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MODEA Based on Multi-Population Strategy With Adaptive Weight and Its Application to Electromagnetic Device Optimization

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ABSTRACT Various intelligent algorithms are applied in optimization design, and the differential evolution (DE) algorithm is widely applied with its excellent convergence speed and convergence precision. This study analyzed the advantages and disadvantages of the existing multi-objective differential evolution (MODE) algorithm, and developed a MODE algorithm based on the adaptive weight and the multi-population strategy (MODE/AWMS). The proposed algorithm was verified using test functions. MODE/AWMS exhibited certain advantages compared with several other multi-objective optimization algorithms. Taking a polarized magnetic relay as an example, MODE/AWMS was used to optimize its key parameters by establishing a rapid calculation model of its electromagnetic mechanism. The electromagnetic force (EMF) of the release position was improved, which verified the validity of MODE/AWMS.

INDEX TERMS Pareto optimization, genetic algorithms, optimization method, electromagnetic device.

I. INTRODUCTION

For most electromagnetic devices, not only is it necessary to simultaneously optimize multiple targets within a given interval, but there is also often a possibility of conflicting and mutually constrained relationships among the objectives. Therefore, in general, none of the existing solutions can on their own optimize all of the objectives at the same time. One of the main problems of multi-objective optimization is the reconciliation and balance among various optimization objectives. Therefore, various optimization methods have been proposed thus far.

In terms of electromagnetic device optimization, domestic and foreign scholars have performed a considerable amount of work. F. G. Guimaraes *et al.* proposed the utilization of continuously differentiable membership functions, which permit the use of gradient-based methods, and applied them to the optimization of an electrostatic micro motor [1]. M. N. Albunni *et al.* presented a new approach for performing fast multi-objective optimization of the design of moving nonlinear electromagnetic devices using parametric reduced-order EM field models [2]. L. dos Santos Coelho *et al.* presents a new quantum-behaved approach using a mutation operator with exponential probability distribution, which performs well in solving a significant benchmark problem in electromagnetics [2]. However, all of the abovementioned methods have disadvantages such as low optimization efficiency and a cumbersome optimization process.

In recent years, the random sampling search algorithm represented by the evolutionary algorithm (EA) has been applied to various optimization problems; it has been widely studied and applied in various fields because of its good performance with respect to seeking the global optimal solution [3]–[6]. In the EA, the differential evolution algorithm (DEA) proposed by Storn and Price is more effective. DEA is an intelligent optimization algorithm based on swarm intelligence and is used to obtain the optimal solution in a continuous search domain. Because of its simple operation and good effect, DEA has been successfully applied in many fields, such as the mechanical industry, pattern recognition, and communication [7]–[9].

Research on multi-objective DEAs has been a hot topic in recent years. Zhang Qingfu *et al.* proposed a multi-objective

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evolutionary algorithm based on decomposition (MOEA/D), which decomposes a multi-objective optimization problem into a number of scalar optimization sub-problems and optimizes them simultaneously [10]. Based on MOEA/D, a new version of MOEA/D based on differential evolution (DE) was proposed later, i.e., MOEA/D-DE, which is very promising in dealing with complicated Pareto set shapes [11]. Gong Wenyin *et al.* proposed the ranking-based mutation operators for the DE algorithm (DE-RMO); here, a higher probability is assigned to the better individuals in the population because of the participation vector in the mutation formula, which effectively improves the optimization performance of the algorithm [12]. However, most of the existing intelligent algorithms suffer from the problems of premature convergence and convergence to the local optimal solutions.

Some scholars have applied intelligent algorithms to the optimization design of electromagnetic devices; the commonly used algorithms include the genetic algorithm, the particle swarm algorithm, and the fish swarm algorithm and its improved algorithm. Tanggong, Wang *et al.* presented a cyclic shift genetic algorithm enlightened by the biology migratory phenomenon and Inversion Operator [13]. N. Baatar *et al.* proposed an adaptive parameter controlling non-dominated ranking differential evolution (A-NRDE) algorithm for the multi-objective optimal design of electromagnetic problems [14]. A. A. Adly *et al.* presented a particle swarm optimization evolutionary methodology for nonlinear electromagnetic eddy-current braking systems. This methodology can be used to predict a configuration yielding the minimum braking distance for a body decelerating from a given speed [15].

In the present study, the original DE algorithm was improved, and a DEA with an adaptive weight and a multi-population strategy (MODE/AWMS) was developed. During the mutation operation and the crossover operation, different mutation numbers and mutation strategies were used to guide the mutation process according to the current population iteration number and the Pareto dominant relationship of each individual. In the selection process, the Pareto dominant relationship was used to screen the current population as dominant and non-dominant populations, and the greedy-based selection strategy was replaced by the selection strategy considering the niche density, which improved the uniformity of the algorithm.

II. IMPROVED DEA

A. MODE AND PARETO OPTIMAL

The DEA is widely used for solving single-objective optimization problems. However, considering the choice of the optimal solution and ensuring the problem of population uniformity, it is more difficult to design a DEA for multi-objective optimization problems than to design a DEA for single-objective one. Different from the traditional single-objective one, the multi-objective optimization problem is to optimize multiple optimization objectives in the search domain space at the same time, making it approach the global optimal value. For different multi-objective optimization problems, the expressions may be different, but the following general mathematical expression can be proposed as below:

$$\begin{cases} \min F(\mathrm{X}) = (f_1(\mathrm{X}), f_2(\mathrm{X}), \ldots, f_i(\mathrm{X})), & i = 1, 2, \ldots, m \\ \text{s.t. } g_j(\mathrm{X}) = 0, & j = 1, 2, \ldots, s \\ h_k(\mathrm{X}) \leq 0, & k = 1, 2, \ldots, l \end{cases} \tag{1}$$

where, $f_1(\mathrm{X}), f_2(\mathrm{X}), \ldots, f_m(\mathrm{X})$ are objective functions; m is the number of objective functions; $\mathrm{X} = [x_1, \ldots, x_n]$ is the vector in the search domain space, and n is the dimension of the search domain space; $g_j(\mathrm{X})$ is the equality constraints; and $h_k(\mathrm{X})$ is the inequality constraints. If $s = l = 0$, i.e., there is no equality constraint, and this optimization problem will be called as unconstrained multi-objective optimization problem.

The earliest method for dealing with multi-objective optimization problems transforms multiple objective functions into one objective function; i.e., the multiple objective functions are accumulated by means of weighted summation and transformed to a global optimization objective function. Then, the single-objective optimization problem after transformation can be solved by using the traditional single-objective optimization method. However, the determination of the weight of each objective function is often based on the experience of the decision maker. If the weight is not set appropriately, it will have a relatively great effect on the optimization result.

Therefore, this study adopted the method of solving the Pareto optimal solution set in the optimization problem, and then, selecting an appropriate value from the non-inferior solution set according to the actual demand.

In the multi-objective optimization problem, the Pareto optimal solution set P^* is a set of all Pareto optimal solutions, satisfying the following: For any individual, if it belongs to the Pareto optimal solution set P^*, then there is no other feasible solution meet the conditions that for each objective function, the objective function value of this feasible solution is not smaller than the objective function value of the individual in the Pareto optimal solution set, or, for one of the objective functions, the objective function value of this feasible solution is better than the objective function value of all of the individual in the Pareto optimal solution set. The mathematical expression is as follows:

$$P^* = \{\mathrm{X} \in \Omega | \ \nexists \mathrm{V} \in \Omega, \text{s.t.} f(\mathrm{V}) \prec f(\mathrm{X})\} \tag{2}$$

where P^* is the Pareto optimal solution set and Ω is the input variable range.

B. MODE ALGORITHM BASED ON ADAPTIVE WEIGHT AND MULTI-POPULATION STRATEGY

Aiming at solving the current problems, this paper developed MODE/AWMS, which changed the original single-population strategy into an adaptive multi-population strategy. The improved DEA adopted the method of a multi-candidate population. Whenever an individual needed to carry out a mutation operation, different mutation strategies were adopted to guide the mutation process according to the current population iteration number and the Pareto dominant relation of each individual. In this section, the multi-objective DEA based on the adaptive weighted multi-population strategy is mainly improved for the original algorithm as follows:

(1) In the process of the mutation operation and the crossover operation, a multi-population strategy was adopted to select different mutation numbers and mutation strategies to guide the mutation process according to the current population iteration number and the Pareto dominant relation of each individual.

(2) In the selection process, the Pareto dominant relation was used to screen the current population into dominant and non-dominant populations, and the selection strategy based on greedy thoughts was replaced by the selection strategy considering the ranking results of the niche density.

(3) The external archive set of the optimal solution was introduced to save the best solution set.

The biggest difference between the improved algorithm described in this paper and the original DEA is the adoption of multiple group strategies. Under the premise that the dominant and non-dominant populations of the previous generation are known, different variants and mutation strategies were used for the dominant and non-dominant populations. The mathematical expression is as follows:

$$n_{Mut} = \begin{cases} [(N-1)(1-\dfrac{G}{G_{max}})^{\epsilon}], & X \in \Omega/P^{*} \\ N-[(N-1)(1-\dfrac{G}{G_{max}})^{\epsilon}], & X \in P^{*} \end{cases} \tag{3}$$

$$V_{i,G} = \begin{cases} X_{best,G} + \mathrm{F}\cdot\left(X_{r_1^i,G} - X_{r_2^i,G}\right), & X \in P^{*} \cap \text{rand} < (\dfrac{G}{G_{max}})^{\epsilon} \\ X_{r_1^i,G} + \mathrm{F}\cdot\left(X_{r_2^i,G} - X_{r_3^i,G}\right), & \text{otherwise} \end{cases} \tag{4}$$

where n_{Mut} is the crossing number of individuals mutation, N is the total number of populations, G is the number of iterations of the current population, G_{max} is the maximum number of iterations of the population, $V_{i,G}$ is the mutation populations, X_{best} is a random individual chosen from P^{*}, X_r is a random individual chosen from Ω/P^{*}, and ϵ is a constant, $\epsilon \geq 1$.

Equations (3) and (4) show that for $X \in \Omega/P^{*}$, which is not the individuals belong to dominant populations set, the number of mutation populations decreased with an increase of population iteration; for individuals with dominant populations, the mutation strategy gradually transitioned from the previous random mutation to the later global optimal mutation. This ensured that the optimization algorithm tended to perform a global search in the entire search domain space in the early stage of optimization to maximize the distribution

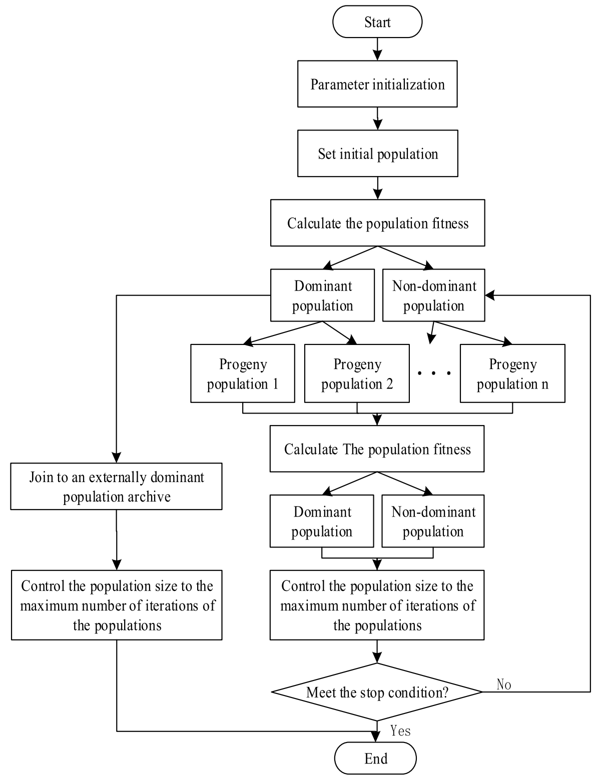

FIGURE 1. Flow diagram of MODE/AWMS.

of its optimal population. With the advancement of evolution, the algorithm gradually searched around the current optimal solution, which improved the local development ability of the algorithm, accelerated the convergence speed of the algorithm, and improved the convergence of the algorithm.

In addition, in order to ensure the uniformity of the Pareto solution set obtained by the algorithm, the niche idea was used to calculate the intensity of each individual in the current generation [16]. The corresponding mathematical expression is as follows:

$$Ft(i) = \frac{1}{\sum_{j=P_j^{*}} s(d(i,j))} \tag{5}$$

$$s(d(i,j)) = \begin{cases} 1-(\dfrac{d(i,j)}{\sigma})^{\alpha}, & d(i,j) < \sigma \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

where P_j^{*} is the current-generation Pareto optimal population, $Ft(i)$ is the niche adaptation of the i-th individual in the current generation of the optimal population, the larger $Ft(i)$ shows that the population is more sparse, $s(d(i,j))$ is the niche density of the i-th individual in the current generation of the optimal population, $d(i,j)$ is the distance between the i-th individuals and the j-the individuals in the optimal population of the previous generation, α is a constant, $\alpha \geq 1$, and σ is the niche radius. With the introduction of niche ideas, the sparsest particles were prioritized to improve the distribution of the algorithm when the optimal population size was very large,

TABLE 1. Test functions on multi-objective optimization problems.

Code	Mathematical expression	Pareto front
ZDT1	$\min f_1 = x_1,$ $f_2 = g(X)(1-\sqrt{\frac{x_1}{g(X)}})$ where $g(X) = 1+\frac{9}{n-1}\sum_{i=2}^{n} x_i$	$x_1 \in [0,1], i=1$ $x_i = 0, i=2,3,\ldots,30$
ZDT2	$\min f_1 = x_1,$ $f_2 = g(X)(1-(\frac{x_1}{g(X)})^2)$ where $g(X) = 1+\frac{9}{n-1}\sum_{i=2}^{n} x_i$	$x_1 \in [0,1], i=1$ $x_i = 0, i=2,3,\ldots,30$
ZDT3	$\min f_1 = x_1,$ $f_2 = g(X)(1-\sqrt{\frac{x_1}{g(X)}}-\frac{x_1}{g(X)}\sin(10\pi x_1))$ where $g(X) = 1+\frac{9}{n-1}\sum_{i=2}^{n} x_i$	$x_1 \in [0,1], i=1$ $x_i = 0, i=2,3,\ldots,30$
ZDT4	$\min f_1 = x_1,$ $f_2 = g(X)(1-\sqrt{\frac{x_1}{g(X)}})$ where $g(X) = 1+10(n\text{-}1)+\sum_{i=2}^{n}(x_i^2-10\cos(4\pi x_i))$	$x_1 \in [0,1], i=1$ $x_i = 0, i=2,3,\ldots,10$
ZDT6	$\min f_1 = x_1,$ $f_2 = g(X)(1-(\frac{x_1}{g(X)})^2)$ where $g(X) = 1+9(\sum_{i=2}^{n}\frac{x_i}{n-1})^{0.25}$	$x_1 \in [0,1], i=1$ $x_i = 0, i=2,3,\ldots,10$

TABLE 2. Data of GD.

		ZDT1	ZDT2	ZDT3	ZDT4	ZDT6
MODE/ AWMS	Mean	2.17E-03	2.47E-03	6.82E-02	2.02E-03	1.42E-03
	STD	2.46E-04	5.24E-04	1.45E-02	**1.80E-04**	1.50E-04
NSGAII	Mean	**9.33E-05**	**6.7E-05**	**5.36E-05**	**3.21E-04**	**7.57E-05**
	STD	**1.36E-04**	**3.24E-05**	**1.50E-05**	2.19E-04	**4.37E-05**
MOEA/ D-DE	Mean	2.95E-03	3.89E-03	9.25E-03	7.55E-02	3.40E-03
	STD	2.18E-03	2.60E-03	9.56E-03	6.23E-02	1.02E-02
RM-MEDA	Mean	4.97E-02	1.99E-01	8.35E-02	1.34E+01	8.93E-01
	STD	3.30E-02	1.14E-01	9.32E-02	2.27E+00	3.76E-01
IM-MOEA	Mean	1.41E-01	2.47E-01	1.63E-01	4.06E-02	7.61E-01
	STD	9.68E-02	2.09E-01	1.50E-01	8.79E-02	1.07E-01

and at the same time, the densest particles were preferentially deleted to improve the uniformity of the algorithm.

The flow diagram of the MODE/AWMS is shown in Fig. 1.

III. ALGORITHM ZDT STANDARD TEST FUNCTION VERIFICATION CALCULATION

In order to verify the validity of MODE/AWMS, the objective functions whose Pareto optimal solution is known were selected for testing. The solution set of the optimization algorithm was compared with the known Pareto optimal solution set to evaluate the advantages and the disadvantages of the algorithm from all the aspects. The five test functions of ZDT1–4 and ZDT6 were selected to test the improved MODE algorithm. The information about the test functions used is as follows [17]:

TABLE 3. Data of IGD.

		ZDT1	ZDT2	ZDT3	ZDT4	ZDT6
MODE/ AWMS	Mean	5.19E-03	5.46E-03	1.29E-01	**4.99E-03**	**3.06E-03**
	STD	3.31E-04	**5.94E-04**	**2.39E-02**	**2.55E-04**	3.46E-04
NSGAII	Mean	**4.70E-3**	**5.39E-03**	**6.88E-02**	6.22E-03	3.85E-03
	STD	**1.41E-4**	1.41E-03	7.39E-02	1.58E-03	2.71E-03
MOEA/ D-DE	Mean	2.91E-02	3.32E-02	8.41E-02	3.55E-01	3.10E-03
	STD	2.05E-02	1.88E-02	5.57E-02	1.67E-01	**3.07E-05**
RM-MEDA	Mean	4.86E-01	8.99E-01	8.35E-01	1.98E+01	6.56E-01
	STD	3.29E-01	3.61E-01	4.35E-01	2.39E+00	3.87E-01
IM-M0EA	Mean	1.79E-01	2.86E-01	1.70E-01	6.25E-03	2.22E+00
	STD	1.06E-02	1.60E-02	1.00E-02	3.52E-04	8.35E-02

TABLE 4. Data of HV.

		ZDT1	ZDT2	ZDT3	ZDT4	ZDT6
MODE/ AWMS	Mean	**7.17E-01**	**4.44E-01**	**6.41E-01**	**7.16E-01**	**3.88E-01**
	STD	**2.08E-04**	**4.53E-04**	**2.66E-03**	**2.67E-04**	**3.12E-04**
NSGAII	Mean	7.15E-1	4.42E-1	4.42E-01	7.16E-01	3.87E-01
	STD	3.67E-4	4.43E-3	4.43E-03	2.71E-03	4.31E-04
MOEA/D-DE	Mean	6.75E-01	4.04E-01	5.06E-01	2.91E-01	3.89E-01
	STD	2.63E-02	2.64E-02	4.16E-02	1.80E-01	2.30E-04
RM-MEDA	Mean	1.51E-01	6.38E-02	1.33E-01	----	1.28E-01
	STD	1.89E-01	1.03E-01	1.41E-01	----	6.06E-02
IM-MOEA	Mean	4.84E-01	1.37E-01	4.80E-01	7.15E-01	----
	STD	1.28E-02	1.64E-02	1.59E-02	4.17E-04	----

NSGAII [17], RM-MEDA [18], MOEA/D-DE [11], and IM-MOEA [19] on the PlatEMO platforms were selected as the comparison algorithms [20]. Set the population size of all the algorithms as $NP = 100$, and the largest iteration number of the population $G_{max} = 25000$. For the algorithm proposed in this paper, set the scaling factor as $F = 0.8$, the crossover probability as $CR = 0.5$, the constant $\epsilon = 2, \alpha = 2$; the parameters of the other algorithms were set according to the original document and system default values.

In order to quantitatively represent the performance of the algorithm, the Generational distance (GD), the Inverted generation distance (IGD), and the Hypervolume (HV) were used to reflect the convergence and the uniformity of the solution set. They were calculated as follows:

$$GD(P, P^*) = \frac{\sqrt{\sum_{z \subset P} min_{x \subset P^*} dis(x, z)^2}}{|P|} \tag{7}$$

$$IGD(P, P^*) = \frac{\sum_{x \subset P^*} min_{z \subset P} dis(x, z)}{|P^*|} \tag{8}$$

$$HV(P) = Vol\left(\bigcup_{x \in P}\left[f_1(x), z_1^*\right] \times \ldots \times \left[f_m(x), z_m^*\right]\right) \tag{9}$$

where P is the Pareto optimal solution set obtained for the algorithm, P^* is the Pareto optimal solution set, x is one

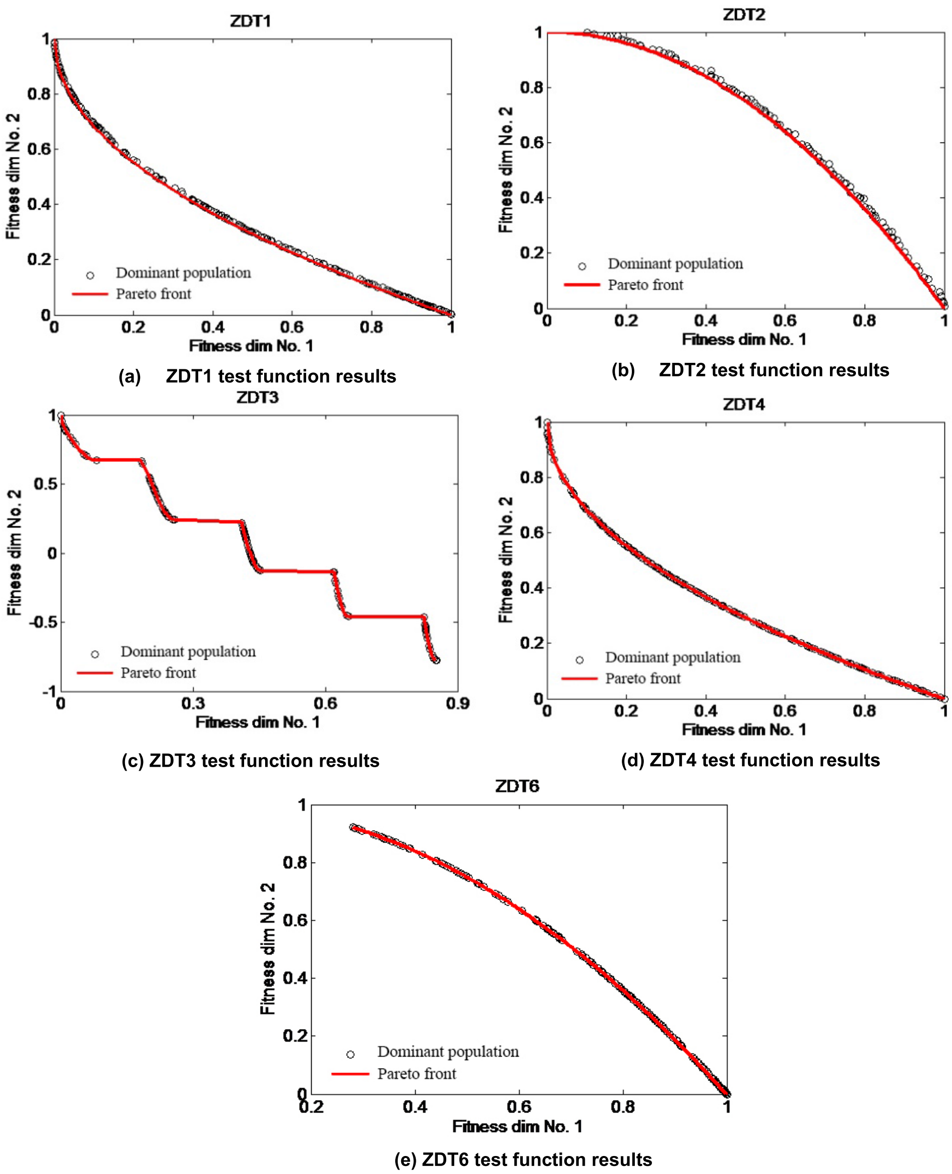

FIGURE 2. Test function results and comparison.

of the population of set P^*, z is one of the individual of set P, $dis(x, z)$ is the Euclidean distance between individual x and individual z, $d_i = min_{\mathrm{j}}(\sum_{k=1}^{m} \left|f_k^i(x) - f_k^j(x)\right|), i, j = 1, 2, \ldots, n$,and $\overline{d}$ are the average of all d_i, $Vol(\cdot)$ is the Lebesgue measure. All the algorithms were run 20 times independently. The average and the variance statistics of the GD, IGD, and SP values are shown in Tables 2–4, in which the best data is bolded.

It can be seen from the data in the above tables that the convergence of MODE/AWMS was better than the other three algorithms except NSGAII for four test functions and performed poorly only on ZDT3, and the uniformity of the solution set is better than all of them for all the test function. The comparison of dominant population get from the improved DE algorithm and the Pareto front is shown in Fig. 2.

Fig. 2 shows that the front of the algorithm calculation results was basically consistent with the theoretical Pareto front, which satisfied the convergence of the algorithm; the distribution of each body on the leading edge was basically uniform, which basically satisfied the uniformity of the algorithm; the algorithm was also effective in terms of coverage. Overall, MODE/AWMS exhibited better performance when dealing with multi-objective optimization problems, which proved the effectiveness of the algorithm.

IV. POLARIZED MAGNETIC RELAY STATIC CHARACTERISTICS OPTIMIZATION

A. RELAY ELECTROMAGNETIC MECHANISM

The MODE/AWMS described above was used to optimize the multi-objective parameter optimization problem of the polarized magnetic system. The direct-acting bi-stable elec-

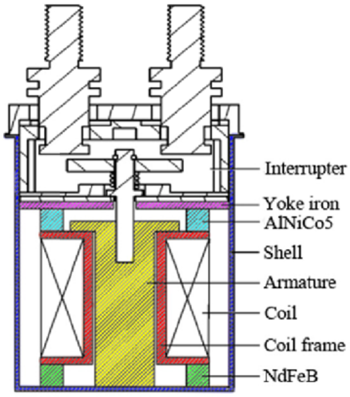

FIGURE 3. Internal structure of the direct-acting PM bi-stable electromagnetic mechanism.

TABLE 5. Upper and lower limits of dimensional parameters.

X	H_{xt}	W_{xt}	T_{gj}	D_{gj}
X_{max} (mm)	2.32	28	3	40
X_{min} (mm)	0.32	20	0.5	30

tromagnetic mechanism with PM shown in Fig. 3 was used as an example.

According to the structure and the working principle of the electromagnetic system, select the following key dimension parameters that needed to be optimized: armature pole face height H_{xt}, pole face width W_{xt}, coil bobbin thickness T_{gj}, and outer diameter for analysis D_{gj}. The electromagnetic force (EMF) of the release position without excitation (0AT) F_0 and with the rated excitation (17.5AT) F_{out} were selected as the optimization objectives. The corresponding mathematical representation of the optimization design goal was as follows:

$$\begin{aligned} &\min F_0, F_{\text{out}} \\ &\text{s.t. } W_{xt} \in [W_{xt,min}, W_{xt,max}], H_{xt} \in [H_{xt,min}, H_{xt,max}], \\ &\quad T_{gj} \in [T_{gj,min}, T_{gj,max}], D_{gj} \in [D_{gj,min}, D_{gj,max}] \end{aligned} \tag{10}$$

Because of the structural limitations of the polarized magnetic system, the upper and lower limits of the dimensional parameters were specified as presented in Table 5.

B. RAPID CALCULATION MODEL AND ITS VERIFICATION

In order to shorten the calculation period, this study used the rapid calculation model based on working point migration to solve the polarized magnetic system [21].

Compared with the traditional equivalent magnetic circuit model of the polarized magnetic system, the equivalent model of the permanent magnet was changed from the linear model of the magnetic potential and the magnetic resistance to the working point migration model, as shown in Fig. 5.

The physical prototype model was built according to the structural dimensions of the polarized magnetic system, as shown in Fig. 6.

The static suction characteristics of the polarized magnetic system were obtained by measuring the static suction

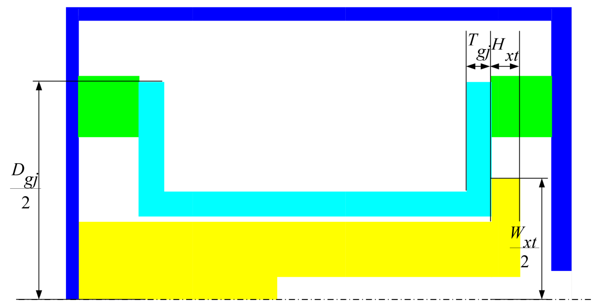

FIGURE 4. Key dimension parameters of polarized magnetic system.

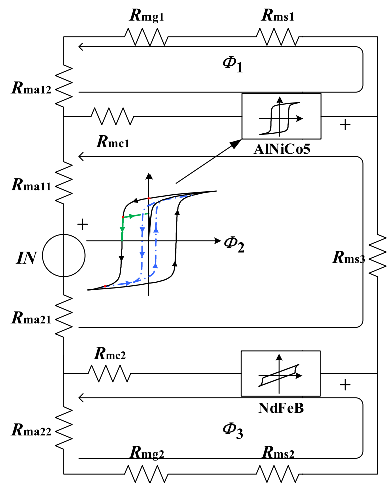

FIGURE 5. Key dimension parameters of polarized magnetic system.

FIGURE 6. Polarized magnetic system physical prototype.

at different voltages and different positions of the polarized magnetic system. At the same time, the improved fast calculation model of the hybrid permanent magnet direct-acting polarized magnetic system was established and calculated, and the holding force of the polarized magnetic system in different states was obtained. Then compare the physical prototype measurement results of the polarization magnetic system's holding force with the magnetic circuit calculation results, as shown in Fig. 7.

The calculation results showed that the magnetic circuit calculation results were in good agreement with the static

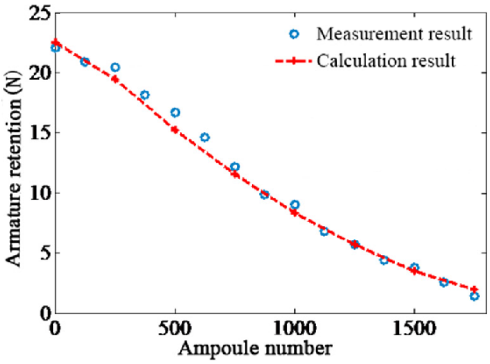

FIGURE 7. Comparison of static retention results of polarized magnetic systems.

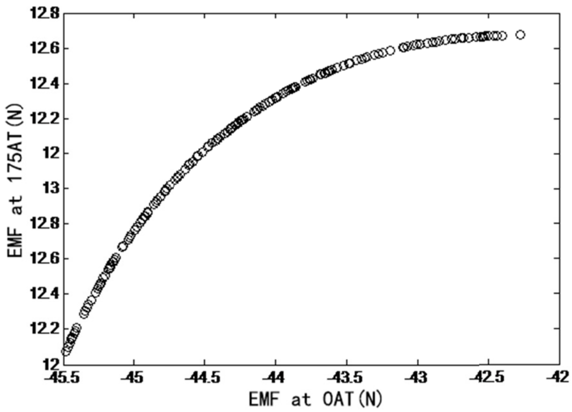

FIGURE 8. Pareto front of the optimal solution.

TABLE 6. Parameters before and after optimization of polarizing magnetic system.

X	H_{xt}	W_{xt}	T_{gj}	D_{gj}
before(mm)	2.32	24	1.5	37.0
after(mm)	2.32	22	3.0	34.5

suction characteristics of the measured results, and the average error was approximately 12%.

C. MULTI-OBJECTIVE PARAMETER OPTIMIZATION OF SIZE PARAMETER OF POLARIZED MAGNETIC SYSTEM

In MODE/AWMS, set the parameters such as the problem dimension, upper and lower limits of the size parameters, and the fitness function. After approximately 140 generations of iterations, the population basically converged to the optimal solution; the corresponding Pareto front is shown in Fig. 8.

A set of optimal solutions was selected considering the actual demand from the occupied population. Taking into account the balance of the polarization magnetic system under the static holding force and the output force, select the following parameters, as shown in Table 6.

A finite element simulation was used to solve the optimized dimensional parameters, and the static suction characteristics of the polarized magnetic system before and after the optimization of the dimensional parameters were obtained, as shown in Fig. 9.

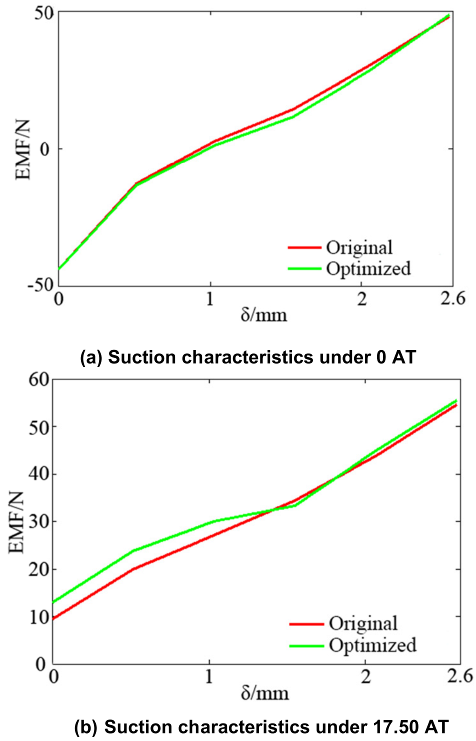

FIGURE 9. Suction characteristic curve of polarized magnetic system before and after multi-objective optimization.

Fig. 9 shows that the polarized magnetic system before and after the optimization of the size parameter had a relatively small difference in the holding force, approximately 0.5%; however, in the case of the output force of the release position under the rated ampoule, the optimized structure suction increased by 38%. This indicated that the static characteristics of the polarized magnetic system after optimization had a certain improvement compared with those of the original structure. At the same time, the optimization results showed that the MODE/AWMS described above was feasible in the multi-objective parameter optimization of the polarizing magnetic system.

V. CONCLUSION

Aimed at the shortcomings of most MODEAs, such as easy convergence to local optimal solution and poor convergence precision, in this paper, this paper proposed an improved DEA based on an adaptive weight and a multi-population strategy, which was compared with some other algorithms by using several performance parameters, and was verified by using an instance. The results were as follows:

(1) In the process of the mutation operation and the cross operation, the MODE/AWMS selected different mutation numbers and mutation strategies to guide the mutation process according to the current population iteration number and the Pareto dominant relationship of each individual.

The global searching ability of the improved DEA was increased according to the HV data, and the convergence of the algorithm doesn't decrease according to the GD and IGD data of the test function results.

(2) In the selection process, the Pareto dominant relationship was used to divide the current population as dominant and non-dominant populations, and the selection strategy based on greedy thinking was replaced by the selection strategy considering the results of niche sequencing, which improved the uniformity of the algorithm according to the SP data.

(3) MODE/AWMS was used to optimize the key parameters of the polarized magnetic system. The results showed that the static characteristics improved compared with those of the original structure, which further proved the effectiveness of the proposed algorithm.

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