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ENHANCING POWER TRANSFORMER OIL QUALITY WEIGHT FACTOR USING A GENETIC ALGORITHM

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ABSTRACT

Power transformers are critical to electrical power systems but are prone to failures due to factors such as heat, electricity, chemical reactions, mechanical stress, and adverse environmental conditions. Monitoring the insulating oil effectively is key to preventing these failures. A major challenge in this process is determining the optimal weights for the oil quality index, which lacks a standardized benchmark and often relies on subjective expert assessments. To reduce expert bias and subjectivity, this research utilizes a genetic algorithm to optimize the weightings for five essential parameters: color, water content, breakdown voltage (BDV), interfacial tension (IFT), and acidity. The algorithm operates through three stages: crossover, mutation, and selection, and analyzes data from 504 oil tests across various transformers. The mean absolute percentage error (MAPE) is used as the fitness value to assess the algorithm's effectiveness. The optimization process determined the best conditions as 132 iterations, a population size of 180, a crossover rate of 0.2, and a mutation rate of 0.8. These parameters achieved an average MAPE of 1.799% over ten trials, indicating high accuracy. This research not only optimizes the weighting of the oil quality index but also significantly reduces the need for expert input and subjective judgments in transformer maintenance. The findings are expected to improve the efficiency and reliability of power transformers, thereby minimizing failures and associated economic costs.

***Keywords**: : electricity, insulating oil, optimization, power system.*

I. INTRODUCTION

TRANSFORMERS are essential components of electrical power equipment. Transformer lifespans typically exceed 40 years. On the other hand, an unfavorable combination of heat, electricity, chemistry, mechanics, and the environment can occasionally cause power transformer failure to occur more quickly. A number of factors, including faults, oil quality, and paper condition, can lead to transformer insulation failure. These factors may shorten the transformer's service life, which could result in malfunctions and explosions while the transformer is in use [1], [2]. Thus, a transformer assessment is necessary to prevent unexpected transformer failure [3].

Oil is needed in various technologies due to recent technological advancements, particularly in power transformers. Power transformers use oil as a heat-transfer medium and for insulation. In order to lower the chance of a power transformer failure, oil insulation needs to be monitored [4], [5]. A suitable designed weighting mechanism is essential to obtaining a high oil quality index and preventing power transformer failure. The color, dissipation factor, kinematic viscosity (cSt), acidity, dielectric strength (kV), and water content (ppm) are the six factors that determine the oil quality index. Inadequate oil quality can lead to the release of dissolved gases, which can impact the transformer's chemical composition and electrical and thermal conditions [6].

No suitable benchmark value can be used as a reference to obtain the correct results or parameter weighting values. Expert judgment determines how each weighting factor should be applied. Because no standards have been established or followed, weighting is therefore extremely difficult to perform and is instead based on the expert's subjective judgments or weights taken from earlier research [7]. A weighting mechanism using artificial intelligence needs to be implemented to overcome this problem.

Entropy Weight Health Index (EWHI) method is one of the weighting techniques that past researchers

TABLE 1
DATA SAMPLES

Color	Water	BDV	IFT	Acidity	OQF	Rating
0.50	7.59	62.10	36.10	0.04	1.00	A
0.60	6.14	76.80	31.60	0.09	1.19	A
1.60	11.57	66.40	28.40	0.17	1.79	C
0.50	8.16	59.20	31.50	0.09	1.19	A
1.60	7.56	64.50	31.80	0.02	1.36	B
1.70	7.73	53.50	31.50	0.01	1.36	B
0.80	12.01	42.50	32.80	0.04	1.71	C
2.20	4.74	99.20	28.10	0.06	1.54	C
0.50	2.81	95.90	33.40	0.03	1.19	A
1.70	7.80	55.00	22.10	0.12	1.77	C

have employed. In order to determine the entropy weight, the parameter entropy was used in conjunction with the entropy weighting method, which was based on a jury matrix generated from the index values in every case. The entropy weight increases with the parameter's importance to the evaluation. The entropy weight method can increase the realism of evaluation results by minimizing the subjectivity of parameter weighting [8]. It is claimed that the primary benefit of the entropy weight method over other subjective weighting models is its ability to prevent human factors from influencing indicator weight, which improves the comprehensive evaluation results' objectivity [9]. In other research, entropy weights were combined with the VIKOR method to obtain alternative rankings after the entropy weight method was applied by the decision maker [10]. However, this method of determining weights still involves subjective evaluations.

Weight parameters can also be determined by applying decision support system techniques, such as the Analytical Hierarchy Process (AHP), which is used extensively. Two AHP models were tested to weight parameters in earlier research by comparing the questionnaire's individual and group form models [11]. A hierarchy is created based on the number of parameters that determine the transformer health index in order to apply AHP to weight parameters. Experts then perform an evaluation and prioritize each parameter [12]. However, the requirement for extensive information from experts is a drawback of the analytical hierarchy process [13]. There was high involvement of experts in previous studies to determine parameter weights.

The identified research gap lies in the reliance on the subjective judgment of experts and the lack of a completely objective method for determining the weighting factors of transformer oil quality. The approach used in previous studies still shows subjectivity, which can be time-consuming and may require extensive input from experts. To overcome this gap, this research proposes a more objective approach by utilizing a genetic algorithm to determine the weighting factors for transformer oil quality. The genetic algorithm is chosen due to its ability to handle discrete and continuous variables effectively, provide multiple optimal solutions, and increase the accuracy of classification results [14]. It can also work effectively with various types of optimizations, including analytical functions and numerical data [15][16]. With these advantages, a genetic algorithm is proposed in this research to determine the weights of a number of parameters, consisting of color, water content, breakdown voltage (BDV), interfacial tension (IFT), acidity, and water. This research aims to develop a genetic algorithm-based weighting method to determine the optimal weighting factors for transformer oil quality parameters. Additionally, the effectiveness of this method in enhancing the accuracy of transformer health index classification will be assessed. Meanwhile, this research novelty is that there is no involvement of experts in determining the oil quality weight factors.

II. RESEARCH METHOD

The tools and materials used in this research include the Python programming language, the Visual Studio Code (VS Code) editor, a laptop based on an Intel Core i7 processor, and Python libraries such as NumPy, Pandas, and SciPy. This study employs 504 data, each containing parameter values for color, water, BDV, IFT, acidity, and water content, from 150 kV transformers [17]. The sample data used is shown in Table 1.

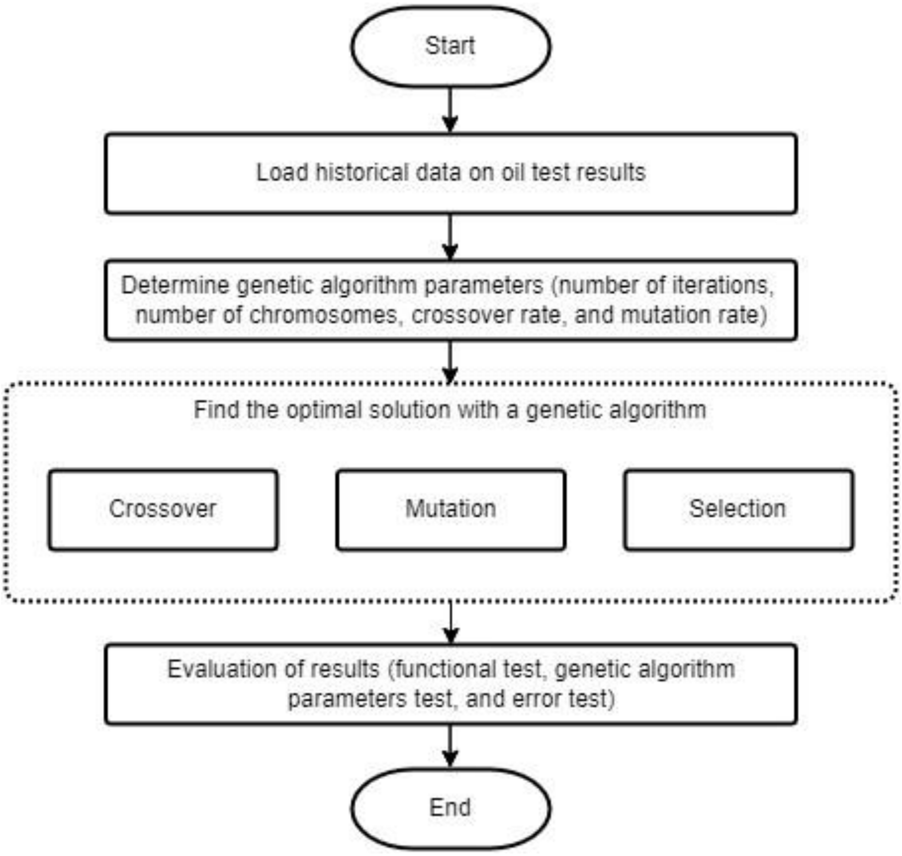

Figure 1. Genetic algorithm implementation workflow

In Table I, color indicates the color measurement value in the oil, water indicates the moisture measurement value in the transformer insulation, BDV indicates the presence of electrically conductive contaminants in the oil, IFT indicates the oil surface tension measurement value, acidity indicates the measurement value of the acid component in the oil, and OQF (Oil Quality Factor) is an oil quality value which is then transformed into an A to D scale as a Rating. The workflow for applying a genetic algorithm to determine the weight factor for power transformer oil quality is shown in Figure 1.

The implementation of the genetic algorithm in this research follows a systematic workflow, as shown in Figure 1. The process begins by loading historical data obtained from oil test results conducted on power transformers. This data serves as the input for the genetic algorithm, providing information on various parameters such as color, water content, breakdown voltage (BDV), interfacial tension (IFT), and acidity. Subsequently, genetic algorithm parameters, including the number of iterations, number of chromosomes, crossover rate, and mutation rate, are determined to guide the optimization process effectively. The genetic algorithm then proceeds to find the optimal solution through iterative stages of crossover, mutation, and selection. During crossover, genetic information from parent chromosomes is combined to generate offspring chromosomes. Mutation introduces random changes to the offspring's chromosomes. Selection determines which chromosomes are retained for the next generation based on their fitness. Through iterations of these stages, the genetic algorithm aims to converge toward the optimal solution for determining the weight of the oil quality index parameters. Following this optimization process, the results are evaluated comprehensively. This evaluation encompasses functional tests to ensure the effectiveness of the proposed solution, genetic algorithm parameter tests to validate the selected parameter settings, and error tests to assess the accuracy and reliability of the results obtained.

A. Data Preprocessing

Table 2 describes the data transformation results using scoring interval values ranging from 1 to 4 at the data preprocessing stage, with reference to Oil Quality Factor Scoring in Table 3 [18]. The value of each parameter obtained from observations of the power transformer in Table 1 is converted into a scale

TABLE 2
DATA PREPROCESSING RESULTS

Color Score	Water Score	BDV Score	IFT Score	Acidity Score
1	1	1	1	1
1	1	1	2	1
2	1	1	2	3
1	1	1	2	1
2	1	1	2	1
2	1	1	2	1
1	1	3	2	1
3	1	1	2	1
1	1	1	2	1
2	1	1	3	2

TABLE 3
OIL QUALITY FACTOR SCORING

Parameters	Score			
	1	2	3	4
Color	<1.5	1.5-2	2-2.5	>2.5
Water (ppm)	<20	20-25	25-30	>30
Breakdown voltage (BDV)	>50	50-45	45-40	<40
Interfacial tension (dyne/cm)	>35	35-25	25-20	<20
Acidity (MgKOH/mg)	<0.1	0.1-0.15	0.15-0.2	>0.2

TABLE 4
CHROMOSOME REPRESENTATION IN A POPULATION

Chromosome	Gene 1	Gene 2	Gene 3	Gene 4	Gene 5
1	0.14	0.56	0.57	0.21	0.42
2	0.72	0.78	0.36	0.35	0.98
3	0.35	0.46	0.12	0.23	0.34
4	0.78	0.58	0.12	0.35	0.36

form, as shown in Table 2. For example, the first row of data in the color parameter is 0.50, so the scale conversion becomes 1.

B. Encoding Scheme

The encoding scheme in this research employs a chromosome representation to describe each individual in the genetic algorithm population. The type of chromosome representation influences the genetic operators used and the organization of the problem within the genetic algorithm [16]. This study utilizes a real-coded chromosome representation, where each gene in the chromosome encodes the weight of an oil quality index parameter in real numbers. Accordingly, each chromosome comprises five real numbers, corresponding to the weights of the five parameters under investigation. Table 4 presents an example of a population with four chromosomes, each representing an alternative solution to the optimization problem.

Table 4 displays the weights for the color, water, BDV, IFT, and acidity parameters in Gene 1 through Gene 5. Early on, the respective values are determined randomly and will continue to be refined to a better solution as the algorithm progresses.

C. Fitness Function

A fitness function, an objective function with a different value for each problem, serves as the primary mechanism for assessing the status of each chromosome [19]. The weight solution for each parameter for each chromosome must be applied to the 504 data used in this study using (1) to calculate the Health Index value before computing the fitness value. Equation (2) illustrates how the estimated Health Index value is compared to the target value to determine the fitness value.

$$HI = \sum_{i=1}^{n} \sum_{j=1}^{p} w_j \times OQF_{ij} \tag{1}$$

$$fitness = \frac{1}{|HI - target\ HI|} \tag{2}$$

In (1) and (2), the Health Index is represented by *HI*, the weight of each parameter generated by each

TABLE 5
CROSSOVER RESULT

Chromosome	Gene 1	Gene 2	Gene 3	Gene 4	Gene 5
Parent-1	0.14	0.56	0.57	0.21	0.42
Parent-2	0.72	0.78	0.36	0.35	0.98
β	0.34	0.67	0.33	0.73	0.65
Offspring	0.33	0.70	0.49	0.30	0.78

TABLE 6
MUTATION RESULT

Chromosome	Gene 1	Gene 2	Gene 3	Gene 4	Gene 5
Parent-4	0.78	0.58	0.12	0.35	0.36
min	0	0	0	0	0
max	1	1	1	1	1
r	-0.01	0.03	0.05	-0.02	0.09
Offspring	0.77	0.61	0.17	0.33	0.45

particle is represented by *w*, the number of parameters is represented by *p* ($p = 5$), the amount of data is represented by *n* ($n = 504$), and the *OQF* displays the outcomes of converting the data into scores.

D. Crossover

The goal of the crossover is to create an offspring from two chosen chromosomes by combining the genes from the two chromosomes. The crossover mechanism begins by choosing two parent chromosomes randomly from the population [20]. The crossover method chosen depends on the type of chromosome representation employed. This research uses the heuristic crossover method by utilizing the random value β with a value range between 0 and 1. Equation (3) is used to produce one offspring using a heuristic crossover involving two selected parent chromosomes [21].

$$offspring = \{\beta_1(p_{m1} - p_{d1}) + p_{m1}, \cdots, \beta_n(p_{mn} - p_{dn}) + p_{mn} \tag{3}$$

In (3), the first gene value for parent-1 is represented by the p_{m1} and the first gene value for parent-2 is represented by the p_{d1}. An illustration of the crossover process using the heuristic crossover is shown in Table 5.

Table 5 shows that the combination of two parent chromosomes produces several new gene values on the offspring chromosome. The tendency for gene values to approach parent-1 or parent-2 is influenced by the random value β.

E. Mutation

One or more genes on a chromosome are replaced during the mutation process. To prevent early convergence of the search results, this replacement aims to increase chromosome variation in the population. This research uses the uniform mutation method. The gene replacement value used is a random number generated using a normal distribution with an average value equal to 0 [22]. The uniform mutation process is carried out using (4) [23][21].

$$x_n = p_n + r(max_n - min_n) \tag{4}$$

In (4), the value of the parent gene at position *n* is represented by p_n, the upper and lower bounds of the gene value at position n are represented by max_n and min_n, respectively, and r is a random value selected from the range -0.1 to 0.1. An illustration of the mutation process using the uniform mutation is shown in Table 6.

In the real-coded chromosome representation, the mutation process changes all the gene values of the selected parent chromosome when forming the offspring chromosome. However, in this case, the gene change is only affected by one parent in contrast to crossover, which involves two parents.

F. Selection

Several chromosomes are chosen from a population to be parents in the following generation. This process is known as selection. Compared with crossover or mutation, the selection method is not influenced by the type of chromosome representation [24]. This research uses the elitism selection method, which is the most widely used method. Chromosomes with high fitness values are maintained

TABLE 7
TEST RESULTS FOR THE NUMBER OF ITERATIONS

Number of Iterations	Trial Number					Average Fitness Values
	1	2	3	4	5	
1	0.245	0.495	0.239	0.318	0.146	0.288
2	0.504	0.583	0.539	0.318	0.301	0.448
3	0.504	0.583	0.539	0.454	0.301	0.476
4	0.504	0.584	0.539	0.525	0.508	0.532
5	0.628	1.313	0.539	0.539	0.514	0.706
6	0.628	1.313	0.811	0.539	0.713	0.801
7	0.628	1.313	0.811	0.593	0.713	0.812
8	0.628	1.968	0.886	1.657	0.713	1.171
9	1.846	1.968	0.886	1.657	0.713	1.171
10	1.846	3.173	0.962	1.657	0.713	1.626
…	…	…	…	…	…	…
200	3.871	3.520	4.501	5.604	7.710	5.041

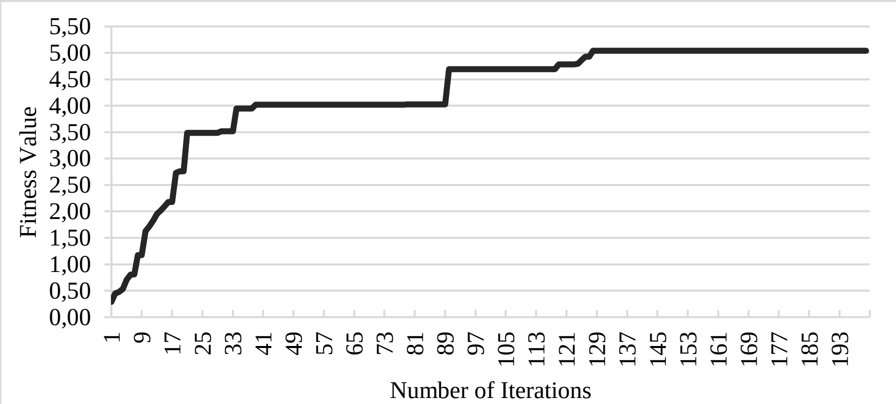

Figure 2. Number of iterations test graph

using this method to ensure their survival for each generation. All chromosomes must first be arranged from the highest fitness value to the lowest (descending) to perform selection using the elitism method. Chromosomes at the top of the population size will survive and be able to pass on to the following generation once all the chromosomes have been sorted.

III. RESULT AND DISCUSSION

To determine the performance of the genetic algorithm in parameter weighting, there are three types of genetic algorithm parameter testing carried out, consisting of the number of iterations test, the number of chromosomes (population size) test, and a combination of crossover rate (cr) and mutation rate (mr) test. Each type of test has several test scenarios with different test parameter values.

A. The Number of Iterations Test

In the number of iterations test, the genetic algorithm searches for a solution in 200 iterations with a static population size of 30 [25]. The experiment is carried out five times to get the average value. Table 7 and Figure 2 display the test results.

Analysis of the test results for the number of iterations showed a continuous increase in the fitness value graph from the first iteration. However, the graph stabilized after iteration 132, showing no further improvement in fitness values in subsequent iterations. This finding indicates that 132 iterations are optimal for efficiently generating a solution with a high fitness value.

B. The Number of Chromosomes Test

Tests of the number of chromosomes (population size) were conducted with 132 iterations, the optimal iteration value. Several test scenarios were run five times to obtain an average fitness value. Table 8 and Figure 3 display the test results.

The population size test results show that the fitness value graph has increased since the population size was 10. The graph, however, tends to stabilize at population sizes greater than 180, and fitness values do not increase further at subsequent population sizes. Therefore, the ideal population size for producing solutions with high fitness values is 180.

TABLE 8
TEST RESULTS FOR THE POPULATION SIZE

Population Size	Trial Number 1	2	3	4	5	Average Fitness Values
10	5.422	3.267	3.943	0.627	3.122	2.333
20	1.511	2.753	5.550	6.905	5.396	3.213
30	3.961	3.086	4.337	3.081	6.308	3.305
40	5.642	2.517	4.010	6.957	4.867	3.690
50	4.423	2.691	16.021	6.645	3.279	5.952
60	12.909	5.613	7.342	3.364	5.858	6.122
70	13.206	8.213	6.448	6.263	4.766	6.951
80	5.920	18.072	8.175	4.681	5.010	7.012
…	…	…	…	…	…	…
200	18.704	7.787	16.308	15.122	13.484	11.934

TABLE 9
COMBINATION OF CROSSOVER RATE AND MUTATION RATE TEST RESULTS

Crossover Rate	Mutation Rate	Trial Number 1	2	3	4	5	Average Fitness Values
0.1	0.9	16.107	19.937	22.569	6.938	12.453	8.022
0.2	0.8	11.683	13.158	21.188	23.066	22.653	12.404
0.3	0.7	7.721	12.869	6.861	12.183	16.149	9.276
0.4	0.6	18.945	11.239	20.316	7.352	12.330	11.263
0.5	0.5	6.173	15.184	11.714	14.637	20.452	11.820
0.6	0.4	10.925	17.113	24.856	6.869	10.848	12.149
0.7	0.3	4.151	6.031	7.039	15.682	10.854	7.838
0.8	0.2	9.621	6.419	9.788	10.380	8.490	8.108
0.9	0.1	7.390	4.926	3.301	2.779	8.689	5.006

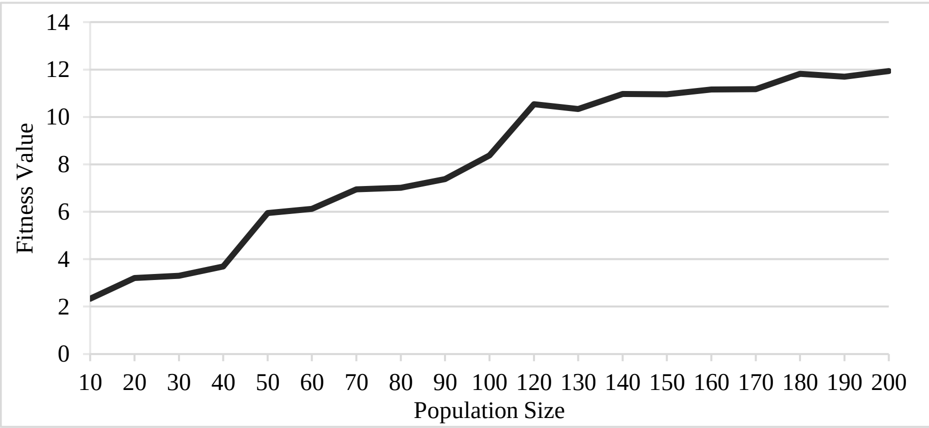

Figure 3. Population size test graph

C. *A Combination of Crossover Rate and Mutation Rate Test*

The goal of crossover rate and mutation rate testing is to determine how many crossover and mutation processes must be completed in tandem to obtain the optimal solution with a high fitness value. The combination parameters for this test were crossover rate 0.1, mutation rate 0.9, and so forth, under the requirement that the total crossover rate and mutation rate be 1. Every scenario was put to the test five times, and Table 9 and Figure 4 display the test results.

Crossover and mutation rate affect the number of offspring produced during reproduction. The more offspring there are, the more alternative solutions are found, opening the opportunity to find the best solution, but the time required for the reproduction process becomes longer. The results show that the best fitness value is obtained when the crossover rate is 0.2 and the mutation rate is 0.8, which indicates that these two values are the optimal combination.

D. *Error Value Test*

The error value test is used to measure the quality of the genetic algorithm in determining the weight of the oil quality index parameters. In this test, the genetic algorithm parameter settings used come from the test results that have been carried out, including the number of iterations 132, population size 180, crossover rate 0.2, and mutation rate 0.8. Trials were carried out on 504 data to find five parameter

TABLE 10
ERROR VALUE TEST RESULTS

Trial Number	Parameters					MAPE (%)
	Color	Water	BDV	IFT	Acidity	
1	0.40	0.46	0.73	0.53	0.60	3.307
2	0.60	0.63	0.99	0.73	0.81	1.820
3	0.63	0.59	0.93	0.83	0.77	2.302
4	0.50	0.52	0.81	0.59	0.66	1.504
5	0.60	0.62	0.98	0.72	0.81	1.569
6	0.70	0.70	1.09	0.79	0.90	0.928
7	0.73	0.68	1.01	0.79	0.89	1.113
8	0.60	0.63	0.98	0.71	0.81	1.691
9	0.56	0.61	0.96	0.71	0.78	2.180
10	0.60	0.62	0.98	0.72	0.80	1.570
Average MAPE						1.799

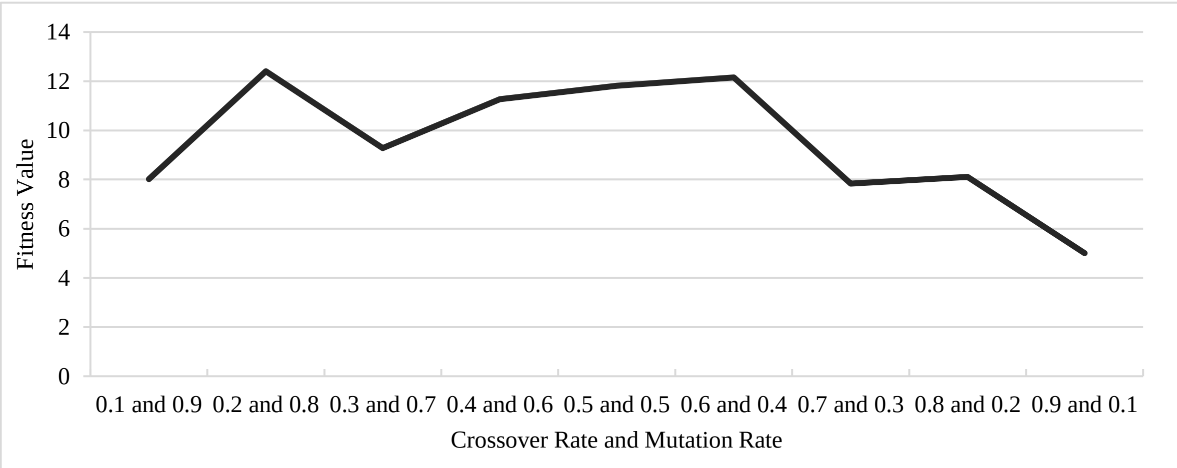

Figure 4. Combination of crossover rate and mutation rate test graph

weights for the oil quality index, each with ten trials. The error value is calculated using the Mean Absolute Percentage Error (MAPE) evaluation metric. Table 10 shows the results of the error value test.

Table 10 shows that, out of ten experiments, the average MAPE was 1,799%, and every experiment produced a MAPE of less than 10%, indicating that the results are highly accurate [26][27]. This implies that the genetic algorithm was successfully applied to determine the weight of the oil quality index parameters. Meanwhile, the lowest error value was obtained in experiment 6 with a MAPE of 0.928%, which means that the five weighted parameters that have been determined can be applied to measure the transformer health index, with details of color 0.70, water 0.70, BDV 1.09, IFT 0.79, and acidity 0.90.

E. Comparison Results with Previous Research

Several approaches used in earlier research were compared with the outcomes of using genetic algorithms to determine the weighting factors for the oil quality index. Table 11 presents the findings from various approaches, which includes key results and limitations.

Based on Table 11, the comparison between the proposed genetic algorithm method and previous methodologies reveals several significant insights. First, the EWHI and AHP methods rely heavily on subjective judgment or expert input to determine parameter weights, whereas the proposed genetic algorithm method eliminates the need for expert involvement, thereby reducing subjectivity. Additionally, a genetic algorithm provides a systematic and objective way to derive weighting factors for each transformer health index parameter based only on historical data. This shift toward data-based decision-making increases the reliability and objectivity of the index.

Comparing the proposed genetic algorithm method with existing approaches highlights its advantages and limitations. In contrast to EWHI and AHP methods, which may suffer from subjectivity and uncertainty due to reliance on expert judgment or subjective decision-making processes, genetic algorithm methods offer a more transparent and reproducible way of determining parameter weights. However, this genetic algorithm approach requires historical data for training, which may pose limitations if such data is unavailable or does not adequately represent all possible scenarios.

TABLE 11
COMPARISON RESULTS

Methods	Results	Limitations
EWHI [8]	The entropy weight health index of the power transformer is obtained from the entropy weight and the entropy of each parameter.	This method presents subjective judgment in the weight determination process
EW and VIKOR [10]	The entropy weight is used to calculate the weight of each parameter, and then the selection of the best scheme is carried out using the VIKOR method for decision-making.	The product design idea development process is subjective and uncertain.
AHP [11]	The AHP model can present parameter weights for individuals and groups using seven comparisons (group form) compared to thirteen paired questionnaires (individual form) when determining parameter weights for creating a water quality index.	This method requires several respondents from stakeholders to obtain independent assessments.
AHP [12]	This method provides weight factors for the transformer health index based on a hierarchy of importance levels for each parameter.	This method requires expert judgment, statistics, or other considerations for pairwise comparison assessments in the AHP stage.
Genetic algorithm (Proposed)	Without the involvement of experts, this method produces a transformer health index weighting factor for each parameter	This method requires historical data which is used as training data to find the right weights.

Genetic algorithm methods have the limitation of being dependent on historical data for their training. Although this eliminates the need for expert judgment, the effectiveness of this method may be influenced by the quality and representativeness of the data. Furthermore, users who do not have sufficient expertise in optimizing the algorithms and tuning the parameters used may face challenges due to the complexity of implementing and tuning genetic algorithms.

The findings of this comparison have several implications for transformer health assessment and decision-making processes. By demonstrating the feasibility and advantages of the genetic algorithm approach, this research highlights the potential for transitioning towards more data-driven and objective methodologies in transformer health management. This shift can enhance the accuracy and reliability of transformer health assessments, leading to improved maintenance strategies and a reduced risk of unexpected failures. Furthermore, the elimination of expert involvement in parameter weighting can streamline the decision-making process and reduce reliance on subjective assessments, thereby increasing efficiency and consistency in transformer health management practices.

IV. CONCLUSION

With optimal parameter settings of the number of iterations 132, population size 180, crossover rate 0.2, and mutation rate 0.8, the genetic algorithm was successfully used to determine the weight of the oil quality index parameters. The optimal outcome of the genetic algorithm employed to determine the weight of the oil quality index parameters was a MAPE value of 1.799%, which resulted in a color weight of 0.70, a water weight of 0.70, a BDV weight of 1.09, an IFT weight of 0.79, and an acidity weight of 0.90. This low MAPE indicates that the results provided are highly accurate so that the parameter weights that have been obtained can be used in measuring the transformer health index. In addition, this research excels in the parameter weighting method without direct involvement of experts. Despite the limitations of historical data, this autonomous approach provides an innovative and efficient solution in parameter weighting methods.

In future research, the exploration of real-time data integration can be improved by developing algorithms and systems that can effortlessly integrate streaming data from various sensors and monitoring devices installed on power transformers into a genetic algorithm framework. This integration would enable the dynamic adjustment of parameter weights in real-time based on current operational conditions, enhancing the adaptability and predictive capabilities of the transformer health index. Moreover, a deeper exploration of multi-objective optimization using a genetic algorithm framework is possible. This could involve developing new optimization techniques that can optimize multiple objectives in transformer health assessment, such as reliability, efficiency, and cost-effectiveness. By considering diverse stakeholder objectives and constraints, this approach can offer a more comprehensive and holistic approach to transformer health management and decision-making, ultimately leading to improved reliability and efficiency in power systems.

REFERENCES

[1] A. Naderian, P. Pattabi, and L. Lamarre, "Improving the Assessment of Remaining Life of Service Aged Power Transformers," in *2019 IEEE Electrical Insulation Conference (EIC)*, 2019, pp. 330–334.
[2] I. Diahovchenko *et al.*, "Mitigation of transformers' loss of life in power distribution networks with high penetration of electric vehicles," *Results in Engineering*, vol. 15, p. 100592, Sep. 2022, doi: 10.1016/j.rineng.2022.100592.
[3] W. R. Tamma, R. A. Prasojo, and Suwarno, "High voltage power transformer condition assessment considering the health index value and its decreasing rate," *High Voltage*, vol. 6, no. 2, pp. 314–327, Apr. 2021, doi: 10.1049/hve2.12074.
[4] M. Badawi *et al.*, "Reliable Estimation for Health Index of Transformer Oil Based on Novel Combined Predictive Maintenance Techniques," *IEEE Access*, vol. 10, pp. 25954–25972, 2022, doi: 10.1109/ACCESS.2022.3156102.
[5] A. Dhini, A. Faqih, B. Kusumoputro, I. Surjandari, and A. Kusiak, "Data-driven fault diagnosis of power transformers using dissolved gas analysis (DGA)," *International Journal of Technology*, vol. 11, no. 2, pp. 388–399, 2020, doi: 10.14716/ijtech.v11i2.3625.
[6] M. E. A. Senoussaoui, M. Brahami, and I. Fofana, "Transformer oil quality assessment using random forest with feature engineering," *Energies (Basel)*, vol. 14, no. 7, Apr. 2021, doi: 10.3390/en14071809.
[7] B. P. Das and L. Cheim, "Transformer assessment using health index - Part II," *Transformers Magazine*, vol. 8, no. 1, pp. 58–64, 2021.
[8] Y. Zhou, L. Ma, J. Yang, and C. Xia, "Entropy Weight Health Index Method of Power Transformer Condition Assessment," in *The Proceedings of 2011 9th International Conference on Reliability, Maintainability and Safety*, IEEE, 2011, pp. 426–431.
[9] Y. Zhu, D. Tian, and F. Yan, "Effectiveness of Entropy Weight Method in Decision-Making," *Math Probl Eng*, vol. 2020, pp. 1–5, 2020, doi: 10.1155/2020/3564835.
[10] S. Luo and P. Yang, "Design and evaluation of a sustainable entropy-weighted and VIKOR-based method for offshore oil collecting," *Heliyon*, vol. 9, no. 11, p. e21256, Nov. 2023, doi: 10.1016/j.heliyon.2023.e21256.
[11] A. D. Sutadian, N. Muttil, A. G. Yilmaz, and B. J. C. Perera, "Using the Analytic Hierarchy Process to identify parameter weights for developing a water quality index," *Ecol Indic*, vol. 75, pp. 220–233, Apr. 2017, doi: 10.1016/j.ecolind.2016.12.043.
[12] R. A. Prasojo, A. Setiawan, Suwarno, N. U. Maulidevi, and B. A. Soedjarno, "Development of Analytic Hierarchy Process Technique in Determining Weighting Factor for Power Transformer Health Index," in *2019 2nd International Conference on High Voltage Engineering and Power Systems (ICHVEPS)*, 2019, pp. 1–5.
[13] A. V. Lubentsov, V. N. Bobrov, D. B. Desytov, and A. N. Noev, "The advantage of the method of hierarchy analysis, the statistical methods of decision support," in *Journal of Physics: Conference Series*, Institute of Physics Publishing, Apr. 2019, p. 012079. doi: 10.1088/1742-6596/1203/1/012079.
[14] K. Varpa, K. Iltanen, and M. Juhola, "Genetic Algorithm Based Approach in Attribute Weighting for a Medical Data Set," *Journal of Computational Medicine*, pp. 1–11, Sep. 2014, doi: 10.1155/2014/526801.
[15] V. N. Wijayaningrum and W. F. Mahmudy, "Fodder composition optimization using modified genetic algorithm," *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, vol. 7, no. 1, pp. 67–74, 2019, doi: 10.11591/ijeei.v7i1.461.
[16] S. Katoch, S. S. Chauhan, and V. Kumar, "A review on genetic algorithm: past, present, and future," *Multimed Tools Appl*, vol. 80, no. 5, pp. 8091–8126, Feb. 2021, doi: 10.1007/s11042-020-10139-6.
[17] D. Rediansyah, R. A. Prasojo, Suwarno, and A. Abu-Siada, "Artificial intelligence-based power transformer health index for handling data uncertainty," *IEEE Access*, vol. 9, pp. 150637–150648, 2021, doi: 10.1109/ACCESS.2021.3125379.
[18] W. R. Tamma, R. A. Prasojo, and Suwarno, "High voltage power transformer condition assessment considering the health index value and its decreasing rate," *High Voltage*, vol. 6, no. 2, pp. 314–327, 2021, doi: 10.1049/hve2.12074.
[19] Z.-D. Xu, Y.-Q. Guo, J.-T. Zhu, and F.-H. Xu, "Intelligent Control Strategies," in *Intelligent Vibration Control in Civil Engineering Structures*, Elsevier, 2017, pp. 21–61. doi: 10.1016/b978-0-12-405874-3.00002-3.
[20] R. A. Pambudi, W. Lubis, F. R. Saputra, H. P. Maulidina, and V. N. Wijayaningrum, "Genetic Algorithm for Teaching Distribution based on Lecturers' Expertise," *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control*, vol. 4, no. 4, pp. 297–304, 2019, doi: 10.22219/kinetik.v4i4.859.
[21] V. N. Wijayaningrum, *Konsep dan Penerapan Algoritma Genetika*. Banda Aceh: Syiah Kuala University Press, 2021.
[22] E. Wirsansky, *Hands-On Genetic Algorithms with Python*. Packt Publishing, 2020.
[23] V. N. Wijayaningrum, W. F. Mahmudy, and M. H. Natsir, "Optimization of Poultry Feed Composition using Hybrid Adaptive Genetic Algorithm and Simulated Annealing," *Journal of Telecommunication, Electronic and Computer Engineering*, vol. 9, no. 2–8, pp. 183–187, 2017.
[24] H. Du, Z. Wang, W. Zhan, and J. Guo, "Elitism and distance strategy for selection of evolutionary algorithms," *IEEE Access*, vol. 6, pp. 44531–44541, Aug. 2018, doi: 10.1109/ACCESS.2018.2861760.
[25] K. Kalaiselvi and A. Kumar, "An empirical study on effect of variations in the population size and generations of genetic algorithms in cryptography," in *2017 IEEE International Conference on Current Trends in Advanced Computing (ICCTAC)*, 2017, pp. 1–5.
[26] J. J. M. Moreno, A. P. Pol, A. S. Abad, and B. C. Blasco, "Using the R-MAPE index as a resistant measure of forecast accuracy," *Psicothema*, vol. 25, no. 4, pp. 500–506, 2013, doi: 10.7334/psicothema2013.23.
[27] M. I. Ananda, "Model Analysis of Gated Recurrent Unit for Multivariate Rice Price Forecasting," *Jurnal ELTIKOM: Jurnal Teknik Elektro, Teknologi Informasi dan Komputer*, vol. 7, no. 2, pp. 125–132, 2023, doi: 10.31961/eltikom.v7i2.770.