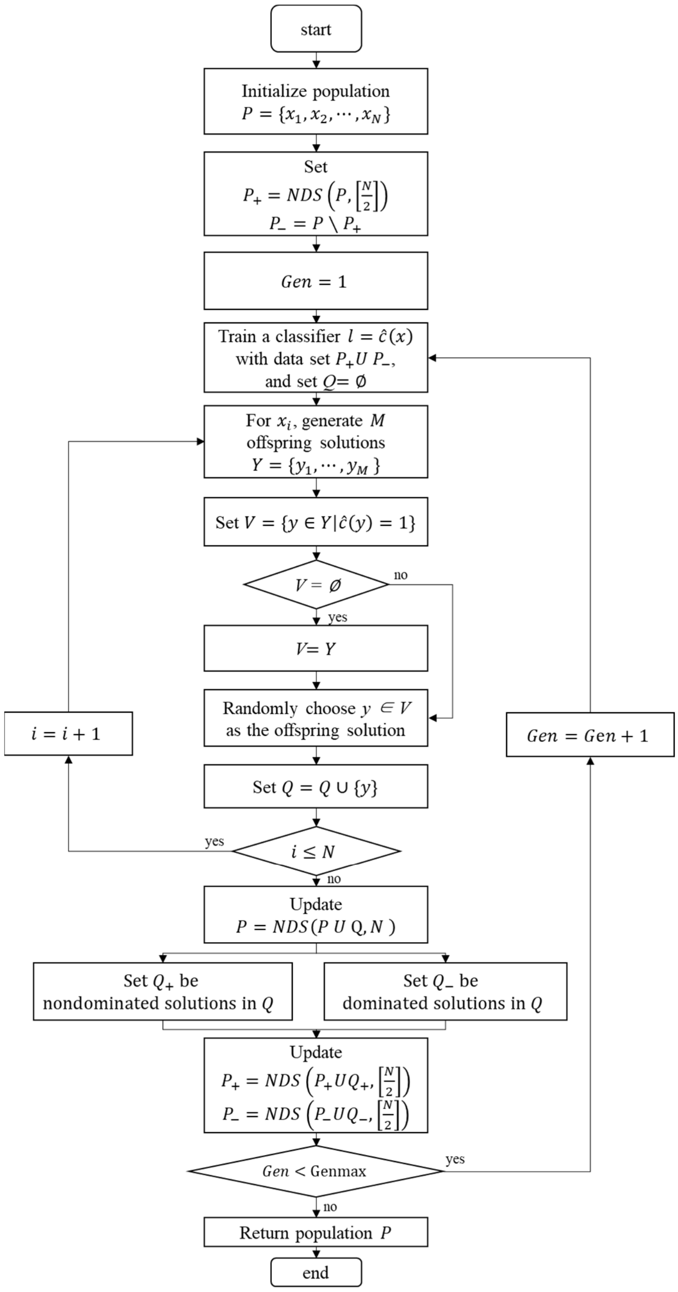

Figure 3. The framework of CPS-MOEA.

First, the population P is divided into several clusters based on Pareto dominance, ensuring that solutions within each cluster do not dominate each other. Second, the crowding distance for each solution is calculated within its cluster. Third, all solutions in P are sorted based on their cluster membership and crowding distance. This process selects the top N solutions, which are then stored in Q.

In each generation, CPS-MOEA maintains a population P consisting of N solutions, an external population P_+ containing the best $N/2$ "good" solutions found so far, and another external population P_- containing the worst $N/2$ "bad" solutions discovered.

To facilitate the comprehension of CPS-MOEA, we provide a pseudocode as shown in Algorithm 1 (Pseudocode of CPS-MOEA).

Algorithm 1: Framework of CPS-MOEA

```
Function InitializePopulation():
// Create an initial population of random individuals
Function TrainClassifier():
    // Train a classifier with the data set
Function ClassifyPopulation():
// Classify individuals in the population using the classifier
Function NonDominatedSort():
// Perform non-dominated sorting on each individual in the population
Function CrowdingDistance():
// Compute the crowding distance of each individual in the population
Function GenerateOffspring():
// Generate offspring by applying crossover and mutation operations on selected parents
Function MergePopulation():
// Merge parents and offspring to create a combined population
Main():
InitializePopulation()
Repeat until termination criteria are met:
TrainClassifier()
For each individual in the population:
        GenerateOffspring()
            ClassifyPopulation()
MergePopulation()
        NonDominatedSort()
CrowdingDistance ()
        UpdateDataSet()
Output the final results
Main()
```

4.2. Second Step: Fuzzy C-means Clustering and Grey Relational Projection

After optimizing the system with CPS-MOEA, the fuzzy C-means clustering and grey relational projection methods were employed for decision analysis of the obtained solutions. This approach aids commanders in choosing reasonable configurations according to their preferences. The detailed algorithm process is not described here. Details can be found in the literature [27,28].

5. Experiments

This algorithm addresses a typical multi-objective optimization problem, aiming to minimize the total weight of the energy system and maximize system reliability.

5.1. Parameter Settings

5.1.1. Parameter Settings for Energy

Due to the simulation process during system optimization taking one hour as the step size, the experimental data related to solar radiation and load demand were also taken as the step size in hours. Moreover, it was assumed that these data are fixed and unchanged every hour. For the convenience of research, it was assumed that the load demand in the mobile photovoltaic-diesel-storage microgrid system is all DC loads, and the DC voltage when the system is connected to the battery pack energy storage system is 48 V. In addition to the meteorological data and load data, the input data for system simulation and optimization processes also include technical parameters and related cost data of each component. The relevant parameters are presented in Table 1.

Table 1. Parameters.

Battery Parameters		Diesel Generator Parameter
Nominal Capacity (Ah)	**Voltage (V)**	**Rated Power (W)**
100	12	2000

5.1.2. Parameter Settings for CPS-MOEA

In applying the CPS-MOEA to the optimization of a mobile photovoltaic-diesel-storage microgrid system, a systematic and methodical approach was employed. The process began with the formation of an initial population of 50 candidate solutions. This size was chosen to ensure a broad and diverse range of starting points for the optimization, which is crucial for the success of evolutionary algorithms. This diversity allows the algorithm to explore a wide variety of solutions, increasing the chance of finding optimal solutions.

The next step involved the genetic operations phase, where crossover and mutation operations were applied to the candidate solutions. These operations are fundamental to the evolutionary algorithm framework, as they introduce variation and enable the exploration of new solution spaces. By simulating natural evolutionary processes, these genetic operations help in discovering potentially optimal solutions by combining and altering existing solutions. Over 100 generations, these genetic operations were repeatedly performed, with each cycle involving the selection of the best solutions, applying genetic operations, and evaluating the new solutions. This iterative process is crucial for gradually enhancing the solution quality, aiming to improve upon the objectives defined for the mobile photovoltaic-diesel-storage microgrid system.

After conducting 5000 function evaluations—a significant achievement in the context of evolutionary algorithms—a set of solutions representing the Pareto front was obtained. The Pareto front is a collection of non-dominated solutions, each representing an optimal trade-off between the multiple objectives pursued in the study.

This outcome is a testament to the capability of evolutionary algorithms, like CPS-MOEA, to achieve well-converged and diverse sets of solutions, especially for complex multi-objective optimization problems.

5.2. Results Analysis

The optimization results, clustering results, and the best compromise solutions were analyzed, respectively.

5.2.1. Optimization Results Analysis

The achievement of an optimal Pareto front, as illustrated in the study's results, underscores the efficacy of the CPS-MOEA in navigating the trade-offs and compromises that are inherent in the multi-objective optimization of mobile photovoltaic-diesel-storage microgrid systems. This Pareto front serves as a visual representation of the optimal solutions achieved, showcasing the balance between different objectives such as reliability and maneuverability. This balance is critical for the practical application and decision-making processes involved in the planning and operation of such microgrid systems.

To properly evaluate the performance of CPS-MOEA, PICEA-g and MOPSO were introduced as comparative algorithms. To further validate the effectiveness of CPS-MOEA, MAPSO was used to generate a reference Pareto optimal frontier by running single objective optimization multiple times. If the solution obtained by the algorithm is close to the reference Pareto optimal frontier, then the algorithm is good. In this article, the Pareto optimal frontier is composed of 100 non dominated solutions obtained from 100 independent runs. As shown in Figure 4, the reference Pareto optimal frontier and PFs obtained from CPS-MOEA PICEA-g and MOPSO are presented.

It can be easily observed from Figure 3 that the PF of CPS-MOEA is superior to that of PICEA-g and MOPSO. This reflects that the curve obtained by optimizing CPS-MOEA is closest to the two coordinate axes. Meanwhile, the PF obtained by CPS-MOEA is closer to the reference Pareto optimal frontier than that obtained by PICEA-g and MOPSO. This confirms the effectiveness and superiority of the proposed method in terms of the optimization capability in the first step. In addition, it can be seen that optimizing CPS-MOEA can achieve more uniform PF. Therefore, it can be concluded that CPS-MOEA has a better optimization ability in distribution than PICEA-g and MOPSO.

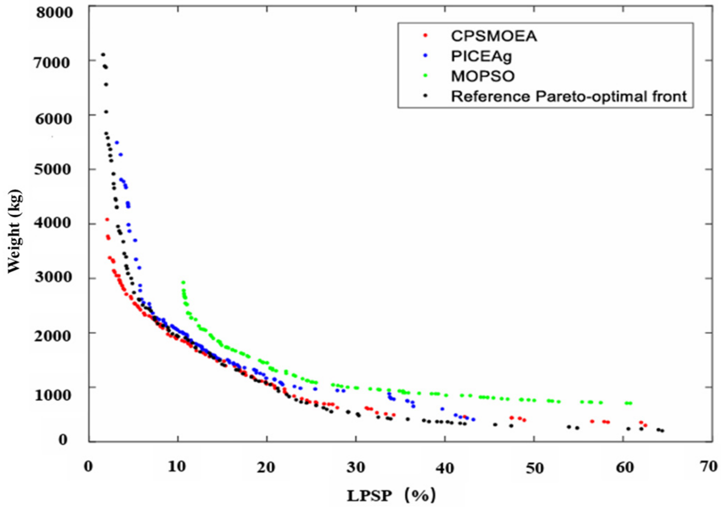

Figure 4. The reference PF and the PF obtained from CPS-MOEA, PICEA-g, and MOPSO.

5.2.2. Clustering Results Analysis

In the first step of the proposed method, the CPS-MOEA was employed to solve the system's optimal planning and configuration model. Figure 5 illustrates the PF distribution obtained from CPS-MOEA. These solutions represent different trade-offs between the objectives of the system's configuration.

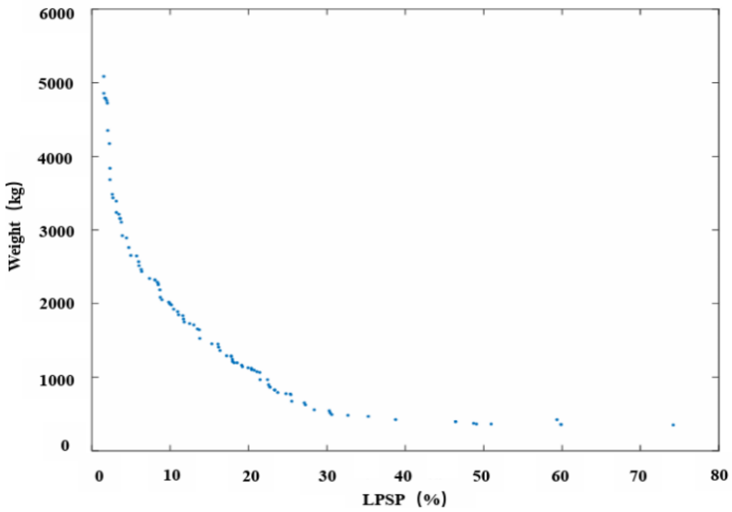

Figure 5. PF distribution of CPS-MOEA before clustering.

To proceed with decision-making, a comprehensive method combining fuzzy C-means clustering (FCM) and grey relational projection (GRP) was utilized. This approach was intended to categorize the obtained Pareto optimal solutions (POSs) into distinct groups, reflecting the varied preferences of decision-makers.

Figure 6 showcases the results of applying FCM to the POSs. The POSs are divided into two distinct categories, each representing a cluster of solutions with similar characteristics. This categorization is essential for facilitating targeted decision-making.

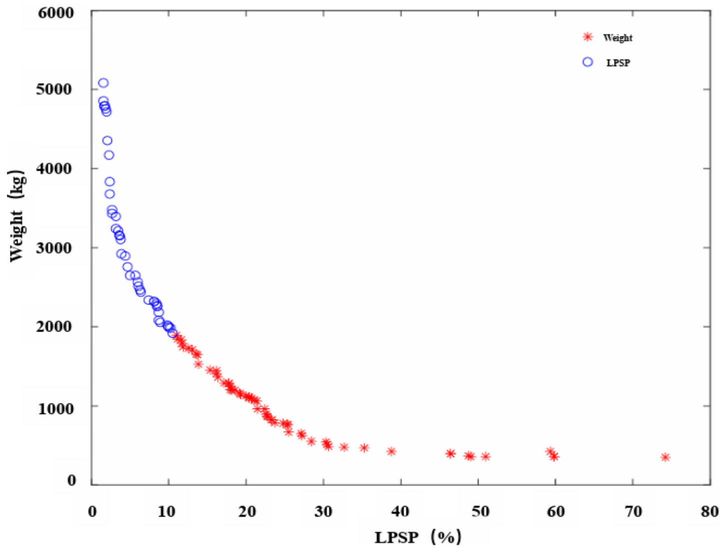

Figure 6. PF distribution of CPS-MOEA after clustering.

5.2.3. Best Compromise Solution Analysis

Subsequently, in the decision-making step, we selected the best compromise solutions (BCSs) from each cluster separately through GRP. BCSs are the solutions that best balance the objectives of the system according to the decision-maker's preferences. This step is crucial for narrowing down the range of feasible solutions to those most aligned with strategic goals.

To verify the effectiveness of the two-step method, three different scenarios were considered. Before making a decision, a Parato optimal solution corresponding to LPSP and weight of the system can be obtained based on the decision variables. After independent simulation runs, 100 Pareto optimal solutions and corresponding individuals can be obtained. The comparison results of three different representative solutions are shown in Table 2.

Table 2. Comparison results of three different solutions.

Variables	Before Decision-Making Initial Solution	After Decision-Making BCS1	BCS2
LPSP (%)	17.46	16.17	17.20
Weight (kg)	6.38	3.93	1.76

BCS 1: The optimized best compromise solution 1 reflects the decision-maker's preference for maneuverability.

BCS 2: The optimized best compromise solution 2 reflects the decision maker's preference for reliability.

Table 2 indicates that the two-step approach can provide reasonable solutions based on the different preferences of decision-makers. Specifically, the LPSP in the optimized BCS 1 decreased by 7.4% compared to the initial solution before decision-making. The LPSP in the optimized BCS 2 is 1.5% lower than the initial solution before decision-making. The reason for this result is that the LPSP of both BCS is reduced through the optimization of the two-step method, while the reduction in LPSP in BCS 1 is greater due to the preference for maneuverability. The same is true for the explanation of weight.

By applying this two-step decision-making process, we successfully distilled the broad set of solutions provided by CPS-MOEA into a more manageable set of optimal configurations. This approach ensures that the final selections are not only technically viable but also aligned with the practical needs and preferences of the system operators.

From the above analysis, it can be seen that BCS can be obtained through GRP. In the process of extracting BCS, GRP is first used to calculate the priority membership degree of POSs, and then the solution with the highest priority membership degree is selected as the BCS. To reasonably evaluate the optimization performance of the proposed method, CPS-MOEA was compared and tested with seven other algorithms (VaEA, NSGAIII, tDEA, IBEA, BiGE, MOPSO, and KnEA). Here, the priority members of these algorithms are calculated using GRP. The comparison results are shown in Figure 7. We can notice that CPS-MOEA and GRP show higher priority than other MOEAs, which demonstrates the efficiency of the method.

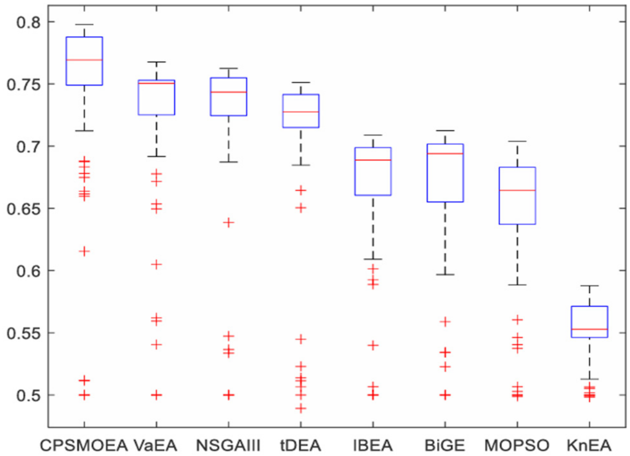

Figure 7. Box diagram of priority members.

5.3. Algorithm Performance Comparison

Convergence and diversity are important factors influencing the performance of multi-objective evolutionary algorithms. Convergence refers to the algorithm gradually approaching the optimal solution of the problem, while diversity refers to the algorithm maintaining a wide distribution of samples in the search space during the search process to avoid falling into local optima. In this section, we compare the CPS-MOEA with some classical multi-objective evolutionary algorithms to demonstrate its superiority in terms of convergence and diversity. Additionally, we compare the computational efficiency of CPS-MOEA with classical algorithms to highlight its superior computational performance.

5.3.1. Convergence and Diversity

To better evaluate the performance of CPS-MOEA, we choose generation distance (GD), spread and inverted generation distance (IGD) as the performance metrics. Given the randomness of MOEAs, the proposed method was independently executed 30 times. After 30 independent simulation runs, Table 3 provides the specific values of three measurement indicators.

- Spread Metric Analysis

The spread metric assesses the distribution of solutions along the Pareto front, focusing on how evenly the solutions are spread out. A lower spread value indicates a more uniform distribution. CPS-MOEA's average spread value matches that of PICEA-g and shows a noticeable improvement over MOPSO and GDE3, with differences of 0.01 and 0.02, respectively. This suggests that CPS-MOEA is capable of producing solutions that cover the Pareto front more uniformly than MOPSO and GDE3. The best spread value achieved by CPS-MOEA further underscores its superior performance in ensuring a more efficient distribution of solutions compared to the other algorithms.

- Inverted Generational Distance (IGD) Metric Analysis

The IGD metric provides insights into both the convergence to the true Pareto front and the distribution of solutions. It measures the distance between the true Pareto front and the obtained Pareto front, with lower values indicating better performance. CPS-MOEA's average IGD value is competitive with PICEA-g and outperforms MOPSO and GDE3 by margins of 0.043 and 0.004, respectively. This superior performance is evident in both the average and the best IGD values obtained by CPS-MOEA, highlighting its effectiveness in achieving closer convergence to the true Pareto front while maintaining a good distribution of solutions.

- Comparative Performance

The comparative analysis with PICEA-g, MOPSO, and GDE3 illustrates that CPS-MOEA not only ensures a more efficient distribution of solutions across the Pareto front but also achieves better convergence to the true Pareto front. The significant improvements in both spread and IGD metrics demonstrate CPS-MOEA's ability to balance the trade-offs between multiple objectives effectively, making it a more suitable choice for solving complex multi-objective optimization problems, such as those encountered in mobile photovoltaic-diesel-storage microgrid systems.

Table 3. The values of measurement indicators GD, spread, and IGD.

Algorithms	Metrics	Average Value	Best Value	Worst Value
CPS-MOEA	GD	2.08	2.06	2.11
	spread	0.97	0.95	0.99
	IGD	20.46	20.44	20.48
PICEA-g	GD	2.09	2.06	2.21
	spread	0.97	0.95	1.19
	IGD	20.50	20.46	20.59
MOPSO	GD	2.13	2.07	2.25
	spread	0.98	0.96	0.99
	IGD	20.67	20.53	20.95
GDE3	GD	2.08	2.06	2.11
	spread	0.99	0.95	1.01
	IGD	20.46	20.47	20.49

In conclusion, the application of CPS-MOEA to the optimization of mobile microgrid systems showcases its superiority in navigating the complexities of multi-objective optimization, achieving a well-balanced and high-performing set of solutions that could significantly benefit decision-making processes in energy management and planning.

5.3.2. Calculation Efficiency Analysis

To accurately evaluate the efficiency of CPS-MOEA, comparative testing was conducted between CPS-MOEA and three other algorithms, PICEA-g, MOPSO, and GDE3. The test results are presented in Table 4. Note that considering the randomness of intelligent optimization algorithms, the average computation time of each algorithm in 30 independent runs is used as the computation time in Table 4.

Table 4. Calculation time of the algorithms.

Algorithms	Calculation Time (s)
CPS-MOEA	138.38
PICEA-g	143.27
MOPSO	153.65
GDE3	143.81

From Table 4, it can be seen that CPS-MOEA has better computational efficiency than other algorithms. In addition, by using more advanced computer hardware and optimized code, the computational efficiency of our method can be further improved. From these results, it can be argued that the method can meet the real-time requirements in practical applications and is superior to other methods used in this study in terms of computational efficiency.

6. Conclusions

The study presented in this paper offers a significant advancement in the field of mobile photovoltaic-diesel-storage microgrid systems by focusing on the system's dependability and maneuverability. The key contributions of this research are twofold and are presented below.

This paper introduces a two-step optimization method, employing the newly applied CPS-MOEA algorithm. This approach is groundbreaking in the optimization of mobile photovoltaic-diesel-storage microgrid systems, marking a first in the domain of optimal design and planning for such systems. The CPS-MOEA algorithm showcases superior performance in generating a well-distributed Pareto front, indicating improved convergence and distribution compared to traditional multi-objective optimization algorithms like PICEA-g, MOPSO, and GDE3.

The research utilizes a combination of fuzzy C-means (FCM) clustering and grey relational projection (GRP) techniques during the decision-making phases. This innovative methodology allows for the effective selection of the best compromise solutions (BCSs) from the Pareto optimal solutions (POSs), catering to the diverse preferences of decision-makers. This approach offers a more nuanced and practical pathway for optimizing systems, presenting decision-makers with a variety of viable options that align with different preferences and requirements.

The simulation results underscore the efficacy of the CPS-MOEA algorithm in handling complex multi-objective problems, demonstrating its ability to achieve better convergence and a more efficient distribution of solutions along the Pareto front. Furthermore, the mobile photovoltaic-diesel-storage microgrid system model considered in the study incorporates critical metrics of mobility and reliability. By leveraging multi-objective evolutionary algorithms, the research successfully derives a set of constrained Pareto optimal solutions. These solutions stand as valuable benchmarks for decision-making in both scientific research and practical applications, ensuring that the designed system fulfills operational and strategic needs effectively.

In conclusion, this paper contributes significantly to the optimization and decision-making processes in the design and planning of mobile photovoltaic-diesel-storage microgrid systems. It introduces a cutting-edge optimization algorithm and a decision-making methodology that together enhance the system's dependability and maneuverability, providing a robust framework for achieving optimal designs that meet a wide range of requirements and preferences.

The experimental results have shown that the application of a multi-objective evolutionary algorithm with classification based on preselection is more effective in the optimization of mobile microgrid systems compared to a single MOEA. However, there are still many issues worth exploring regarding CPS-MOEA. Firstly, in the selection of classification methods, what impact do different classification methods (such as reinforcement learning, Naive Bayes classification, support vector machines, random forests, etc.) have on the same MOEA? At the same time, what kinds of effects are produced by the combination of different MOEAs with different classification methods, and which combinations are suitable for application in different kinds of optimization problems? In the future, our research will focus on these issues and apply them in the field of microgrids.

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