SARAP Algorithm of Multi-Objective Optimal Capacity Configuration for WT-PV-DE-BES Stand-Alone Microgrid

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\section*{ABSTRACT}
The typical stand-alone microgrid (MG) composed of wind turbine (WT), photovoltaic (PV), diesel generator (DE), and battery energy storage (BES) is taken as the research object. Firstly, a multi-objective optimal capacity configuration model considering economic efficiency, reliability, and environmental protection is established. Secondly, in view of the complex characteristics of the optimization model, such as strong nonlinearity and multi-constrained conditions, combining the enumeration that can find the complete real Pareto solution set with the intelligent algorithm that has the characteristics of fast convergence, a search algorithm referencing adjacent points based on SPEA2 (SARAP) is proposed. The algorithm obtains the contour of the real Pareto optimal solution set by SPEA2, and then repeatedly extracts the adjacent points that satisfy certain conditions from the solution set solved by SPEA2. A small search space based on the adjacent points is constructed, and an omnidirectional search in this space to achieve the complete real Pareto optimal solution set is performed. The algorithm performance analysis of both computational complexity and convergence shows that the operation speed of SARAP is approximately five times higher than that of the enumeration, and the obtained result is close to the complete real Pareto optimal solution set. Finally, the optimization calculation and typical daily production simulation are carried out according to the resource and load characteristics of a region, and the results further prove the rationality and validity of the proposed algorithm.

\section*{INDEX TERMS}
Microgrid, capacity configuration, multi-objective optimization, SPEA2, SARAP.

\section*{NOMENCLATURE}
\textbf{A. ABBREVIATIONS}
\begin{itemize}
\item AEC Annual emissions of CO\textsubscript{2}
\item BES Battery energy storage
\item DE Diesel generator
\item DG Distributed generation
\item EAC Equivalent annual cost
\item LPSP Loss of power supply probability
\item MG Microgrid
\item PV Photovoltaic
\item SP Search process referencing adjacent points
\item WT Wind turbine
\end{itemize}

\textbf{B. INDICES}
\begin{itemize}
\item $i$ Index of DG
\item $t$ Time
\end{itemize}

\textbf{C. VARIABLES}
\begin{itemize}
\item $c_{f1}, c_{f2}$ Coefficients of the fuel consumption parameters (L/kW)
\item $C_{EAC}$ Equivalent annual cost (¥)
\item $C_{Fuel}$ Fuel cost (¥)
\end{itemize}
I. INTRODUCTION

The MG is of great significance for improving the quality of renewable energy supply, reducing transmission loss, improving power safety, and promoting the intelligent development of power grids [1]–[3]. For remote areas where the grid is uncovered and abundant renewable resources, it is suitable to generate, transmit, and use electric energy in the form of stand-alone MG [4]–[6]. The optimal capacity configuration for MG is the primary task of the construction of MG projects, and is related to the initial investment, operation, and maintenance, and post-expansion [7], [8].

Many studies on the various aspects of optimal capacity configuration for the MG have been carried out. Among these, the optimization algorithm with excellent performance for the optimization model has consistently been a focus of research. In particular, the establishment of the optimization model and the design of optimization algorithm are not only the problems that must be faced but are also a research
hotspot. The current research on the optimization model and the corresponding optimization algorithm can be roughly divided into three categories. The first approach is to directly establish a mathematical model with the economic efficiency as the single optimization objective, and then use an algorithm to solve the model [9]–[13].

The second approach is to establish a multi-objective optimization model, then convert multiple optimization objectives into a single optimization objective by using the weight coefficients, and use an algorithm to solve the model [14], [15]. The problem for this approach is that the selection of the weight coefficients lacks a clear meaning and is unconvincing.

The third approach is to establish a multi-objective optimization model and employ the multi-objective optimization algorithm to solve the model directly. This approach provides multiple configuration solutions for a wide range of applications, and has been intensively investigated [16]. In [17], an MG capacity configuration model with reliability, complementarities between wind and solar, and the economic efficiency as the optimization objective is established and solved by enumeration. The advantage of enumeration is that it can determine the complete real Pareto optimal solution set of the multi-objective optimization model, but its convergence is slow, and it can only be employed for a small search space. In [18], multi-objective placement of the renewable energy sources in the distribution system with the objectives of loss reduction and reliability improvement is solved using the grey wolf optimizer. In [19], for a PV-WT-ES MG, non-dominated sorting in genetic algorithm (NSGA-II) is used to solve the multi-objective optimization model with the goal of minimizing investment, and reducing the line loss and expected load loss. In [20], a self-adaptive differential evolution algorithm is used to optimize the size of WT-PV-DE-BES MG with economic efficiency and reliability as the objectives. In [21], based on the predicted wind speed, temperature, solar irradiance and other parameters, an optimization model considering economic efficiency and reliability is solved by a comprehensive method that combines chaotic search, harmony search, and simulated annealing. In [22], taking economic efficiency, reliability, adaptability, security, and coordination as the optimization objectives, the improved particle swarm optimization algorithm is used to optimize the calculation. Similarly, the multi-objective optimization algorithms applied to MG capacity configuration also includes ant colony optimization [23], line-up competition algorithm [24], crow search algorithm [25], [26], cuckoo search algorithm [27] and so on. Compared with enumeration, these intelligent algorithms converge much faster, but also have two disadvantages: first, the solution set solved by the intelligent algorithm is usually only a set close to the subset of the real Pareto set, that is, relative to the real Pareto set, the solution set solved by intelligent algorithm is incomplete, and there is no guarantee that each solution belongs to the real Pareto set. Second, the intelligent algorithm is usually random, so the results of each operation are not the same.

It is observed from the abovementioned literature that there is still a lack of optimization algorithm that can quickly find out the complete real Pareto optimal solution set for the multi-objective optimization model of MG capacity configuration. Considering that enumeration and intelligent algorithm have complementary advantages, if the two algorithms can be organically combined to fully exploit their respective advantages, a new optimization algorithm with fast convergence and operation results close to the complete real Pareto set will be obtained; such an algorithm will represent a significant advance. From the analysis of these two algorithms, it is observed that the enumeration can obtain the complete real Pareto set, but its convergence is slow, mainly because its search method is full-space and omnidirectional, while the intelligent algorithm is fast, but cannot obtain the complete real Pareto set, mainly because its search process is “survival of the fittest” and random. If the search space of enumeration can be narrowed in an appropriate manner, or the search direction of the intelligent algorithm can be supplemented appropriately, the optimization algorithm with advantages both speed and completeness can be obtained. To achieve this goal, based on the SPEA2 algorithm with good convergence and distribution in the genetic algorithm class, this work performs an in-depth analysis of the optimization process of the SPEA2 algorithm and the characteristics of its optimal solution set, and proposes the search algorithm referencing adjacent points based on SPEA2 (SARAP). The algorithm first narrows the search space through the SPEA2 and then omnidirectional searches in the newly constructed small space, in order to rapidly find the complete real Pareto solution set.

II. MULTI-OBJECTIVE OPTIMIZATION MODEL OF MG

A multi-objective optimization model considering the economic efficiency, reliability and environmental protection is established [16], [28], the number of DG are optimization variables, and the historical data including wind speed, solar irradiance, and load in a certain area are the constrains. Among these, economic efficiency is calculated as the equivalent annual cost (EAC); reliability is expressed by the loss of power supply probability (LPSP); and environmental protection is measured by annual emissions of CO₂ (AEC) because these emissions comprise the largest percentage of all emissions in fuel combustion [29]. Each of the three optimization objectives is searched for the minimum value. The other constraints mainly include: keeping the system power balanced in each sampling period, limiting the power operation range of each class of DG and its maximum installed number, setting the range of the state of charge, limiting the load loss rate under the set upper limit, setting the maximum ratio of the DE power supply, and setting the maximum discarded ratio of renewable energy. The specific expressions are shown in
equations (1)-(19).

\[
\begin{align*}
\text{III. OPERATION POLICY} \\
\text{IV. SARAP ALGORITHM} \\
\end{align*}
\]

will be adopted. If the net load power is greater zero, it means that the current renewable energy is insufficient to meet the load demand. In this case, the adjustment method of BES discharging is adopted priority to maintain the MG power balance. If the state of charge reaches the lower limit or the BES is discharged at maximum power, the MG power balance still cannot be maintained, then the adjustment method of starting the DE will be adopted. If the MG power balance is still not met after the DE is started, the load is limited. The operation policy takes maintaining the power balance of the system as the core rule; the operating power of each DG must be within the limited range; the state of charge also must be within the limited range. That is, the scheduling strategy always meets the constraints (2) to (4) in the optimization model.

\[
\begin{align*}
R_{LPSP} &= \frac{\sum_{t=1}^{8760} (P_{DL}(t) \times T_s)}{\sum_{t=1}^{8760} (P_{L}(t) \times T_s)} = \frac{\sum_{t=1}^{8760} P_{DL}(t)}{\sum_{t=1}^{8760} P_{L}(t)} \\
C_{EAC} &= C_{Init} + C_{OM} \\
C_{Init} &= \sum_{i \in DG} (N_{DG,i} \times P_{R,i} \times C_{RP,i}) \times \frac{r(1 + r)^j}{(1 + r)^j - 1} \\
C_{OM} &= C_{OMFix} + C_{OMVar} + C_{Fuel} + C_{Replace} \\
C_{OMFix} &= \sum_{i \in DG} (N_{DG,i} \times P_{R,i} \times C_{OMP,i}) \\
C_{OMVar} &= \sum_{t=1}^{8760} (P_{DE}(t) \times T_s \times C_{OME}) \\
C_{Fuel} &= F_{uel} \times U_{Fuel} \\
F_{uel} &= \sum_{t=1}^{8760} (c_{f1} \times P_{DE}(t) + c_{f2} \times P_{DER}) \\
C_{Replace} &= \frac{E_{CTBES}}{390} \times E_{BES} \\
E_{CTBES} &= \sum_{t=1}^{8760} (P_{BES}(t) \times T_s) \\
E_{CO2} &= \epsilon \times F_{uel} \\
\end{align*}
\]
(1) The number of elements in the optimal solution set solved by SPEA2 is determined by the initial population size, while it is difficult to determine the number of elements in the real Pareto optimal solution set.

(2) The contour of the objective function corresponding to the optimal solution set solved by SPEA2 is close to that of the real Pareto optimal solution.

(3) In the early stage of evolution, SPEA2’s convergence speed is high, and both crossover and mutation can generate excellent individuals; however, in the late stage of evolution, the convergence slows down, and excellent individuals are mainly generated by mutation.

(4) Based on the conclusion (3), the mutation rate should be increased, but with the increase of mutation rate, the genetic algorithm gradually tends to become a completely random search algorithm that cannot improve the convergence speed.

(5) The fundamental reason for the slow convergence in the late stage of evolution is that it is difficult to find better search directions through crossover and mutation.

Two enlightenments can be drawn from the above conclusions:

(1) Similar to the interpolation method, to find the entire real Pareto optimal solution set based on the optimal solution set solved by SPEA2, more non-dominated solutions should be searched between each pair of adjacent solutions in the optimal solution set solved by SPEA2.

(2) Each solution in the optimal solution set solved by SPEA2 is already close to a certain solution in the real Pareto optimal solution set solved by SPEA2.

Further combing the above enlightenments and conclusions, this paper proposed the search algorithm referencing adjacent points based on the SPEA2, namely, the SARAP algorithm. The search process referencing adjacent points (SP) will be described in detail.

For the convenience of description, the double-objective optimization problem with the minimum value is taken as an example for illustration. As shown in Fig. 2, it is assumed that $P_1$, $P_2$ and $P_3$ are three points in the objective function space corresponding to the optimal solution set solved by SPEA2. Based on the partial order domination relation, it is observed that the non-dominated solution between $P_1$ and $P_2$ must be distributed in the rectangular area with $P_1$ and $P_2$ as the diagonal, so that the non-dominated solution can be searched in all directions in the space constructed by the independent variables $X_1$ and $X_2$ corresponding to $P_1$ and $P_2$. Similarly, $P_2$ and $P_3$ can also construct a search space. It is also observed from Fig. 2 that if there are non-dominated solutions distributed within the rectangular $BP_2DF$, these non-dominated solutions cannot be found only in the search space determined by adjacent points $P_1$ and $P_2$. Therefore, it is necessary to expand the search range, the most direct approach is to increase the interval distance between the reference points, such as using $P_1$ and $P_3$ to determine a larger search space $P_1EP_3F$, so that the rectangular $BP_2DF$ can be covered. It should be noted that this method for expanding the search range also includes the rectangular range $P_2AEC$ without the non-dominated solution, that is, increasing the reference point interval distance can find more and better non-dominated solution, but this advantage comes at the cost of increasing the computational complexity; therefore, the interval distance between the reference points should be limited to a certain range. In the objective function space, the search range determined by $P_1$, $P_3$ covers the search range determined by $P_1$, $P_2$ and by $P_2$, $P_3$. However, the latter cannot be ignored because the optimal capacity configuration model for MG has strong nonlinear characteristics rather than a simple linear correspondence between the objective function and the independent variable.

From the above statement, the complete SARAP algorithm is divided into two steps, i.e., SPEA2 and SP. Among them, the SP is the original achievement of this paper. Its function is to find more and better non-dominant solutions based on the solution set solved by SPEA2 and then obtain an optimal solution set that is close to the real Pareto optimal solution set. The first step is to determine the contour of the optimal solution set. In fact, any algorithm that can determine the contour of the optimal solution set can be the first step of the SARAP algorithm.

**B. CALCULATION OF SARAP**

For the iterative evolution process of SPEA2, the reader is referred to the literature [30]. From the perspective of the calculation flow, the SP is further summarized as follows: a loop is constructed in which the search interval distance changes from 1 to its maximum with a step size of 1. In this loop, all of the individual pairs are sequentially picked from the optimal solution set solved by SPEA2. All new individuals in the search space constructed by each pair of individuals are determined, and the fitness of these new individuals are calculated. These new individuals together with their referencing individuals constitute a small population, and the non-dominated solutions in the population are incorporated into the overall optimal solution set according to the dominance relationship. The specific algorithm flow is shown in Fig. 3.
V. PERFORMANCE ANALYSIS OF SARAP

For the MG multi-objective optimal capacity configuration model, the goal of optimization algorithm is to find the complete real Pareto optimal solution set quickly and accurately, that is, the computational complexity of the algorithm should be low and its convergence should be high. In Fig. 2, the area surrounded by the red line is the feasible domain of the multi-objective optimal model. According to the partial order relationship, the real Pareto optimal solution set can be roughly represented by the red solid line (if it is a discrete problem, the non-dominated solutions are points on the red solid line). The contour of the optimal solution set solved by SPEA2 can be roughly denoted by the green solid line. It is observed that the process of determining the contour of the optimal solution set through SPEA2 has narrowed the search space for the subsequent SP. In addition, the search space determined by the solution set solved by SPEA2 is further divided into several smaller subspaces in the SP, further reducing the search space. Therefore, the SARAP is not a simple balance between SPEA2 and enumeration, but an organic combination that leads to comprehensively improved performance with respect to both computational complexity and convergence.

In the following, the effectiveness of the SARAP with respect to computational complexity and convergence is analyzed using an example and is compared with enumeration and SPEA2. The data used in the example are composed of wind speed, solar irradiance and load measured from a certain region. The sampling period of these data is one hour, and the time span is one year, so there are 8760 groups of data in total. Other parameters are described as follows. The discount rate is 6%; engineering life is 20a; WT, PV and BES configuration number range of 0 to 30; DE configuration number range from 0 to 10; $S_{OC}$ range from 0.4 to 0.85, charging efficiency of BES is 0.9; discharge efficiency of BES is 0.95; maximum load loss rate is 5%; the population size of the SPEA2 is 70; the cross rate is 0.8; the mutational rate is 0.2; the evolutionary algebra is 100; and the maximum search interval distance between the reference point is 10. Other parameters of DG are shown in Table 1. The hardware used to execute the algorithm is a Lenovo PC520 computing workstation and the software is MATLAB2016.

TABLE 1. DG parameters.

| DG          | Parameters                                      | Value |
|-------------|-------------------------------------------------|-------|
| DG          | Rated power (kW)                                | 750   |
| WT          | Cut-in wind speed (m/s)                         | 4     |
| WT          | Cut-out wind speed (m/s)                        | 25    |
| WT          | Rated wind speed (m/s)                         | 14    |
| WT          | Unit power cost (¥/kW)                         | 7000  |
| WT          | Operation and maintenance cost per unit power (¥/kW) | 6.7   |
| PV          | Rated power (kW)                                | 200   |
| PV          | Unit power cost (¥/kW)                         | 9000  |
| PV          | Operation and maintenance cost per unit power (¥/kW) | 20    |
| BES         | Rated energy capacity (kWh)                    | 500   |
| BES         | Unit capacity (¥/kWh)                          | 700   |
| BES         | Operation and maintenance cost per unit capacity (¥/kWh) | 8     |
| BES         | Rated power of converter (kW)                  | 500   |
| BES         | Unit power cost of converter (¥/kW)             | 550   |
| DE          | Rated power (kW)                                | 1000  |
| DE          | Unit power cost (¥/kW)                         | 1380  |
| DE          | Operation and maintenance cost per unit power (¥/kW) | 20    |
| DE          | Operation and maintenance cost per unit power (¥/kWh) | 0.05  |
| DE          | $c_a$ (L/kW)                                   | 0.24  |
| DE          | $c_p$ (L/kWh)                                  | 0.06  |
| DE          | $c_c$ (Kg/L)                                   | 2.5   |

A. COMPUTATIONAL COMPLEXITY ANALYSIS

In the optimization algorithm, 8760 sets of data consisting of wind speed, solar irradiance and load are used in a one-year production simulation (production simulation refers to the power state of DG, BES and load in the MG under the
guidance of the proposed operation policy based on wind speed, solar irradiance and load for a period of time), so that a very large amount of data must be processed. Therefore, the production simulation process is the main factor affecting the operation speed of the optimization algorithm, and this process is located in the calculation of the individual fitness after a new individual is generated. Next, taking the calling one-year production simulation process as the measurement standard, the computational complexity of SARAP is analyzed by comparison with SPEA2. For the convenience of description, some symbols used in the algorithm are first presented. The algorithm adopts binary coding; the population size is \( N_{\text{Ind}} \); cross rate is \( q_c \); mutation rate is \( q_m \); Hamming distance and its maximum value between referencing adjacent points are \( D_H \) and \( D_{H\text{Max}} \), respectively; and reference point interval distance and its maximum value are \( D_S \) and \( D_{S\text{Max}} \), respectively.

1) NUMBER OF TIMES THAT THE PRODUCTION SIMULATION PROCESS IS CALLED BY SPEA2

In the evolutionary iteration of SPEA2, new individuals are generated by the crossover and mutation operators. In the process executed by the crossover operator, two parent individuals generate two child individuals through exchanging the gene position. In SPEA2, each evolution generation must execute the crossover operator approximately \( N_{\text{Ind}}/2 \) times, and the probability of crossover is \( q_c \). Therefore, the number of times that the production simulation process caused by the crossover operator is executed is given by:

\[
T_{\text{cross}} = \frac{N_{\text{Ind}}}{2} \times 2 \times q_c = q_c \times N_{\text{Ind}}
\]

(20)

In the process executed by the mutation operator, a parent individual generates a child individual through changing the gene position. In SPEA2, each evolution generation must execute the mutation operator approximately \( N_{\text{Ind}} \) times, and the probability of mutation is \( q_m \). Therefore, the number of times that the production simulation process caused by the mutation operator is executed is given by:

\[
T_{\text{mutation}} = q_m \times N_{\text{Ind}}
\]

(21)

The total number of times that an evolution generation of SPEA2 must call the production simulation process is given by:

\[
T_{\text{SPEA2}} = T_{\text{cross}} + T_{\text{mutation}} = (q_c + q_m) \times N_{\text{Ind}}
\]

(22)

2) NUMBER OF TIMES THAT THE PRODUCTION SIMULATION PROCESS IS CALLED BY SP

Based on the principle of SARAP described above, the number of times that the production simulation process is called by SP is expressed as follows:

\[
T_{\text{SP}} = \sum_{D_S=1}^{D_{\text{SMax}}} \left( \sum_{A_{\text{Ind}}=1}^{N_{\text{Ind}}-D_S} \left( 2^{D_H(A_{\text{Ind}}, A_{\text{Ind}}+D_S)} - 2 \right) \right)
\]

(23)

where \( D_H(A_{\text{Ind}}, A_{\text{Ind}}+D_S) \) is the Hamming distance between two reference points \( A_{\text{Ind}} \) and \( A_{\text{Ind}} + D_S \), considering that \( A_{\text{Ind}} + D_S \) represent the number of DG for which the two objective function values are close, and therefore the value of \( D_H(A_{\text{Ind}}, A_{\text{Ind}} + D_S) \) is not too large. In addition, to avoid high computational complexity, when \( D_H(A_{\text{Ind}}, A_{\text{Ind}}+D_S) \geq D_{H\text{Max}} \), the search is no longer performed.

Approximate analysis, \( D_H(A_{\text{Ind}}, A_{\text{Ind}}+D_S) \) is assumed to be a constant \( D_H \), and \( D_{S\text{Max}} \ll N_{\text{Ind}} \), so that it is obtained:

\[
T_{\text{SP}} = \left( 2^{D_H} - 2 \right) \sum_{D_S=1}^{D_{\text{SMax}}} (N_{\text{Ind}} - D_S)
\]

\[
\approx \left( 2^{D_H} - 2 \right) \times D_{S\text{Max}} \times N_{\text{Ind}}
\]

(24)

From the above analysis, the computational complexity of the SP is approximately equivalent to the algebraic evolution of the SPEA2:

\[
\frac{T_{\text{SP}}}{T_{\text{SPEA2}}} \approx \frac{\left( 2^{D_H} - 2 \right) \times D_{S\text{Max}}}{(q_c + q_m)}
\]

(25)

Combined with the example, a set of typical parameter values and estimated values for \( D_H \) are given: \( q_c = 0.8 \), \( q_m = 0.2 \), \( D_{H\text{Max}} = 8 \), \( D_{S\text{Max}} = 10 \), \( D_H = (1+D_{H\text{Max}})/2 = 4.5 \). Thus, it can be calculated that \( T_{\text{SP}}/T_{\text{SPEA2}} \approx 206 \). This means that the SP is equivalent to approximately 206 generations of SPEA2 evolution.

3) COMPUTATIONAL COMPLEXITY OF SARAP

Since SARAP is composed of SPEA2 and SP, its computational complexity is the sum of the complexities for these two processes. For the specific example in this paper, the results of multiple tests show that 100 evolution generations can be used as the termination condition of the optimization calculation using SPEA2 alone. Therefore, in SARAP, the evolutionary algebra of SPEA2 performed in the first step is also set to 100. According to the above computational complexity analysis, the total computational complexity of SARAP is approximately equivalent to 300 evolution generations of SPEA2 by the number of times that the production simulation process is called. In addition, the size of the population that needs to be dealt with by SP is relatively small because the interval distance between a pair of adjacent reference points is generally short, while the size of the population that needs to be dealt with by SPEA2 is large because SPEA2 needs to process the entire population. Moreover, roulette selection, archive truncation procedure and other operations are performed in the SPEA2. As a result, SP is much less time-consuming than SPEA2 except for production simulation. In order to test the correctness of the time complexity analysis of SPEA2, SP and SARAP, the example is repeatedly solved 100 times by SARAP, and the mean value of running time of SPEA2, SP and SARAP are shown in Table 2. At the same time, for comparison, the running time of enumeration is also given (no randomness, constant running time). It is observed that the running time of SP is 1.77 times greater than that of SPEA2, which is consistent with the aforementioned analysis. In addition, it is observed that the time consumption of SARAP is only 19.52% of that of enumeration.
TABLE 2. Running time.

| Algorithm/Process | SPEA2 | SP  | SARAP | Enumeration |
|-----------------|-------|-----|-------|-------------|
| Running time(s)  | 79.07 | 140.13 | 220.95 | 1132.21 |

B. CONVERGENCE ANALYSIS

To verify the convergence of the SARAP proposed in this paper, the improved inverted generational distance (IGD\(^+\)) indicator, the method for convergence verification by intersection set and hypervolume (HV) indicator are used. To deal with the randomness and to make the convergence analysis process more credible, the calculation process using SARAP to solve the multi-objective optimization model of the microgrid is repeated 100 times.

1) USING IGD\(^+\) INDICATOR TO VERIFY CONVERGENCE

The IGD indicator is widely used to verify the convergence of the multi-objective optimization algorithm [31]. Studies reported in literature [32] have improved the calculation process of IGD, making it more applicable, and further improving the evaluation performance, developing the IGD\(^+\) indicator. The IGD\(^+\) indicator is given by:

\[
IGD^+(B) = \frac{1}{|Z|} \sum_{j=1}^{|Z|} \min_{b_i \in B} d_{IGD^+}(b_i, z_j)
\]

\[
d_{IGD^+}(b_i, z_j) = \left( \sum_{k=1}^m \left( \max \left( \frac{b_{i,k} - z_{j,k}}{f_{k}^{\text{max}} - f_{k}^{\text{min}}}, 0 \right) \right) \right)^2
\]

where B is solution set to be evaluated, \(b_i \in B\), \(b_{i,k}\) is the \(k\)th objective function value of \(b_i\), \(z_i \in Z\) is real Pareto solution set, \(z_{j,k}\) is the \(k\)th objective function value of \(z_j\), and \(f_{k}^{\text{max}}\) and \(f_{k}^{\text{min}}\) represent the maximum and minimum values of the \(k\)th objective function respectively.

It is easy to see from the formula that a smaller IGD\(^+\) indicator corresponds to the better performance of the algorithm.

It is observed that in the first stage of SPEA2 iterative process, the IGD\(^+\) indicator first decreases rapidly, and then gradually tends to be stable, which is consistent with the previous summary of the characteristics of SPEA2; in the second stage of SP process, the IGD\(^+\) indicator decreases rapidly, and its final value is very close to 0. The evolution of the IGD\(^+\) indicator shows that the SP process significantly improves the convergence of the SPEA2, further demonstrating that the convergence of SARAP is significantly better than that of SPEA2.

With respect to the second aspect of dealing with randomness, Fig. 5 shows the IGD\(^+\) indicator of SPEA2 and SARAP corresponding to each execution of SARAP algorithm that has been repeatedly executed 100 times, and the corresponding mean, standard deviation, minimum and maximum values are shown in Table 3. It is observed that for the microgrid multi-objective optimization example in this paper, the IGD\(^+\) indicator of SARAP is significantly better than that of SPEA2. From the perspective of the mean value, minimum value and maximum value, the IGD\(^+\) indicator of SARAP is significantly smaller than that of SPEA2, which shows that the optimal solution set solved by SARAP is closer to the real Pareto optimal solution set than the optimal solution set solved by SPEA2. From the perspective of the standard deviation, the IGD\(^+\) indicator of SARAP is also smaller than that of SPEA2, which shows two points. First, when the optimization algorithm is run many times, the optimal solution set solved by SARAP changes little, while the

![FIGURE 4. Tracking the IGD\(^+\) indicator of a complete evolution process of SARAP.](image)

![FIGURE 5. IGD\(^+\) indicators of SPEA2 and SARAP corresponding to 100 runs of SARAP.](image)

TABLE 3. IGD\(^+\) indicator statistics of SPEA2 and SARAP corresponding to 100 runs of SARAP.

|         | Mean | Std  | Min  | Max  |
|---------|------|------|------|------|
| SPEA2   | 0.0154 | 0.0010 | 0.0135 | 0.0176 |
| SARAP   | 0.0004 | 0.0002 | 0.0001 | 0.0014 |

In this paper, the IGD\(^+\) indicator is used to evaluate the convergence of SARAP in two aspects. First, one complete search process of SARAP is tracked, the population of each generation in the evolution process is recorded, and the corresponding IGD\(^+\) indicator is calculated, as shown in Fig. 4.
optimal solution set solved by SPEA2 changes greatly, that is, the optimal solution set solved by SARAP is more stable than the optimal solution set solved by SPEA2. Second, the instability of the optimal solution set solved by SPEA2 has little effect on the SP, that is, the SP does not have high requirements on the basic algorithm.

2) THE METHOD FOR CONVERGENCE VERIFICATION BY INTERSECTION SET

To further verify the convergence of SARAP and describe the proximity of the optimal solution set solved by SARAP to the real Pareto optimal solution set, the method for convergence verification by intersection set is proposed.

The method for convergence verification by intersection set is based on two facts. (1) If an algorithm can provide the real Pareto optimal solution set of a multi-objective optimization problem, then the algorithm is completely convergent. Therefore, the convergence of SARAP can be verified by the proximity of the optimal solution set solved by SARAP to the real Pareto optimal solution set. (2) According to the dominated relationship of the optimal solution of the discrete multi-objective optimization problem, any group of feasible solutions that do not belong to the real Pareto optimal solution set will be dominated by a group of solutions in the real Pareto optimal solution set. Therefore, if the optimal solution set solved by SARAP is close to the real Pareto optimal solution set, there are more global non-dominated solutions and less dominated solutions in the optimal solution set solved by SARAP.

The above analysis can also be expressed as follows: if most of the elements in the optimal solution set solved by SARAP are global non-dominated solutions, and the number of global non-dominated solutions in the optimal solution set solved by SARAP is close to the number of elements in the real Pareto optimal solution set, then SARAP has good convergence. Because the real Pareto optimal solution set is composed of all global non-dominated solutions, the number of global non-dominated solutions in the optimal solution set solved by SARAP can be calculated as the number of the elements in the intersection set of the optimal solution set solved by SARAP and the real Pareto optimal solution set, so that this method is called the method for convergence verification by intersection set.

Define two variables:

\[ R_{IP} = \frac{N_{Intersection}}{N_{Pareto}} \]  
\[ R_{IS} = \frac{N_{Intersection}}{N_{SARAP}} \]  

where \( N_{Intersection} \) is the number of elements in the intersection set of the optimal solution set solved by SARAP and the real Pareto optimal solution set, \( N_{Pareto} \) is the number of elements in the real Pareto optimal solution set, and \( N_{SARAP} \) is the number of elements in the optimal solution set solved by SARAP.

To summarize, the method for convergence verification by intersection set for SARAP can be summarized as follows.

1) \( R_{IP} \) closer to 1 indicates better convergence of SARAP;
2) \( R_{IS} \) closer to 1 indicates that the number of global non-dominated solutions in optimal solution set solved by SARAP is higher (the number of dominant solutions is smaller), and then the convergence of SARAP is better under the assumption that condition (1) is satisfied.

Based on the above analysis, and to deal with randomness, Fig. 6 shows the values of \( R_{IP} \) and \( R_{IS} \) corresponding to each execution of the SARAP algorithm that was repeatedly executed 100 times, and the corresponding mean, standard deviation, minimum, and maximum are shown in Table 4.

![Figure 6. Values of \( R_{IP} \) and \( R_{IS} \) corresponding to 100 runs of SARAP.](image)

Based on an examination of the results presented in Fig. 6 and Table 4 and the principle of the SARAP, the following conclusions can be drawn:

1) The number of non-dominated solutions obtained by SARAP is clearly greater than that obtained by SPEA2. For SPEA2, the number of the elements in the optimal solution set is determined by the population size, and if it is increased by increasing the population size, it will lead to a significant decrease in the calculation speed. For SPEA2, it is difficult to determine the number of non-dominated solutions of the multi-objective optimization problem in advance, while SARAP does not have high requirements for the initial population size.

2) The value of \( R_{IS} \) is very close to 1 indicating that most of the elements in the optimal solution set solved by SARAP are global optimal solutions; the value of \( R_{IP} \) is also close to 1 indicating that SARAP algorithm can find most of the global optimal solutions. Therefore, the optimal solution...
The set solved by SARAP is very close to the real Pareto optimal solution set, and then it is verified that the SARAP algorithm has good convergence for solving the MG multi-objective optimization model established in this paper.

3) USING HV INDICATOR TO VERIFY CONVERGENCE

The above two methods to verify the convergence of SARAP algorithm are related to the real Pareto optimal solution set. However, there are a large number of multi-objective optimization models whose real Pareto optimal solution set are difficult to be found. In this case, it is more reliable to use the HV indicator to verify the convergence of the algorithm [33]. For the definition and calculation method of HV indicator, the reader is referred to the literature [34]. A larger HV indicator corresponds to the better convergence performance of the algorithm. In the calculation of HV indicator, the three objectives function are normalized respectively. Fig. 7 shows the HV indicator of SPEA2 and SARAP corresponding to each execution of SARAP algorithm that has been repeatedly executed 100 times. It can also be seen that the HV indicator of the SARAP is larger and the volatility is smaller than that of SPEA2, which shows that SARAP has better convergence and stability than SPEA2.

FIGURE 7. HV indicators of SPEA2 and SARAP corresponding to 100 runs of SARAP.

In summary, the SARAP proposed in this paper effectively combines the characteristics of enumeration and SPEA2. Based on the computational complexity, the running time of SARAP is less than 20% of enumeration, is approximately 3 times greater than that of SPEA2, so that SARAP is clearly better than enumeration and is slightly inferior to SPEA2. The convergence results indicate that the solution set solved by SARAP is stable, close to the real Pareto solution set, and SARAP is clearly superior to SPEA2 and is almost equivalent to enumeration.

VI. MULTI-OBJECTIVE OPTIMIZATION RESULTS AND ANALYSIS

Based on hourly data, including wind speed, solar irradiance, and load, the multi-objective optimization model for the MG configuration established in Section II is solved by SARAP proposed in Section IV under the operational policy designed in Section III, and the optimization results are analyzed.

There is a problem that needs additional explanation. How to meet the constraints in the optimization model and how to combine the optimization process with the operation policy. In fact, all the scheme of DG configuration number that meets the constraints (2) to (8) constitutes the feasible region of the optimization variables. In the optimization calculation process, each new individual representing the optimization variable needs to check whether it meets the constraints. Condition (5) is easily met by setting conditions on the individual’s coding process. When the fitness of individuals is calculated, the one-year production simulation process needs to be called. The production simulation process is carried out under the operation policy which meets the constraint (2) to (4). In addition, according to the results of the production simulation, parameters such as LPSP, power supply ratio of DE and the discarded ratio of renewable energy can be calculated, so as to determine whether the constraints (6) to (8) are met. If these constraints are not met, the fitness of this individual is set to 0, so that it cannot participate in the optimization calculation.

A. OPTIMIZATION RESULTS

The 3D graphs of the optimization results considering the three optimization objectives of the EAC, the LPSP, the AEC are shown in Fig. 8. It is observed that SARAP has good optimization capability. Combined with the specific values of optimization variables and objectives, it is observed from Fig. 8 that the 3D graphics are clearly divided into several groups with the change in the configuration number of DE. To find the change law of the capacity configuration results, all configuration schemes are taken in descending order according to the configuration number of DEs, BES, WT and PV, and the 2D expansion graphs of the optimization...
results are obtained, as shown in Fig. 9. Table 5 shows four sets of the typical optimized configuration schemes, where the schemes 1 has the lowest $E_{AC}$, scheme 2 has the lowest $R_{LPSP}$, scheme 3 has the lowest $E_{CO2}$, and scheme 4 is a set of non-dominated solution that is decided by weight method.

Based on the results presented in Fig. 9 and the specific values, the following conclusions can be drawn:

(1) With the exception of PV, both optimization variables and objective function are clearly divided into several groups. With the change in the number of DE, and there is no scheme with the configuration number of DE equal to 0 in all optimized configuration schemes. Among these, the LPSP decrease monotonically with the increases in the configuration number of DE, showing that the DE has a significant impact on the reliability. When the configuration number of DE is increased by 1, the reliability is improved by one level.

Therefore, it is necessary to configure a certain number of controllable DG, such as DE, to ensure the reliability for a stand-alone MG.

(2) All of the two-dimensional expansion diagrams obtained by adjusting the keyword order show that there is no optimization variable that is monotonically related to EAC and AEC, and it is observed that the influencing factors of EAC and AEC are comprehensive. The sorting method shown in Fig. 9 is still best for show the relationships of EAC and AEC. It is observed that when the number of DE is determined, with the increasing numbers of BES and WT, EAC increases, AEC decreases, and LPSP decreases slightly.

The above analyses are directly based on the three-objective optimization problem. Since the constraints are relatively complex, the three-objective optimization results are projected onto the coordinate planes, and the double-objective optimization results are obtained. The projection results are shown in Fig. 10.

The essence of solving the process of the multi-objective optimization algorithm is to find the non-dominated solution in the feasible region. It is clear that the optimal solution set of the three-objective contains its corresponding double-objective solutions. The non-dominated solutions after projection are marked with red stars in Fig. 10. It is observed that the two sets of objectives exhibit a contradictory constraint relationship for the non-dominant solutions, but from the perspective of a feasible solution, a change of the configuration scheme can make the two optimization objectives improve at the same time, as marked by arrows in Fig. 10 (a). Meanwhile, the number of the non-dominated solutions is significantly reduced by removing one optimization objective, and the average value of the optimization objectives of the double-objective results is better than that of the three-objective results.

B. PRODUCTION SIMULATION RESULTS WITH TYPICAL CONFIGURATION SCHEME

To carry out production simulation, a set of non-dominated solutions must be selected from the optimal solution set using certain decision-making methods. The weight method is a commonly used decision-making method that expresses the preference of the decision-makers for each objective function.

| Scheme 1 | Scheme 2 | Scheme 3 | Scheme 4 |
|----------|----------|----------|----------|
| $N_{WT}$ | 19 | 19 | 25 | 24 |
| $N_{PV}$ | 21 | 24 | 29 | 30 |
| $N_{DE}$ | 4 | 9 | 3 | 4 |
| $N_{BT}$ | 3 | 3 | 30 | 19 |

| $C_{EAC}$ ($\$/h) | 32166687 | 34727732 | 38103170 | 37539630 |
| $R_{LPSP}$ | 2.79% | 0.00% | 4.44% | 2.15% |
| $E_{CO2}$ (kg) | 7260648 | 7823045 | 4117628 | 5227086 |
| $E_{LP}$ (kWh) | 35040002 | 35004002 | 35040002 | 35040002 |
| $E_{PV}$ (kWh) | 21428161 | 21415085 | 24576805 | 23886621 |
| $E_{BT}$ (kWh) | 2933505 | 3221787 | 3777023 | 3700484 |
| $E_{DE}$ (kWh) | 9761044 | 10461927 | 5541911 | 7001052 |
| $E_{CTRES}$ (kWh) | 727690 | 727381 | 5014660 | 3707762 |
The objective function on coordinate plane is shown in Fig. 10. Through a set of weight coefficients with a sum of 1, the weights of the non-dominated solutions given in scheme 4 of Table 5 corresponding to the three goals of economic efficiency, reliability, and environmental protection are 0.28, 0.27, and 0.45 respectively. A typical daily production simulation with this set of non-dominated solutions was performed. The results of this simulation are shown in Fig. 11.

The typical daily production simulation process is divided into four stages. In the first stage, corresponding to the time period of 0:00-4:00, the wind speed is less than the cut-in wind speed, and the solar irradiance is 0, so that the power of the WT and PV is 0, the net load power is greater than 0, the $SOC$ is greater than the set lower limit and the output power of BES can meet the load requirements, so that the net load is followed by the BES, and the DE does not need to be started. In the second stage, corresponding to the time period of 4:00-8:00, the power of the WT and PV still cannot meet the load requirements, the net load power is still greater than 0, the $SOC$ has reached the lower limit, the BES cannot continue to discharge, the DE start-up and follows the net load. In the third stage, corresponding to the time period of 8:00-12:00, the wind and solar resources are abundant, the WT and PV power is greater than the load demand, the net load power is less than 0, the DE is shut down, and the BES is charged. In the fourth stage, corresponding to the time period of 12:00-24:00, the net load power is still less than 0, the BES is full, and the WT and PV power are limited. In summary, the typical daily production simulation shows that each DG can operate according to a predetermined operation policy, and all of the operating states meet the capacity configuration constraints.

VII. CONCLUSION

In this paper, the typical stand-alone MG composed of WT, PV, DE and BES is studied. A multi-objective optimal capacity configuration model is established to minimize the EAC,
LPSP and AEC. By comparing SPEA2 with enumeration, the SARAP is proposed and its computational complexity and convergence are analyzed. The optimization model is solved by SARAP, and the optimal result is analyzed. Finally, a scheme is selected to conduct a production simulation for a typical day. Based on the results of this research, the following conclusions are drawn:

1. SARAP organically integrates the enumeration that can find the complete real Pareto solution set, and intelligent algorithm that has the characteristics of fast convergence. It can obtain results close to the complete real Pareto optimal solution set at a higher speed. In addition, SARAP algorithm can be used to solve not only the microgrid multi-objective optimization model, but also other similar multi-objective optimization models.

2. The optimal solution set solved by SARAP is more stable than the optimal solution set solved by SPEA2. The SP process of the SARAP algorithm does not have high requirements for the basic algorithm. SP process can be used not only to improve the convergence of SPEA2 but also to improve the convergence of other similar algorithms.

3. The DE has a significant impact on the reliability of the stand-alone MG. It is necessary to configure a certain number of controllable DG for the construction of a stand-alone MG.

4. The influencing factors of EAC and AEC are complex, and there is no optimization variable that changes monotonically with EAC and AEC. However, when the number of DEs is a specific value, with the increase of BES and WT, EAC increased, AEC decreased, and LPSP decreased slightly.

5. The optimal solution set of the three-objective optimization problem contains the corresponding double-objective solutions. When one optimization goal is removed, the number of elements in the optimal solution set is significantly reduced. The average value of the objective is significantly increased.

REFERENCES

[1] L. M. Mariam, M. Basu, and M. F. Conlon, “Microgrid: Architecture, policy and future trends,” Renew. Sustain. Energy Rev., vol. 64, pp. 477–489, Oct. 2016.

[2] P. Fazlalipour, M. Ehsan, and B. Mohammadi-Ivatloo, “Optimal participation of low voltage renewable micro-grids in energy and spinning reserve markets under price uncertainties,” Int. J. Electr. Power Energy Syst., vol. 102, pp. 84–96, Nov. 2018.

[3] U. Akram, M. Khalid, and S. Shafiq, “An innovative hybrid wind-solar and battery-supercapacitor microgrid system—Development and optimization,” IEEE Access, vol. 5, pp. 25897–25912, 2017.

[4] A. López-González, B. Domenech, D. Gómez-Hernández, and L. Ferrer-Martí, “Renewable microgrid projects for autonomous small-scale electrification in andean countries,” Renew. Sustain. Energy Rev., vol. 79, pp. 1255–1265, Nov. 2017.

[5] M. D. A. Al-falah, S. D. G. Jayasinghe, and H. Enshaei, “A review on recent size optimization methodologies for standalone solar and wind hybrid renewable energy system,” Energy Convers. Manage., vol. 143, pp. 252–274, Jul. 2017.

[6] Y. Sawle, S. C. Gupta, and A. K. Bohre, “Review of hybrid renewable energy systems with comparative analysis of off-grid hybrid system,” Renew. Sustain. Energy Rev., vol. 81, pp. 2217–2235, Jan. 2018.

[7] S. A. A. Kazmi, M. K. Shahzad, A. Z. Khan, and D. R. Shin, “Smart distribution networks: A review of modern distribution concepts from a planning perspective,” Energies, vol. 10, no. 4, p. 501, Apr. 2017.

[8] F. A. Khan, N. Pal, and S. H. Saeed, “Review of solar photovoltaic and wind hybrid energy systems for sizing strategies optimization techniques and cost analysis methodologies,” Renew. Sustain. Energy Rev., vol. 92, pp. 937–947, Sep. 2018.

[9] Z. Ding, H. Hou, G. Yu, E. Hu, L. Duan, and J. Zhao, “Performance analysis of a wind-solar hybrid power generation system,” Energy Convers. Manage., vol. 181, pp. 223–234, Feb. 2019.

[10] G. Zhang, B. Wu, A. Maleki, and W. Zhang, “Simulated annealing-chaotic search algorithm based optimization of reverse osmosis hybrid desalination system driven by wind and solar energies,” Sol. Energy, vol. 173, pp. 964–975, Oct. 2018.

[11] A. Y. Hatawa, G. Osman, and M. M. Aladl, “An optimization method for sizing a solar/wind/battery hybrid power system based on the artificial immune system,” Sustain. Energ. Technol. Assess., vol. 27, pp. 83–93, Jun. 2018.

[12] A. Maleki, F. Pourfayaz, and M. A. Rosen, “A novel framework for optimal design of hybrid renewable energy-based autonomous energy systems: A case study for namin, iran,” Energy, vol. 98, pp. 168–180, Mar. 2016.

[13] N. Ghorbani, A. Kasaeania, A. Toopshekan, L. Bahrami, and A. Maghami, “Optimizing a hybrid wind-PV-battery system using GA-PSO and MOPSO for reducing cost and increasing reliability,” Energy, vol. 154, pp. 581–591, Jul. 2018.

[14] C.-M. Huang, S.-J. Chen, S.-P. Yang, Y.-C. Huang, and P.-Y. Chen, “Capacity optimisation for an SAMS considering LCOE and reliability objectives,” IET Renew. Power Gener., vol. 12, no. 7, pp. 787–796, May 2018.

[15] X. Yang, J. Long, P. Liu, X. Zhang, and X. Liu, “Optimal scheduling of microgrid with distributed power based on water cycle algorithm,” Energies, vol. 11, no. 9, p. 2381, Sep. 2018.

[16] K. Anoune, M. Bouya, A. Astito, and A. B. Abdellah, “Sizing methods and optimization techniques for PV-wind based hybrid renewable energy system: A review,” Renew. Sustain. Energy Rev., vol. 93, pp. 652–673, Oct. 2018.

[17] L. Xu, X. Ruan, C. Mao, B. Zhang, and Y. Luo, “An improved optimal sizing method for Wind-Solar-Battery hybrid power system,” IEEE Trans. Sustain. Energy, vol. 4, no. 3, pp. 774–785, Jul. 2013.

[18] S. A. Nowdeh, I. F. Davoudkhani, M. J. H. Moghaddam, E. S. Najmi, A. Y. Abdelaziz, A. Ahmadi, S. E. Razavi, and F. H. Gandoman, “Fuzzy multi-objective placement of renewable energy sources in distribution system with objective of loss reduction and reliability improvement using a novel hybrid method,” Appl. Soft Comput., vol. 77, pp. 761–779, Apr. 2019.

[19] W. Zhang, K.-Y. Liu, X. Meng, X. Ye, and Y. Liu, “Research and practice on typical modes and optimal allocation method for PV-Wind-ES in microgrid,” Electr. Power Syst. Rev., vol. 120, pp. 242–255, Mar. 2015.

[20] M. A. M. Ramli, H. R. E. H. Bouchekara, and A. S. Alghamdi, “Optimal sizing of PV/wind/diesel hybrid microgrid system using multi-objective self-adaptive differential evolution algorithm,” Renew. Energy, vol. 121, pp. 400–411, Jun. 2018.

[21] W. Zhang, A. Maleki, M. A. Rosen, and J. Liu, “Sizing a stand-alone solar-wind-hydrogen energy system using weather forecasting and a hybrid search optimization algorithm,” Energy Convers. Manage., vol. 180, pp. 609–621, Jan. 2019.

[22] Z. Liu, X. Wang, R. Zhuo, and X. Cai, “Flexible network planning of autonomy microgrid,” IET Renew. Power Gener., vol. 12, no. 16, pp. 1931–1940, Dec. 2018.

[23] F. K. Abo-Elyour and A. Elnozahy, “Bi-objective economic feasibility of hybrid micro-grid systems with multiple fuel options for islanded areas in egypt,” Renew. Energy, vol. 128, pp. 37–56, Dec. 2018.

[24] B. Shi, W. Wu, and L. Yan, “Size optimization of stand-alone PV/wind/diesel hybrid power generation systems,” J. Taiwan Inst. Chem. Eng., vol. 73, pp. 93–101, Apr. 2017.

[25] M. Jamshidi and A. Askarzadeh, “Techno-economic analysis and size optimization of an off-grid hybrid photovoltaic, fuel cell and diesel generator system,” Sustain. Cities Soc., vol. 30–32, Jun. 2019.

[26] Z. Movahediyan and A. Askarzadeh, “Multi-objective optimization framework of a photovoltaic-diesel generator hybrid energy system considering operating reserve,” Sustain. Cities Soc., vol. 41, pp. 1–12, Aug. 2018.

[27] O. Nadjemi, T. Nacer, A. Hamidat, and H. Salhi, “Optimal hybrid PV/wind energy system sizing: Application of cuckoo search algorithm for Algerian dairy farms,” Renew. Sustain. Energy Rev., vol. 70, pp. 1352–1365, Apr. 2017.
[28] R. Siddaiah and R. P. Saini, “A review on planning, configurations, modeling and optimization techniques of hybrid renewable energy systems for off grid applications,” Renew. Sustain. Energy Rev., vol. 58, pp. 376–396, May 2016.

[29] M. Ming, R. Wang, Y. Zha, and T. Zhang, “Multi-objective optimization of hybrid renewable energy system using an enhanced Multi-objective evolutionary algorithm,” Energies, vol. 10, no. 5, p. 674, May 2017.

[30] J. Zhen and J. Zhou, Multi-Objective Evolutionary Optimization. Beijing, China: Science Press, 2017, pp. 101–122.

[31] Y. Sun, G. G. Yen, and Y. Zhang, “IGD indicator-based evolutionary algorithm for many-objective optimization problems,” IEEE Trans. Evol. Comput., vol. 23, no. 2, pp. 173–187, Apr. 2019.

[32] H. Ishibuchi, H. Masuda, Y. Tanigaki, and Y. Nojima, “Modified distance calculation in generational distance and inverted generational distance,” in Evolutionary Multi-Criterion Optimization (Lecture Notes in Computer Science). Berlin, Germany: Springer, 2015, pp. 12–110.

[33] M. Li and X. Yao, “Quality evaluation of solution sets in multiobjective optimisation: A survey,” ACM Comput. Surv., vol. 52, no. 2, pp. 1–38, 2019.

[34] L. While, P. Hingston, L. Barone, and S. Huband, “A faster algorithm for calculating hypervolume,” IEEE Trans. Evol. Comput., vol. 10, no. 1, pp. 29–38, Feb. 2006.

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