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A Novel Multi-Objective Optimal Design Method for Dry Iron Core Reactor by Incorporating NSGA-II, TOPSIS and Entropy Weight Method

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Abstract: Dry iron core reactors are widely used in various power quality applications. Manufacturers want to optimize the cost and loss simultaneously, which is normally achieved by the designers' experience. This approach is highly subjective and can lead to a non-ideal product. Thus, an objective dry iron core reactor design approach to balance the cost and loss with a scientific basis is desired. In this paper, a multi-objective optimal design method is proposed to optimize both the cost and loss of the reactor, which provides an automatic and scientific design method. Specifically, a three-dimensional finite element model of dry iron core reactor is established, based on which the dependency of cost and loss upon the wire size of the reactor's winding is studied by using joint Matlab-finite element method (FEM) simulation. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is used to search for the Pareto optimal solution set, out of which the optimal wire size of the reactor is determined by using the fusion of the technique for order preference by similarity to ideal solution (TOPSIS) method and the entropy weight method. TOPSIS helps the designer to balance the concern between cost and loss, while the entropy weight method can determine the weight information through the dispersion degree of cost and loss. This methodology can avoid personal random subjective opinion when selecting the design solution out of the Pareto set. The calculation shows that the cost and loss can be reduced by up to 17.85% and 19.45%, respectively, with the proposed method. Furthermore, the obtained optimal design is approved by experimental tests.

Keywords: dry iron core reactor; multi-objective optimization; NSGA-II; matlab-finite element; TOPSIS; entropy weight method

Citation: Li, Y.; Liu, Y.; Li, S.; Qi, L.; Xie, J.; Xie, Q. A Novel Multi-Objective Optimal Design Method for Dry Iron Core Reactor by Incorporating NSGA-II, TOPSIS and Entropy Weight Method. *Energies* **2022**, *15*, 7344. https://doi.org/10.3390/en15197344

Academic Editor: Zbigniew Nadolny

Received: 20 August 2022
Accepted: 3 October 2022
Published: 6 October 2022

1. Introduction

Electrical reactors are essential equipment in power systems used for reactive power compensation, current limiting, over-voltage suppression, etc. [1]. There are two types of reactors, namely dry-type and oil-immersed. Compared with oil-immersed reactors, the oil-free dry-type reactors eliminate the risk of oil leakage and fire hazard. Thus, dry-type reactors have gradually overtaken oil-immersed reactors in the 35 kV and below market, especially in places with a high safety awareness such as airports, railway stations, etc. Two kinds of dry-type reactors exist, namely air core and iron core reactors. Dry iron core reactors, which are the focus of this paper, are favored for applications with installation space limitations due to their small size. The great demand has urged manufacturers to pay attention to the design optimization [2–4]. The current design of dry iron core reactors follows a similar process as a transformer, which relies on electromagnetic field theory to design the core and coil, with loss and temperature rise as the validation checks [5]. Thus, loss is a key optimization objective for reactor design and has been studied by researchers. For example, in [6], the effect of air gaps on the core losses of shunt iron core reactors was analyzed to select the optimal air gap. Fating Yuan et al. optimized the rain cover structure based on loss evaluation [7]. Takaaki Ibuchi et al. minimized the copper loss for dry-type reactors in the high frequency range [8]. Additionally, manufactures want to reduce their costs, which makes cost also an optimized parameter. Yuan et al. proposed to design dry air core reactors with the minimum amount of metal conductors, which referred to the minimum cost [9]. In [10], genetic algorithms were introduced to reduce the cost of single-phase dry air core reactors.

As discussed, the studies above take only the loss or the cost of reactor as the one optimized parameter. However, it is of more significant engineering importance to optimize the loss and cost simultaneously for a reactor.

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is an effective method for solving such multi-objective optimization problems [11,12], which has been applied in different fields [13–16]. It has been used to optimize designs for electrical equipment. In [17], the optimal design for transformer locations, taking account of investment and operating costs, was realized by using the NSGA-II algorithm. Reference [18] used the NSGA-II algorithm to optimize the transformer conductor size considering the eddy current loss and the temperature gradient of the winding. NSGA-II was also applied for the design of a dry-type air-core reactor, with the goal of minimizing production costs and operating costs [19,20]. However, the NSGA-II algorithm gives a set of Pareto solutions, and the designer may arbitrarily pick one from this set for subsequent design, but not necessarily the best one. Selecting one of the Pareto solutions requires weighing the importance of different objectives, which is normally highly randomly subjective and lacks a scientific basis [21]. It can be imagined that different electrical reactor designers may choose different solutions from the Pareto set, which leads to products with different performance.

To this end, the research question is to find the best design solution for an electrical reactor with an objective approach, considering both the loss and cost. Thus, the designer can scientifically derive the best solution. In this paper, NSGA-II is utilized for the reactor's design with the cost and loss as two optimized objectives. To overcome the drawbacks of random subjective selection, this paper incorporates the technique for order preference by similarity to ideal solution (TOPSIS) and the entropy weight method into the NSGA-II algorithm. In this way, the designer can focus more on a certain aspect of the design process, i.e., loss or cost, eliminating the disadvantages of random selection. This proposed approach is successfully implemented in the design of a 10 kV three-phase dry iron core reactor.

The paper is organized as follows. Firstly, the three-dimensional (3D) finite element model of a dry iron core reactor is established, based on which the cost and loss of the reactor are taken as two optimized objectives. A set of Pareto optimal solutions are obtained using the joint Matlab-FEM simulation with the NSGA-II algorithm, after which the TOPSIS method and entropy weight method are implemented to determine the optimal wire size in the reactor design process. A validation experiment is performed at the end.

2. Multi-Objective Optimization Modeling of Dry Iron Core Reactors

2.1. Three-Dimensional Finite Element Model

A 3D finite element model of a 10 kV three-phase dry iron core reactor was developed using COMSOL Multiphysics software as shown in Figure 1, based on which the cost and loss were derived. The dimensions of the model geometric are shown in Appendix A. As shown in Figure 1 and Appendix A, the structure of the reactor was constructed in detail. There are 6 air gaps in each iron core and 3 layers for each winding. The implementation of the calculation includes geometric design, material addition, electromagnetic field boundary setting and mesh dissection [22,23]. The relevant material parameters are listed in Table 1.

The reactor core diameter is fixed at 160 mm to meet the rated power while the wire size is varied as a control parameter. The reactor cost includes the core cost and winding coil cost, neglecting accessories. Each result is calculated by multiplying the price of related material per unit volume and its total volume.

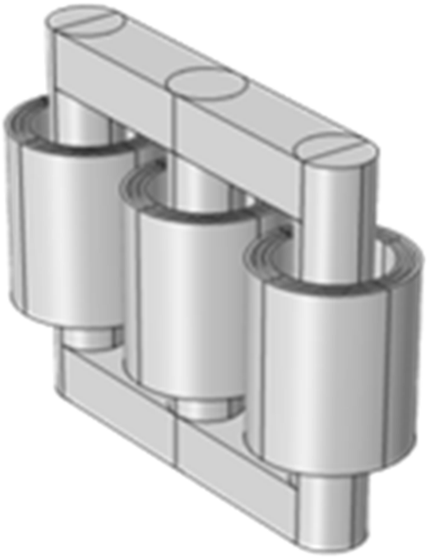

Figure 1. Three-dimensional finite element model of reactor.

Table 1. Relevant material parameters.

Materials	Relative Permeability	Relative Permittivity	Conductivity [S/m]
winding coil	1	1	2.8×10^7
air	1	1	0
core	9500	1	0

The loss of the reactor includes two parts. One is copper loss, caused by the heat generated from the current passing through the winding coil [24]. For the calculation of copper losses, the following equation is derived according to Joule's law:

$$P_{cu} = I^2R_1 + I^2R_2 + I^2R_3 \tag{1}$$

where R_1–R_3 are the three-phase winding resistance.

The other part is the core loss, including hysteresis loss, eddy current loss and additional loss [25]. Hysteresis loss is generated by the memory of a magnetic material. More force is necessary to demagnetize magnetic material than it takes to magnetize it, and the magnetic domains in the material resist realignment. Eddy current losses are from circulating currents in the core material, which is induced by an alternating magnetic field [26]. Additional loss is the loss that cannot be directly attributed to eddy current or hysteresis phenomena. Based on the magnetic field distribution in the core, the core loss can be calculated by the following formula [25,27]:

$$P_{ir} = P_h + P_{ec} + P_e = afB_m^x + bf^2B_m^2 + ef^{1.5}B_m^{1.5} \tag{2}$$

where P_{ir} is the core loss; P_h is the hysteresis loss; P_{ec} is the eddy current loss; P_e is the additional loss; f is the frequency; and B_m is the flux density amplitude. Values of a, b, x, e are dependent upon the selected ferromagnetic material.

The distribution of the final flux density is obtained using the finite element study as shown in Figure 2.

As seen in Figure 2, the flux density is larger at the corners of the core, and the magnitude and distribution of the flux density are consistent with the design.

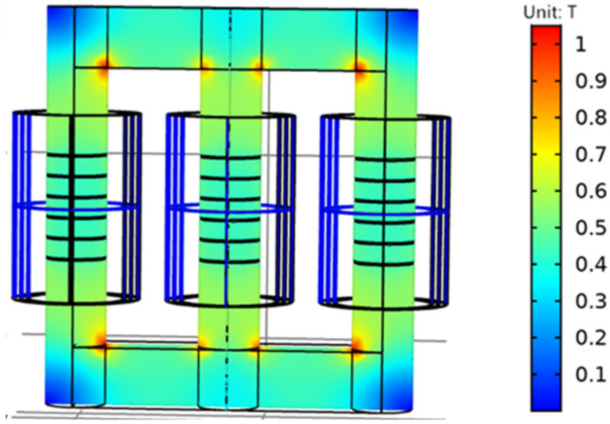

Figure 2. Magnetic flux density distribution chart.

2.2. Multi-Objective Optimization Mathematical Model

The optimal design of reactors is essential to solve a nonlinear problem with constraints. The input variables and objective function are the key to solving such optimization issues. In the design process of the three-phase dry iron core reactor, the sizes of the wire were used as input variables. The cost and loss of the reactor were used as the optimized indexes to form a multi-objective optimization function as shown in Equation (3):

$$\begin{cases} \min f_1(X) = f(x_1, x_2) \\ \min f_2(X) = f(x_1, x_2) \end{cases} \tag{3}$$

where x_1 is the wire length and x_2 is the wire width, as shown in Figure 3. f_1 is the total cost while f_2 denotes the loss, which is the sum of Equations (1) and (2), i.e., P_{ir} + P_{cu}. The f_1 and f_2 are taken as the objectives for design optimization.

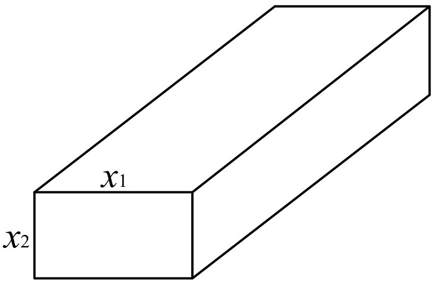

Figure 3. Illustration of conductor wire.

3. Optimization of Reactor Incorporating NSGA-II and TOPSIS and Entropy Weight Method

The NAGA-II algorithm is widely used in the design of multi-objective optimization; the algorithm performs a non-dominated sorting of all design solutions to find the Pareto optimal solution set. In this paper, the optimal wire size was selected by combining the TOPSIS method and entropy weight method on the basis of the NSGA-II algorithm. The flowchart for the optimized design of the dry iron core reactor is shown in Figure 4. Firstly, the 3D model of the reactor was built, based on which the reactor loss and cost were obtained with different wires via FEM. Then, the NSGA-II algorithm was used for iterative calculation to obtain the optimized sets of wires' dimensions. Finally, TOPSIS combined with the entropy weight method was applied to derive an optimal wire size.

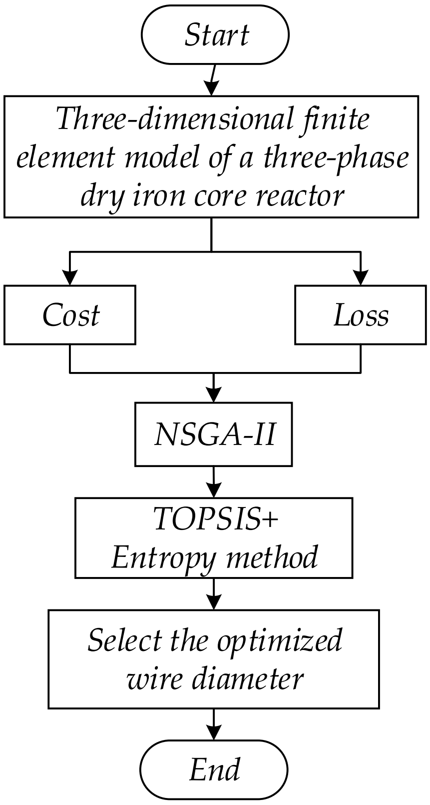

Figure 4. Dry iron core reactor optimization design process.

3.1. Implementation of NSGA-II Algorithm

The NSAG-II algorithm was applied to the 3D finite element model of a three-phase dry core reactor with the following procedure.

(1) Population initialization. Since this paper aims to analyze the effect of different wire size on the optimized indexes, i.e., cost and loss, the common standard wire size was selected as the initialized population, as shown in Table 2. Twenty-eight combinations of different wire lengths and wire widths were formed. These 28 individuals were entered into the COMSOL model as the initial population to calculate the cost and loss under various wire sizes.

(2) Fast non-domination sorting and crowding distance calculation of the initial population. Dominance and non-dominance are the focus of the process, as shown in Figure 5. If both the cost and loss for individual i are smaller than individual j, then i dominates j. Otherwise it is a non-dominated relationship. As shown in Figure 5, the cost and loss of individual i are less than individual j, indicating that i dominates j. However, though the loss of individual i is smaller than that of $i + 1$, the cost of individual i is higher than that of $i + 1$. Thus, i and $i + 1$ does not constitute a dominant relationship. This is the same for individuals i and $i - 1$. All the solutions in the population that are not dominated by other solutions constitute the non-dominated frontier, i.e., the Pareto optimal solution set. The rank of all the individuals in the non-dominated frontier was set to 1. After that, all the individuals with rank 1 were removed and the above operation was repeated for the rest of the population until the non-dominated sorting of all the individuals was completed. The crowding distance of individuals under the same dominance rank was sorted and calculated according to the magnitude of the optimized indexes, where the crowding distance of two boundary solutions is infinity and the crowding distance of the ith individual can be defined as the sum of its distances to individual $i - 1$ and individual $i + 1$ on each axis component, which is half of the perimeter of the rectangle in Figure 5.

(3) Selection, crossover and mutation. The parent that is suitable for reproduction is selected from the original population to form the elite population. Each selection is a competition between two randomly selected individuals from the original population to compare their non-dominance rank, and the individual with smaller rank will be selected for the elite population. If the non-dominance rank of two individuals is the same, the individual with the larger crowding is selected to enter the elite population to ensure the diversity of the population. Since there were 28 individuals in the initial population, an elite population containing 14 individuals was obtained after the selection process. After that, a suitable cross-variance operator was selected to cross-variance this population to obtain the offspring population, and the final offspring were 14–28 because the probability of cross-variance was different.

(4) Merging parent and child generations to generate a new population. The parent–child population was merged into a new population, and the elite retention strategy was used to calculate the new population's non-dominated sorting and crowding distance. Afterwards, a new population containing 28 individuals was selected to participate in the subsequent evolution based on the sorting and crowding distance. The subsequent step was to repeat the process of (3)–(4) until the number of iterations was satisfied to obtain the Pareto optimal solution set. The above process of NSGA-II can be represented as Figure 6, where Gen indicates the number of generations of genetic evolution.

Table 2. Selected line length and line width.

wire length (mm)	3.15	3.35	3.55	3.75	-	-	-
wire width (mm)	1.4	1.5	1.6	1.7	1.8	1.9	2.0

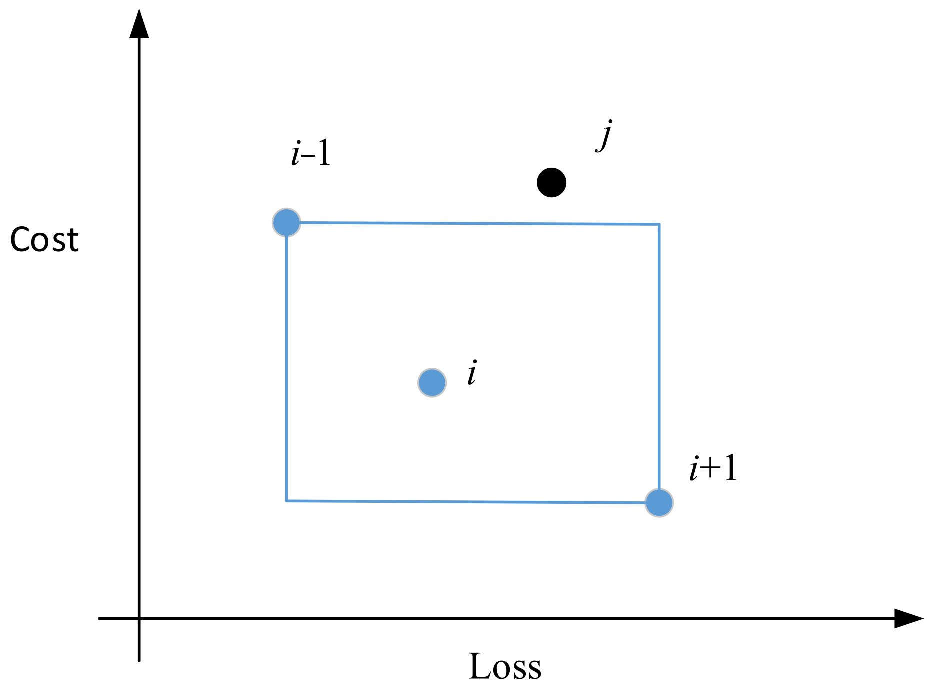

Figure 5. Schematic diagram of dominance relationships and crowding distance. (There is no dominance relationship between the blue dots. The black dot is dominated by the blue dot. The perimeter of the rectangle represents 2 times crowding distance of the *i*th individual).

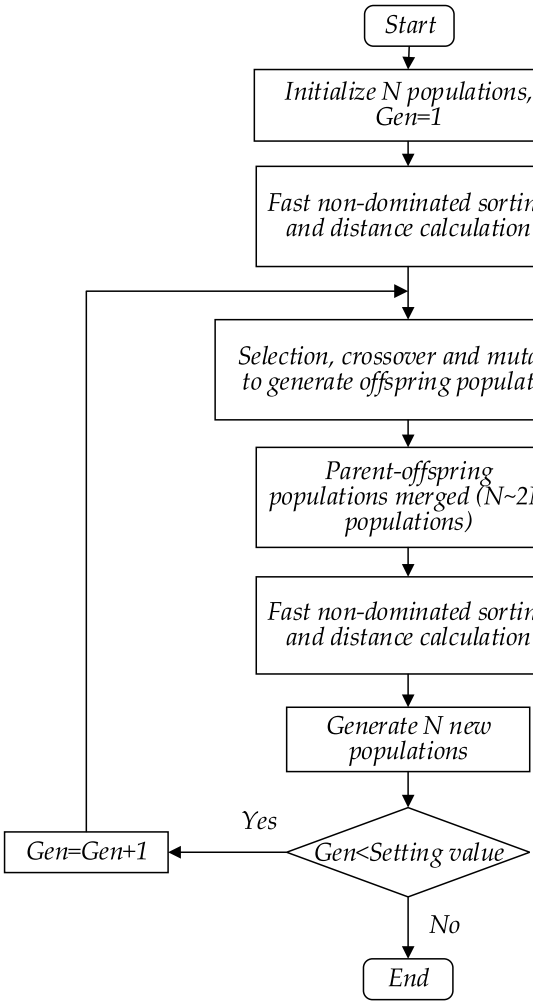

Figure 6. NSGA-II algorithm flowchart.

3.2. Implementation of TOPSIS Method

The NSGA-II algorithm produces an optimal solution set. In order to obtain the optimal solution from it, the TOPSIS method [28] was used. The basic principle of TOPSIS is to rank the evaluation objects by detecting the distance between the ideal solution and the negative ideal solution. If the evaluation object is closest to the ideal solution and far from the negative ideal solution, the object is the best design solution, and vice versa.

In order to obtain the optimal individual in the optimal solution set obtained by the NSGA-II algorithm, the samples to be evaluated and their evaluation indexes are collected at first. If there are m evaluation samples and n evaluation indexes, the original matrix as in (4) can be formed.

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \tag{4}$$

The collected data are normalized for the indicators. Specifically for this paper, the two evaluation indicators of cost and loss are normalized according to Equation (5):

$$x_{ij} = \max_{1 \le i \le m} \{x_{ij}\} - x_{ij} \tag{5}$$

where x_{ij} is the jth evaluation index of the ith evaluation object.

In order to eliminate the influence of different indicators, we need to use the method of vector normalization to obtain the normative decision matrix, as shown in Equation (6), where z_{ij} is the jth evaluation index of the ith evaluation object after normalization, and Z is the normative decision matrix.

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{6}$$

$$Z = \begin{pmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{m1} & \cdots & z_{mn} \end{pmatrix} \tag{7}$$

Based on Equations (8) and (9), the ideal solution Z^+ and the negative ideal solution Z^- of each index can be found.

$$Z^+ = (\max\{z_{11}, \cdots, z_{m1}\}, \cdots, \max\{z_{1n}, \cdots, z_{mn}\}) \tag{8}$$

$$Z^- = (\min\{z_{11}, \cdots, z_{m1}\}, \cdots, \min\{z_{1n}, \cdots, z_{mn}\}) \tag{9}$$

The distance between the ith evaluation object and the ideal/negative ideal solution, are defined as follows, respectively:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (Z_j^+ - z_{ij})^2} \tag{10}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (Z_j^- - z_{ij})^2} \tag{11}$$

where D_i^+ is the distance between the ith evaluation object and the ideal solution, D_i^- is the distance between the ith evaluation object and the negative ideal solution, Z_j^+ is the ideal solution of the jth evaluation index, and Z_j^- is the negative ideal solution of the jth evaluation index.

The score of the evaluation object is finally determined with Equation (12). Obviously, $0 \leq C^i \leq 1$. The default n evaluation indicators of the formula have the same weight, but different designers may place different weight on loss or cost. One can use an analytic hierarchy process to give weights to these n evaluation indicators according to Equation (13). The analytic hierarchy process needs weight information as input, which is normally carried out by subjective assignment and can be biased. The entropy weight method instead can be used to obtain objective values through the dispersion degree of loss and cost.

$$C^i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{12}$$

$$\sum_{j=1}^{n} w_j = 1 \tag{13}$$

3.3. Implementation of the Entropy Method

Entropy is a measure of the degree of disorder of the system [29]. Thus, for a certain index (such as cost and loss in this paper), the entropy value can be used to determine its dispersion degree. The smaller its entropy value, the greater the dispersion degree of the index and the greater the influence of the index on the design evaluation (i.e., the weight). The entropy method effectively avoids the interference of subjective factors and makes the weight determination of evaluation indicators more objective [30,31]. In this paper, TOPSIS combined with the entropy weighting method was used to obtain the weights.

(1) First, the weight of the jth index value of the ith sample was calculated and the weight matrix P was built.

$$p_{ij} = \frac{x_{ij}}{\sum\limits_{i=1}^{m} x_{ij}} \tag{14}$$

$$P = \begin{pmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{m1} & \cdots & p_{mn} \end{pmatrix} \tag{15}$$

(2) Calculate the entropy e_j of the jth index according to Equation (16). A larger value means less variation. The redundancy value d_j of the jth index is obtained referring to Equation (17), and finally the entropy weight w_j of each index is obtained by normalizing it based on Equation (18). Obviously, the entropy weight sum of all indicators is 1.

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln p_{ij} \ \mathrm{e}_j \in [0,1] \tag{16}$$

$$d_j = 1 - e_j \tag{17}$$

$$w_j = \frac{d_j}{\sum\limits_{j=1}^{n} d_j} \tag{18}$$

Based on the entropy weighting w_j, the weighting matrix z_{ij}* and the weighting matrix are constructed as shown in Equations (19) and (20).

$$z_{ij}^{*} = z_{ij} \cdot w_j \tag{19}$$

$$Z^{*} = \begin{pmatrix} z_{11} \cdot w_1 & \cdots & z_{1n} \cdot w_n \\ \vdots & \ddots & \vdots \\ z_{m1} \cdot w_1 & \cdots & z_{mn} \cdot w_n \end{pmatrix} \tag{20}$$

4. Algorithm Implementation

In this paper, the finite element model of a three-phase iron core reactor was established by Comsol software(Manufacturer: COMSOL, city: Stockholm, country: Sweden). The NSGA-II algorithm, TOPSIS method and entropy weight method were implemented in Matlab(Manufacturer: MathWorks, city: Massachusetts, country: USA). The joint simulation derives the cost and loss of the reactor with different wire sizes from the finite element model. The optimized wire size was selected by integrating NSGA-II, TOPSIS and the entropy weight method, which can significantly save human operation time and avoid subjective design preference.

In this example, 28 individuals were selected, and the convergence of NSGA-II algorithm was achieved by iteration. Figure 7 shows the loss and cost distribution of the initial population. The 28 initial individuals were dispersed with multiple domination relationships. Figure 8 shows the same result for the fifth generation. It can be seen that after the algorithm iteration is completed, there is no domination relationship between all individuals, which indicates the dominated individuals are removed and the remaining ones constitute the Pareto optimal solution set. When the number of evolutionary generations exceeds 5, the offspring have all been located in the Pareto dominance frontier. Therefore, the Pareto frontier curve at the 5th generation was selected as the optimal solution set in this study [32].

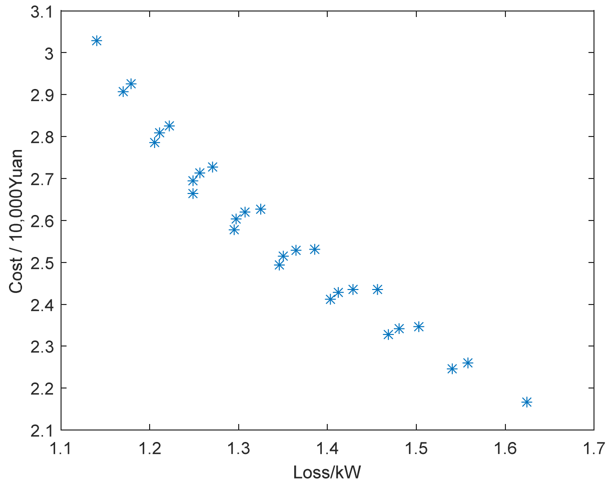

Figure 7. Distribution of the initial population in space. (An asterisk corresponds to an individual's cost and loss).

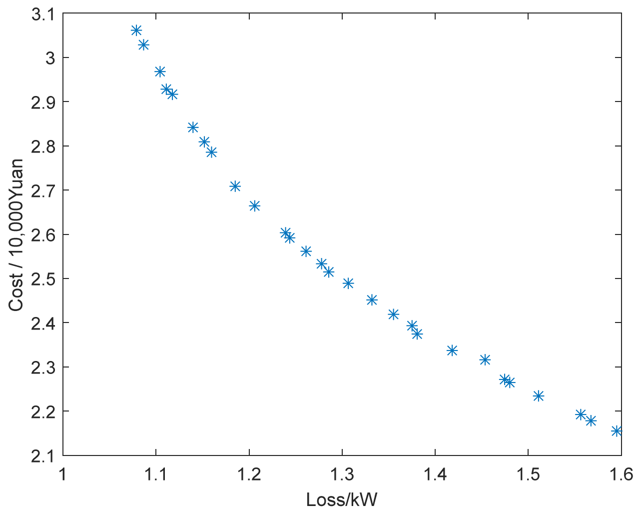

Figure 8. Distribution of populations in space after 5 generations of genetic evolution. (An asterisk corresponds to an individual's cost and loss).

Table 3 shows the final iterative results. The loss was given by copper loss and iron loss, respectively. The sum of both is the total loss. The price of iron core material was taken as CNY 16/kg, and the price of copper conductor material was taken as CNY 55/kg. The maximum loss was 1.5954 kW (P_{max}) and the minimum value was 1.0786 kW (P_{min}). Based on Equation (21), the difference of loss ΔP was calculated and the result was 32.39%. Similarly, the variation of cost can be calculated to be 29.62%.

$$\Delta P = \frac{P_{\max} - P_{\min}}{P_{\max}} \tag{21}$$

Using the TOPSIS method to assign different weights to the two indexes, the results in Figure 9 were obtained. It can be seen that with the increase of cost weight, cost decreases while loss increases. The trend validates the TOPSIS method applied to the wire selection. The TOPSIS method integrated with the entropy weight method provides a scientific way to obtain the weight of the indicators, avoiding the subjectivity of random selection. Based on Equations (16)–(18), the cost weight of 0.5051 and loss weight of 0.4949 were obtained, which provides an objective basis for the selection of wire size. The corresponding result is also shown in Figure 9, with the detailed values in Appendix B. The loss and cost results obtained by the TOPSIS–entropy weight method are shown in the 7th row of Appendix B. Compared with the other design results, this solution balances the cost and loss. It is located near the crossing point of the loss and cost curve in Figure 9, which represents the optimal design solution. Following the calculation in Equation (21), the final design reduced loss up to 19.45% and cost up to 17.85%, respectively.

Table 3. NSGA-II algorithm combined with finite element model simulation results.

Wire Length (mm)	Wire Width (mm)	Copper Loss (kW)	Iron Core Loss (kW)	Total Loss (kW)	Core Quality (kg)	Copper Quality (kg)	Cost (CNY 10,000)	Overcrowding Distance
3.8070	1.9994	0.8030	0.2756	1.0786	716.97	348.20	3.0622	Inf
3.1459	1.3873	1.3586	0.2368	1.5954	673.86	195.81	2.1551	Inf
3.1503	1.4846	1.2739	0.2369	1.5108	674.23	210.05	2.2340	0.2298
3.4231	2.0134	0.8867	0.2530	1.1397	691.95	315.48	2.8422	0.1878
3.3500	2.0000	0.9114	0.2487	1.1601	687.23	306.40	2.7848	0.1721
3.1599	1.4258	1.3186	0.2375	1.5561	674.71	202.17	2.1915	0.1690
3.1377	1.6171	1.1816	0.2365	1.4181	673.44	228.94	2.3367	0.1674
3.6784	1.9838	0.8368	0.2678	1.1045	708.45	333.57	2.9681	0.1575
3.7500	2.0000	0.8149	0.2720	1.0869	713.13	343.08	3.0279	0.1539
3.1632	1.9212	1.0008	0.2388	1.2396	675.07	277.14	2.6044	0.1521
3.5645	2.0024	0.8560	0.2614	1.1175	701.13	326.46	2.9173	0.1493
3.1500	2.0000	0.9689	0.2375	1.2064	674.15	288.21	2.6638	0.1479
3.0589	1.7147	1.1482	0.2321	1.3803	668.22	237.37	2.3747	0.1444
3.1713	2.0382	0.9461	0.2390	1.1851	675.51	296.13	2.7095	0.1412
3.1351	1.8900	1.0250	0.2366	1.2616	673.18	269.75	2.5607	0.1311
3.1500	1.7944	1.0697	0.2374	1.3071	674.17	256.42	2.4890	0.1309
3.1447	1.5271	1.2431	0.2366	1.4796	673.80	215.95	2.2658	0.1100
3.1449	1.5331	1.2385	0.2366	1.4751	673.75	216.92	2.2711	0.1054
3.1492	1.7106	1.1179	0.2370	1.3549	674.11	243.76	2.4193	0.1034
3.3877	2.0000	0.9013	0.2509	1.1523	689.60	309.94	2.8080	0.1029
3.3308	1.4819	1.2073	0.2466	1.4539	685.97	221.57	2.3162	0.0995
3.1412	1.7553	1.0945	0.2372	1.3317	673.57	249.87	2.4520	0.0947
3.1487	1.9188	1.0066	0.2375	1.2441	673.97	275.19	2.5919	0.0908
3.1347	1.8575	1.0414	0.2368	1.2783	673.11	264.74	2.5330	0.0901
3.1506	1.4171	1.3301	0.2369	1.5670	674.14	200.14	2.1794	0.0833
3.5416	2.0276	0.8518	0.2597	1.1115	699.65	328.85	2.9281	0.0811
3.0693	1.8805	1.0516	0.2335	1.2851	668.95	262.75	2.5155	0.0769
3.1494	1.6784	1.1376	0.2374	1.3750	674.14	238.81	2.3921	0.0733

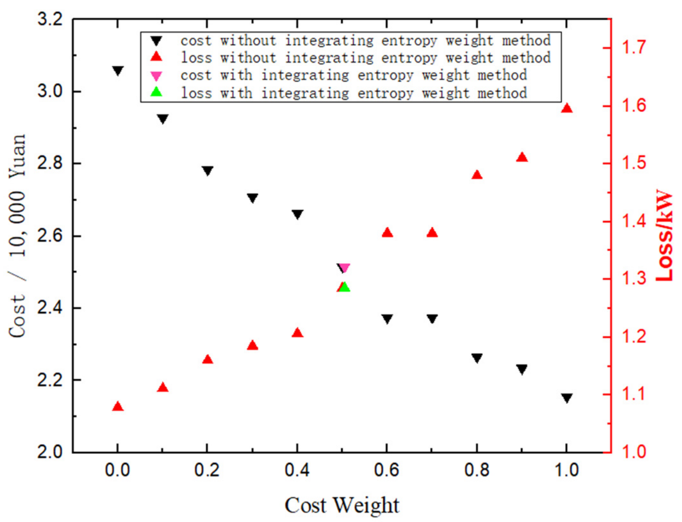

Figure 9. The cost and loss with/without integrating entropy weight method.

5. Experiment Validation

The optimization result gave the desired wire dimension as 3.07 mm × 1.88 mm, which is not a standard wire size. Thus, the closest size of 3.15 mm × 2 mm was selected. The trial reactor was made with this wire, and the loss test was conducted. The principle is shown in Figure 10a and the measurement is shown in Figure 10b. The test result was 1.25 kW, with an error of less than 5% compared to the calculated value, which verified the accuracy of the simulation calculation. The cost was also calculated, showing that the maximum cost saving of this design solution was about CNY 4000 compared to other wire options.

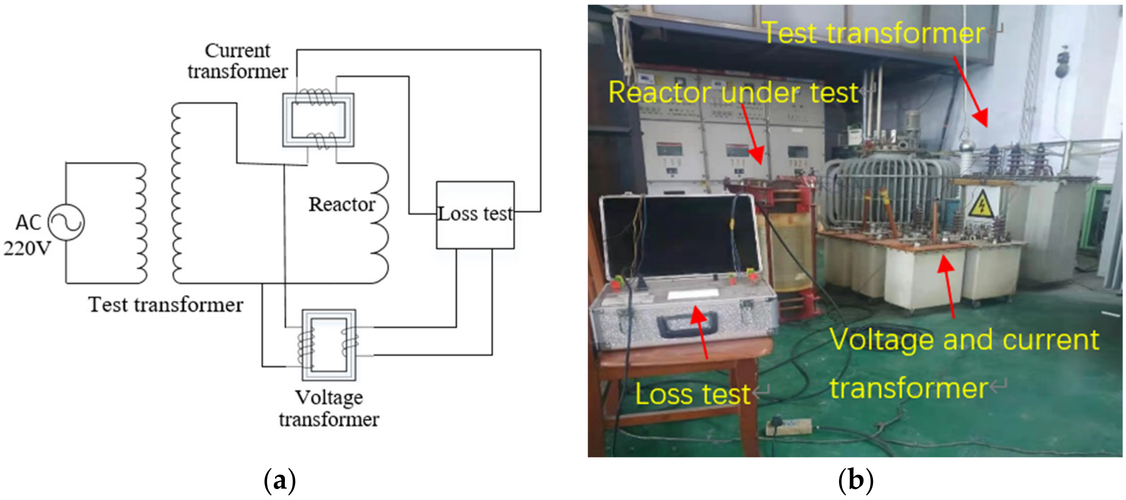

Figure 10. (**a**) The principle of loss test. (**b**) Loss measurement for the trial reactor.

6. Conclusions

In this paper, an optimal design approach for a dry iron-core reactor was proposed to balance its loss and cost. To implement the method, a three-dimensional FEM was constructed with the detailed geometry of the reactor. Joint Matlab-FEM calculation was utilized to obtain the magnetic field distribution and the reactor loss with arbitrary wire dimensions. The calculated result matches the tested value with less than 5% error. Additionally, the cost can be easily derived with the materials' information.

Based on the three-dimensional model, the influence of wire size on a three-phase dry iron core reactor's cost and loss was analyzed. To achieve an optimal design, cost and loss were used as the objective functions to perform the multi-objective optimization. The approach of integrating NSGA-II, TOPSIS and the entropy weight method is proposed for the design of the reactor. This novel approach can not only optimize the two parameters simultaneously, but also avoid the randomness of personal choice, which offers better quality guarantee for manufacture. The method was validated via a 10 kV reactor design. The trial product validates the method by comparing the loss and cost. The results show that the cost and loss of the reactor can be reduced by 17.85% and 19.45%, respectively.

This method can also be used for the design of other types of reactors and other electrical equipment, such as transformers. More constraints or objectives can be integrated into the algorithm for future research work, for example the size/weight of the product and the percentage of environmentally friendly materials that are used.

Author Contributions: Programming and simulation, Y.L. (Yan Li) and Y.L. (Yifan Liu); typesetting, Y.L. (Yifan Liu); review and revisions, S.L., L.Q. and J.X.; supervision, Q.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Fundamental Research Funds for the Central Universities under Grant 2022MS068.

Data Availability Statement: The study did not report any data.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

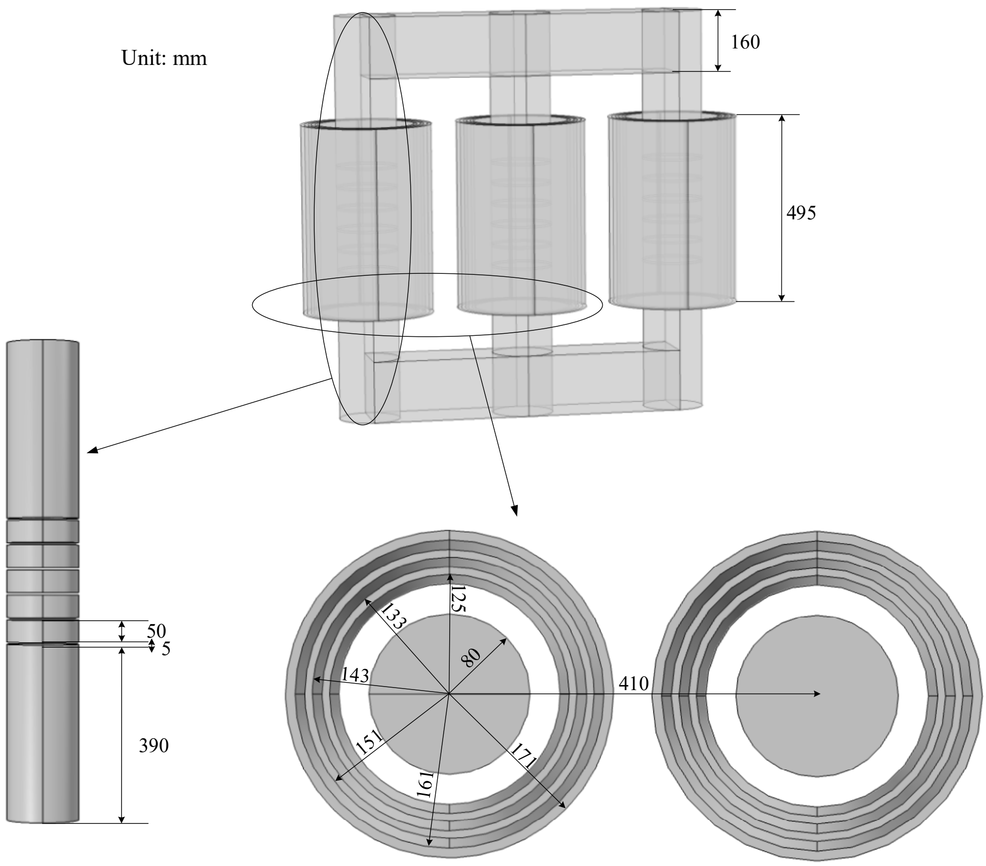

Figure A1. The dimensions of the model geometric.

Appendix B

Table A1. The detailed values in Figure 9.

Loss Weight	Cost Weight	Wire Length (mm)	Wire Width (mm)	Total Loss (kW)	Cost (CNY 10,000)
1	0	3.8070	1.9994	1.0786	3.0622
0.9	0.1	3.5416	2.0276	1.1115	2.9281
0.8	0.2	3.3500	2.0000	1.1601	2.7848
0.7	0.3	3.1713	2.0382	1.1851	2.7095
0.6	0.4	3.1500	2.0000	1.2064	2.6638
0.5	0.5	3.0693	1.8805	1.2851	2.5155
0.4949	0.5051	3.0693	1.8805	1.2851	2.5155
0.4	0.6	3.0589	1.7147	1.3803	2.3747
0.3	0.7	3.0589	1.7147	1.3803	2.3747
0.2	0.8	3.1447	1.5271	1.4796	2.2658
0.1	0.9	3.1503	1.4846	1.5108	2.2340
0	1	3.1459	1.3873	1.5954	2.1551

References

1. Li, S.; Man, Y.; Sun, Z.; Li, S.; Chen, R.; Zhao, C. A typical dry-type iron core reactor failure and its treatment measures. In Proceedings of the 2020 International Conference on Green Development and Environmental Science and Technology, Changsha, China, 18–20 September 2020.
2. Manuel Arias Velásquez, R.; Vanessa Mejía Lara, J. Magnetically controlled reactors design for weak grids. *Ain Shams Eng. J.* **2021**, *12*, 1183–1195. [CrossRef]
3. Yuan, F.; Lv, K.; Tang, B.; Wang, Y.; Yang, W.; Qin, S.; Ding, C. Optimization Design of Oil-Immersed Iron Core Reactor Based on the Particle Swarm Algorithm and Thermal Network Model. *Math. Probl. Eng.* **2021**, *16*, 536–544. [CrossRef]
4. Shen, L.; Xie, F.; Xiao, W.; Ji, H.; Zhang, B. Thermal Analyses of Reactor under High-Power and High-Frequency Square Wave Voltage Based on Improved Thermal Network Model. *Electronics* **2021**, *10*, 1342. [CrossRef]
5. Georgilakis, P.S. *Transformer and Inductor Design Handbook 3/E-Wm*; McLyman, T., Ed.; Springer: London, UK, 2013; pp. 1–30.
6. Dönük, A. Effects of Air Gaps on Core Losses of Shunt Reactors. *Celal Bayar Univ. J. Sci.* **2016**, *12*.
7. Yuan, F.; Yuan, Z.; Wang, Y.; Liu, J.; He, J.; Pan, Y. Thermal optimization for nature convection cooling performance of air core reactor with the rain cover: Thermal Optimization of Reactor with The Rain Cover. *IEEJ Trans. Electr. Electron. Eng.* **2018**, *13*, 995–1001. [CrossRef]
8. Ibuchi, T.; Funaki, T. A study on copper loss minimization of air-core reactor for high frequency switching power converter. In Proceedings of the 2013 4th IEEE International Symposium on Power Electronics for Distributed Generation Systems (PEDG), Rogers, AR, USA, 8–11 July 2013.
9. Yuan, F.; Yuan, Z.; Wang, Y.; Liu, J.; Su, H.; He, J. Research of electromagnetic and thermal optimization design on air core reactor. *IEEJ Trans. Electr. Electron. Eng.* **2018**, *13*, 725–731. [CrossRef]
10. Ma, C.; Zhao, Y.; Ma, X. Efficient optimization design of dry-type air-core reactors with the improved genetic algorithm. *Int. J. Appl. Electromagn. Mech.* **2017**, *55*, 235–242. [CrossRef]
11. Yuan, Y.; Wang, X.; Cao, J.; Chen, Q. Multi-objective optimization of laminar flow characteristics in helical coiled tubes based on NSGA-II. In Proceedings of the 6th International Symposium on Energy Science and Chemical Engineering, Harbin, China, 22–24 January 2021.
12. Xu, Y.; Guo, Q.; Tan, A.; Xu, L.; Tu, Y.; Liu, S. Multi-objective Route Planning of Museum Guide based on an Improved NSGA-II Algorithm. In Proceedings of the 2020 International Symposium on Automation, Information and Computing (ISAIC 2020), Beijing, China, 2–4 December 2020.
13. Tiong Teck, T.; Thillainathan, L.; Wai Lok, W.; Abidi, K.; John, T.; Wade, N.S.; Greenwood, D.M.; Patsios, C.; Taylor, P.C. Optimization of Fuzzy Energy-Management System for Grid-Connected Microgrid Using NSGA-II. *IEEE Trans. Cybern.* **2021**, *51*, 5375–5386.
14. El-Nemr, M.; Afifi, M.; Rezk, H.; Ibrahim, M. Finite Element Based Overall Optimization of Switched Reluctance Motor Using Multi-Objective Genetic Algorithm (NSGA-II). *Mathematics* **2021**, *9*, 576. [CrossRef]
15. Rabothata, M.; Muthu, J.; Wegner, L. Optimum design parameters and mechanical properties of polymeric nanocomposites using NSGA-II optimization method. *J. Compos. Mater.* **2021**, *55*, 949–972. [CrossRef]
16. Liu, X.; He, W.; Wei, F. Design of High Altitude Propeller Using Multilevel Optimization. *Int. J. Comput. Methods* **2020**, *17*, 32. [CrossRef]
17. Bolaos, R.I.; Isaza, R. Optimal Relocation of Distribution Transformers Using the Multiobjective Optimization Algorithm NSGA II. *Ing. Cienc.* **2014**, *10*, 77–97.
18. Orosz, T.; Karban, P.; Pánek, D.; Doležel, I. FEM-based transformer design optimization technique with evolutionary algorithms and geometric programming. *Int. J. Appl. Electromagn. Mech.* **2020**, *64*, 1–9. [CrossRef]
19. Cheng-fen, Z.; Yan-zhen, Z.; Feng, C.; Xi-kui, M. Multi-objective Optimum Design of Dry-type Air-core Reactor Based on Improved NSGA-II Algorithm. *Proc. CSEE* **2010**, *30*, 115–121.
20. Zhang, C.; Ma, X. NSGA-II Algorithm with a Local Search Strategy for Multiobjective Optimal Design of Dry-Type Air-Core Reactor. *Math. Probl. Eng.* **2015**, *2015*, 839035. [CrossRef]
21. Duan, Z.; Qian, X.; Wang, R.; Duo, Y.Q. Power Distribution System Evaluation in Chemical Industry Park Using Subjective and Objective Comprehensive Weight Method. *Adv. Mater. Res.* **2014**, *986*, 419–423. [CrossRef]
22. Wang, J.; Wang, X.; Yang, D.; Wang, K.; Zhou, Y. Magnetic Induction Tomography Simulation Analysis Based on Comsol Multiphysics Soft. In Proceedings of the 2018 5th International Conference on Advanced Composite Materials and Manufacturing Engineering, Xishuangbanna, China, 16–17 June 2018.
23. Khelifa, H.; Bentounsi, A.; Rebahi, F.; Machmoum, M. FE Simulation and Experiment of a Self-Excited SynRel Generator Based on COMSOL Software. *J. Electr. Eng. Technol.* **2020**, *16*, 899–905. [CrossRef]
24. Hiruma, S.; Igarashi, H. Fast computation of copper and iron losses using model order reduction. *Int. J. Appl. Electromagn. Mech.* **2019**, *60*, S79–S86. [CrossRef]
25. Bertotti, G. General properties of power losses in soft ferromagnetic materials. *IEEE Trans. Magn.* **2002**, *24*, 621–630. [CrossRef]
26. Amoiralis, E.I.; Tsili, M.A.; Kladas, A.G. Transformer Design and Optimization: A Literature Survey. *IEEE Trans. Power Deliv.* **2009**, *24*, 1999–2024. [CrossRef]
27. Liu, X.; Wang, Y.; Zhu, J.; Guo, Y.; Lei, G.; Liu, C. Calculation of core loss and copper loss in amorphous/nanocrystalline core-based high-frequency transformer. *AIP Adv.* **2016**, *6*, 4167–4182. [CrossRef]

28. Lin, Y.-K.; Chang, P.-C.; Yeng, L.C.-L.; Huang, S.-F. Bi-objective optimization for a multistate job-shop production network using NSGA-II and TOPSIS. *J. Manuf. Syst.* **2019**, *52*, 43–54. [CrossRef]
29. Jin, M.; Zhang, J.; Cui, S.; Kang, M.; Xiao, Y.; Xiang, R.; Yan, Z. Research on comprehensive evaluation of data link based on G1 method and entropy weight method. In Proceedings of the 2021 International Conference on Mechanical Engineering, Intelligent Manufacturing and Automation Technology (MEMAT), Guilin, China, 15–17 January 2021.
30. Rengaraj, M.; Subbaraj, S. Decision making on the state of transformers based on insulation condition using AHP and TOPSIS methods. *IET Sci. Meas. Technol.* **2020**, *14*, 137–145.
31. Dhiman, H.S.; Deb, D. Fuzzy TOPSIS and fuzzy COPRAS based multi-criteria decision making for hybrid wind farms. *Energy* **2020**, *202*, 117755. [CrossRef]
32. Lin, Y.; Zhang, W. Pareto efficiency in the infinite horizon mean-field type cooperative stochastic differential game. *J. Frankl. Inst.* **2021**, *358*, 5532–5551. [CrossRef]