IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 19 March 2024, accepted 27 March 2024, date of publication 1 April 2024, date of current version 16 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3383856

RESEARCH ARTICLE

Enhancement of Maintenance Scheduling of Distribution Transformers Using Carnivorous Plant Algorithm Based Optimization Approach

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ABSTRACT This paper employs the carnivorous plant growth-based optimization approach to optimize the maintenance scheduling of distribution transformers, encompassing inspection and overhaul tasks. The resulting maintenance schedule not only mitigates cost investments but also guarantees a reliable power supply. The study comprehensively incorporates maintenance costs and operational reliability, accounting for factors such as salt corrosion and insulation lifetime loss. Mathematical models are formulated with consideration of operational constraints, followed by the implementation of the proposed approach to achieve a schedule close to optimality. Validation of the method is conducted through both a sample system and a practical Taipower system with varying numbers of transformers. The test results confirm the feasibility of the proposed method for the considered application.

INDEX TERMS Carnivorous plant algorithm, maintenance scheduling, distribution transformer.

I. INTRODUCTION

The total number of distribution transformers (DTRs) in Taiwan was estimated approximately 1.4 million according to 2021 data [1]. Maintaining and operating this large number of DTRs can be a significant burden for electric power companies. While prevailing maintenance methods have focused on fixed time intervals, the increasing failure rate, maintenance costs, insulation aging, and salt corrosion of DTRs since the rising demand requires more attention than ever. In addition, due to issues such as a declining birthrate and a trend towards employment in the manufacturing industry, the workforce involved in power distribution maintenance shows very limited signs of growth [2]. This could ultimately result in a decline in the maintenance quality of power companies and an increase in the probability of power outages. These factors must be carefully considered to develop a maintenance schedule that ensures higher reliability, better economic benefits, and greater efficiency.

Given the importance of maintenance scheduling, various methods have been developed and applied to power transmission and distribution systems to solve this problem. Some of these methods utilized analytical approaches such as linear programming [3], [4], which were shown to reach global solutions systematically. However, these methods were not always feasible for practical scheduling and required additional efforts to address this limitation. Other methods have suggested modeling equipment outage behavior using Markov decision trees and dynamic programming to tackle this issue [5], [6], [7]. Yet, the effective establishment of Markov decision trees relied on sufficient data collected from monitoring and acquisition, which was often complicated due to the substantial number of DTRs. Furthermore, since these published methods were intended for transmission systems,

The associate editor coordinating the review of this manuscript and approving it for publication was Hazlie Mokhlis.

the focus of this study may be fundamentally different. This is because the maintenance procedures for transformers are intricate and consume a considerable amount of time and manpower, primarily due to the large quantity of distribution transformers. Without well-organized maintenance efforts, not only are maintenance resources wasted, but it also adversely affects the maintenance of other distribution equipment. Meanwhile, the maintenance scheduling optimization problem with a vast number of variables belongs to the class of non-deterministic polynomial (NP) problems. The challenge lies in the inability to estimate the time required to find the optimal solution, and in some cases, it is uncertain whether an optimal solution can be found at all [8]. The algorithms such as dynamic programming and linear programming, as mentioned above, exhibit limited efficiency in solving maintenance scheduling problems for distribution equipment.

Due to the disadvantages mentioned above, recent studies have started to utilize heuristic algorithms such as genetic algorithms (GA) [10], [11], evolutionary algorithms [12], particle swarm optimization (PSO) [13], [14], [15], and artificial bee colony algorithm [16] to solve this maintenance scheduling problem. This type of algorithm has randomness and can adjust the search direction based on the current value of the objective function. Although it cannot guarantee finding the optimal solution, it can achieve a balance among computational time, resource investment, and solution efficiency [17], [18]. Many people have questioned the need for so many heuristic algorithms. However, according to the No Free Lunch (NFL) theorem [19], if algorithm A outperforms algorithm B in solving problem X, it does not necessarily mean that algorithm A will outperform algorithm B in solving problem Y. In other words, there is no one-size-fits-all algorithm for all optimization problems. Therefore, in the face of increasingly complex problems, the academic community still encourages the continuous development of diverse optimization algorithms.

In this paper, by mimicking the bionic random process, a carnivorous plant growth-based optimization approach is applied to solve the maintenance scheduling problem of DTRs. The performance and robustness of this method in solving mathematical problems and engineering design have been verified. Simulations were conducted for both classic and CEC2017 benchmark functions, and the results demonstrated that the performance of CPA is superior to GA, PSO and Differential Evolution (DE), Cuckoo Search Algorithm (CSA) and Bat Algorithm (BA). Moreover, CPA has been utilized for solving various problems, such as the Traveling Salesman Problem [9] and the design of speed reducers [20]. Additionally, CPA shows excellent performance in solving high-dimensional problems [21], making it suitable for addressing scheduling issues with a large number of devices.

The CPA method is inspired from the preying and growth mechanisms observed in carnivorous plants. In this approach, the maintenance scheduling process is analogized to the growth of a plant. The maintenance strategy is emulated through the simulation of a plant's fitness change, employing a scheme that involves grouping, preying, and growing. The research delves into the failure patterns of DTRs, formulating mathematical models for multi-objective functions that considers environmental factors and operating conditions. Subsequently, the carnivorous plant algorithm is applied, and a comprehensive validation is conducted on both example systems and real-world scenarios across various testing scenarios. The feasibility of this method has been assessed, and its primary features can be summarized as follows:

1) Previous studies have given less consideration to insulation life loss and salt corrosion in their mathematical models. In contrast, this study takes both factors into account, resulting in a more comprehensive maintenance strategy than previous approaches.
2) The study proposes an optimization approach that includes local search, global search, and local escape mechanisms, making it more effective for solving optimization problems.
3) The proposed algorithm is systematic and expandable, which can be easily integrated with other commercial software for utility equipment maintenance applications.

The paper is organized as follows: Section II describes the problem of failure and maintenance of DTRs. Section III formulates the paradigms of maintenance scheduling. Section IV explains the proposed method, Section V illuminates the computation procedure, Section VI discusses the numerical tests, and Section VII presents the conclusions.

II. PROBLEM DESCRIPTIONS

The maintenance work of DTRs involves two primary tasks: inspection and overhaul. During the inspection task, DTRs undergo a visual examination, complemented by the utilization of handheld infrared and ultrasonic instruments for enhanced precision. If a defect is found, it will be repaired immediately on site or at a later time depending on its level of urgency. To the best of our knowledge, DTRs are inspected once a year in Taiwan [22]. The overhaul task focuses on the refurbishing and thorough electrical examination of DTRs. In the past, the power department in Taiwan established a fixed overhaul period of once every 12 years with consideration of the durability, failure frequency, and maintenance complexity of DTRs. While a higher overhaul frequency might enhance stability, it would also require more maintenance resources. In order to enhance the practical value of this study, we also conducted field visits to maintenance facilities and gathered a wealth of information. It was found that the vast majority of transformers undergoing regular major maintenance were in good condition, yet there were still frequent reports of failures. This indicates that the current fixed-cycle maintenance approach needs improvement in its ability to detect faults early. Therefore, based on the existing 12-year planning schedule and under the condition of not increasing the current personnel maintenance burden, this article takes the effects of load and operating temperature into account, aiming to conduct early inspections or replacements for transformers with higher potential failure rates while delaying maintenance for the rest. This approach not only allows for the completion of all transformer maintenance within 12 years but also reduces the probability of distribution system failures, thereby enhancing the efficiency of maintenance work.

This study begins by examining the failure events of DTRs, which can be primarily attributed to either external faults or internal faults. External faults include issues such as (a) oil leakage caused by aging tanks or gaskets, (b) poor contact between primary and secondary terminals, and (c) partial discharge resulting from dirt or salt buildup on bushings. In contrast, internal faults often arise from the deterioration of insulation material such as insulation paper, pressboard, support tube and insulation oil, leading to insulation breakdowns between coil windings. Given the distinct differences in repairability and maintenance requirements, the failure models for internal and external faults are developed separately. The study utilizes the Weibull failure model to represent external faults and the insulation lifetime loss function to model internal faults. It is also noted that relevant studies indicate that salt corrosion has a significant impact on the failure of insulators [23], and the demand for maintenance frequency is also different. Therefore, the modeling of the external fault rate curve of distribution transformers must be distinguished between severe and light salt corrosion areas. Based on these formulated models, the study aims to achieve a maintenance schedule that provides higher reliability, lower insulation life loss, and reduced maintenance expenses.

III. PARADIGM OF MAINTENANCE SCHEDULING

The effectiveness of maintenance scheduling can be evaluated by analyzing various indices, including service reliability, maintenance cost, and insulation life loss. This section utilizes the Weibull model to analyze the failure rate of DTR and investigate service reliability, which is followed by the examination of maintenance cost that consists of the personnel cost and equipment investment required for inspection and overhaul. Additionally, insulation life loss is also considered as an objective function during the optimization process. By summing up these objective functions with constraints, a maintenance scheduling plan for DTRs is formulated.

A. FAILURE MODEL AND RELIABILITY INDEX

The failure rate of DTRs increases as the number of operating hour increases. The analysis methods for solving the failure rate can be divided into distribution-free statistics and parametric statistics. The distribution-free statistics directly calculates the failure rate by dividing the number of equipment failures by the total amount of equipment without applying any distribution model. Although the calculation of distribution-free statistics is simple, yet, the accuracy may be lower if it is used for equipment with a specific probability distribution pattern. As for the parametric statistics, it includes normal distribution and Weibull distribution. Several studies have pointed out that the Weibull distribution model is suitable for the analysis of transformers and power equipment [24], [25]. Related applications include remaining life assessment [26], failure prediction [24], and risk assessment [27]. This study also utilizes the Weibull failure model to comprehend the failure trend [31], [32]. The probability density function (PDF) p(t) for the Weibull failure model is expressed below:

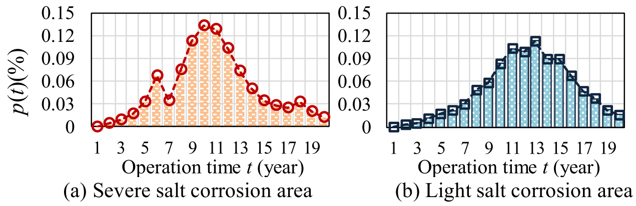


FIGURE 1. PDF of DTRs operated in salt corrosion areas.

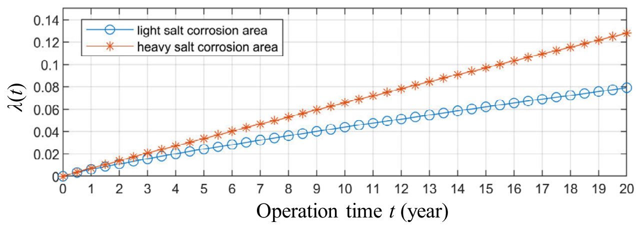


FIGURE 2. Failure rate of DTR.

$$p(t) = \frac{\beta}{\theta}\left(\frac{t}{\theta}\right)^{\beta-1} e^{-\left(\frac{t}{\theta}\right)^{\beta}}, t \geq 0 \in R \tag{1}$$

where β and θ represent the shape parameter and scale parameter, respectively, while t indicates the operation time of DTR. The cumulative distribution function (CDF) of $F(t)$ is formulated by integrating $p(t)$ over t:

$$F(t) = \int_0^t p(t)dt = 1 - e^{-(t/\theta)^{\beta}} \tag{2}$$

This cumulative distribution function represents the accumulated failure probability or total failure percentage since the product began operating to a certain time point t. By dividing $p(t)$ by 1-$F(t)$, the failure rate of $\lambda(t)$ becomes

$$\lambda(t) = \frac{p(t)}{1 - F(t)} = \frac{\beta}{\theta}\left(\frac{t}{\theta}\right)^{\beta-1} \tag{3}$$

This function provides insight into the proportion of faulty DTRs compared to the normal ones, facilitating the comprehension of the operating scenario at a specific time.

The study next goes to the establishment of fault rate model for salt erosion areas. It is known that the surging and pounding of waves along the costal would cause the salt in seawater to diffuse into the air in the form of salt mist. When exposed for a long time, insulators will have their insulation strength reduced due to the salt adhering to their surfaces [28]. To express the severity of salt pollution, the

TABLE 1. Parameters of different distribution transformers.

	25kVA	50kVA	100kVA	167kVA
ρ	3.846	4.091	4.294	4.706
$\Delta\theta_{OA,r}$, $\Delta\theta_{HO,r}$	65°C, 20°C			

IEC 60815 Standard recommends using indicators such as equivalent salt deposit density (ESDD) and site equivalent salinity (SES) [29], where the ESDD is the most widely used indicator because of its intuitive definition and the simplicity of measurement [30]. Taiwan also utilized the ESDD indicator to reflect the situation of salt pollution [39]. In this study, the area is deemed the severe salt erosion area when its ESDD is larger than 0.125.

Subsequently, for the development of Weibull failure model, 38,000 failure data points of DTR recorded by electric utility of Taiwan are first collected. The dataset comprises 25,247 data points from areas with severe salt corrosion and 12,753 data points from areas with light salt corrosion. Fig. 1 illustrates the probability density function of DTR operating in salt corrosion areas. Using the least square method, the shape parameter β and scale parameter θ were calculated to be 17.45 and 1.96 for the severe salt corrosion area and 21.76 and 1.85 for the light salt corrosion area, respectively. Based on the results presented in Fig. 1, Fig. 2 illustrates the failure rate of DTR when operating in these two areas.

Since most external defects of DTR can be removed after inspection and overhaul, it is assumed that the failure rate will return to its initial state after maintenance. Thus, the failure rate $\Lambda_i(t)$ of each DTR can be derived as below following inspection or overhaul at a certain year:

$$\Lambda_i(t) = \lambda_i(0) + \left(\lambda_i(t) - \lambda_i(0)\right)(1 - I_i(t))(1 - \mathrm{O}_i(t)) \quad (4)$$

where $I_i(t)$ and $\mathrm{O}_i(t)$ are indicators for the inspection and overhaul of DTR conducted in the t-th year. An indicator value of 1 represents the completion of maintenance task, while a value of 0 indicates that no maintenance was performed in that particular year. At this time, considering integrating reliability indicators to achieve a more comprehensive assessment of the impact of altering maintenance strategies on power supply reliability, this paper incorporate the failure rate to formulate the System Average Interrupt Duration Index (SAIDI) as depicted below:

$$SAIDI = \frac{1}{Y}\sum_{t=1,t\in N}^{Y}\sum_{i=1,i\in N}^{N_{tr}}\left[\Lambda_i(t)\cdot\frac{U_i\cdot T_b}{U_t}\right] \quad (5)$$

where $\Lambda_i(t)$ represents the failure rate of the i-th DTR at time t, N_{tr} is the total number of DTRs, U_i is the number of users impacted by the i-th DTR outage, U_t is the number of system users, and T_b is the duration of the power interruption. This objective function is preprocessed as follows:

$$f_1 = \left(\frac{SAIDI - SAIDI_{\min}}{SAIDI_{\max} - SAIDI_{\min}}\right) \quad (6)$$

where $SAIDI_{min}$ and $SAIDI_{max}$ is the minimum and the maximum value of $SAIDI$.

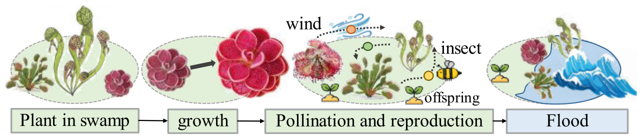


FIGURE 3. Concept of carnivorous plant algorithm.

B. MAINTENANCE COST

The maintenance cost takes the personnel cost and equipment investment of inspection and overhaul into account [33]. By considering the times of maintenance along with route scheduling and failure rate, the maintenance cost can be formulated as

$$C_t = \sum_{t=1,t\in N}^{Y}\left[d_i(t)\,C_{ip} + \sum_{i=1,t\in N}^{N_{tr}}\left[\Lambda_i(t)\cdot\left(C_f + p_{b,i}T_b\cdot c_e\right)\right]\right] \quad (7)$$

where C_t is the total maintenance cost, C_{ip} is the inspection cost per kilometer that includes consumable material and labor cost, C_f is the repair cost of a damaged DTR, $p_{b,i}$ is the undelivered loss of the i-th DTR due to interruption, c_e is the electricity price in dollars per kilowatt-hour (\$/kWh), and $d(t)$ is the distance covered during the inspection and overhaul at time t. To ensure the consistent computation, this cost is normalized below:

$$f_2 = \frac{C_t - C_{\min}}{C_{\max} - C_{\min}} \quad (8)$$

where C_{min} and C_{max} is the minimum and the maximum value of maintenance cost. It is also emphasized here that this study's maintenance costs include personnel expenditures, vehicle usage expenses, and consumable costs. Reducing the objective function of maintenance costs can improve resource utilization and alleviate labor shortage problems.

C. INSULATION LIFETIME LOSS

Internal failure is intricately linked to the insulation life [34], [35], [36], [37]. In practical operation, electricity consumption data is used to infer the load conditions of DTRs. This information can be used to formulate a model that helps to understand the relationship between the load and the rate at which the insulation ages. To develop this model, we refer to the IEEE C57.91 standard for guidance on formulating the insulation lifetime loss model for DTRs. The level of aging in insulation material is determined by the hottest coil temperature θ_H. Equation (9) shows that the ambient temperature, oil temperature rises, and coil temperature rise are represented by the first, second, and third terms on the right-hand side, respectively. The hottest coil temperature θ_H is calculated by adding these terms together as shown below:

$$\theta_H(p) = \theta_A + \left(\frac{p^2\rho + 1}{\rho + 1}\right)^m \Delta\theta_{OA,r} + p^{2m}\Delta\theta_{HO,r} \quad (9)$$

where p represents the DTR load in per unit, ρ is the ratio of rated load loss to no-load loss, $\Delta\theta_{OA,r}$ is the surface

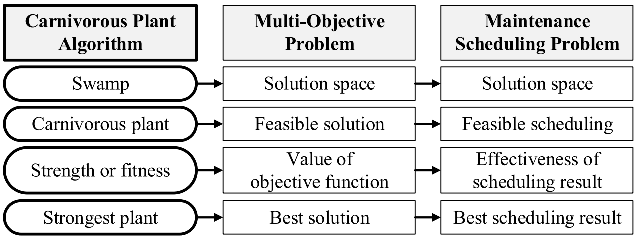


FIGURE 4. Relation mapping of algorithm and problem.

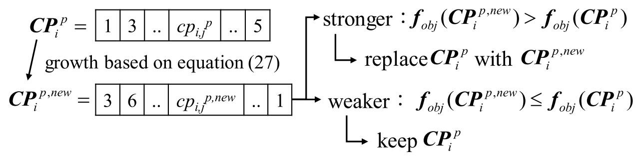


FIGURE 5. Mechanism of growth.

temperature rise of the insulation oil at rated load, $\Delta\theta_{HO,r}$ is the rise of the hottest spot over the top-oil temperature at rated load, and m is an empirical constant that is set to 0.8 for oil-immersed DTRs. Table 1 tabulates the values of parameter ρ, $\Delta\theta_{OA,r}$ and $\Delta\theta_{HO,r}$ for DTRs of various capacities, which is determined according to the IEEE C57.91 and CNS 598 standard [38].

Following the formulation of the hottest coil temperature, the aging acceleration factor F_{AA} is calculated as below:

$$F_{AA}(p) = e^{15000\left(\frac{1}{c+273} - \frac{1}{\theta_H(p)+273}\right)} \tag{10}$$

where c is the rated operating temperature of insulation material, which is 110°C (383°k) for DTRs. By multiplying the aging acceleration factor with the time interval $\Delta\tau$, the insulation lifetime loss is computed as

$$ILL = \frac{1}{L}\sum_{i=1,i\in N}^{N_{tr}}\sum_{\tau=0,\tau\in N}^{N\tau} F_{AA}\left(p_i(\tau)\right)\cdot\Delta\tau\cdot 100 \tag{11}$$

where N_τ is the number of time intervals, L is the rated life of the insulation material, which is set at 20.55 years for oil-immersed DTR according to [38]. Since the meter records the electricity data every 15 minutes, $\Delta\tau$ corresponds to 35,040 intervals in a year. The insulation lifetime loss index is also normalized as follows:

$$f_3 = \frac{ILL - ILL_{\min}}{ILL_{\max} - ILL_{\min}} \tag{12}$$

where ILL_{min} and ILL_{max} is the minimum and the maximum value of insulation lifetime loss.

D. OBJECTIVE FUNCTIONS WITH CONSTRAINS

Combining the objective functions f_1, f_2 and f_3, discussed above, this study expresses a multi-objective function as follows:

$$\begin{aligned} f_{obj} &= \min\left(w_1 f_1(t) + w_2 f_2(t) + w_3 f_3(\tau)\right) \\ subject\ to &\begin{cases} w_1 + w_2 + w_3 = 1 \\ t \in N\{1, 2, \cdots, Y\}, \tau \in N \end{cases} \end{aligned} \tag{13}$$

where w_1, w_2 and w_3 are weights of f_1, f_2 and f_3. The weights assigned to each objective can be adjusted based on the priority of the task. Following the assigning weights, the study also takes the constraints into consideration, in which the maximum and the minimum number of DTRs that can be inspected is expressed below:

$$\begin{cases} N_{\min}^{insp} \le N_t^{insp} \le N_{\max}^{insp}, & t = 1, 2, \ldots Y \\ N_{\min}^{ovh} \le N_t^{ovh} \le N_{\max}^{ovh}, & t = 1, 2, \ldots Y \end{cases} \tag{14}$$

where N_t^{insp} and N_t^{ovh} is the number of inspected and overhauled DTRs at year t, $N_{min}{}^{insp}$, $N_{max}{}^{insp}$, $N_{min}{}^{ovh}$ and $N_{max}{}^{ovh}$ is the minimum and maximum allowable number of inspected and overhauled DTRs. Meanwhile, the minimum number of inspections and overhauls that must be performed during the scheduling period is also listed as constraints, which are written as follows:

$$\begin{cases} T_{\min}^{insp} \le T_i^{insp}, & i = 1, 2, \ldots N \\ T_{\min}^{ovh} \le T_i^{ovh}, & i = 1, 2, \ldots N \end{cases} \tag{15}$$

where T_i^{insp} and T_i^{ovh} represent the number of times the i-th DTR must be inspected and overhauled, respectively, while $T_{min}{}^{insp}$ and $T_{min}{}^{ovh}$ represent the minimum number of times each DTR must be inspected and overhauled. This completes the formulation of the objective functions and corresponding constraints.

IV. CARNIVOROUS PLANT GROWTH-BASED OPTIMIZATION

The carnivorous plant growth-based optimization method is utilized in this study to schedule the maintenance of DTRs. This approach incorporates the simulation of the preying and growing behavior of carnivorous plants and accounts for the impact of flooding disasters [21]. The concept of the algorithm is illustrated in Fig. 3. Similar to carnivorous plants that capture insects with their enzymes to gain nutrients for breeding stronger plants, the proposed algorithm generates a brand-new offspring with higher survivability by spreading pollen through wind or insects. In the study, each feasible maintenance schedule for DTRs is represented as a carnivorous plant. By repeatedly applying the search mechanism, the algorithm breeds the strongest plant, which is eventually decoded as the optimal maintenance schedule.

Fig. 4 depicts the relationship between the algorithm, multi-objective optimization, and maintenance scheduling. Within a swamp, each plant represents a feasible solution. The strength or fitness of each plant reflects the magnitude of the objective function, and the plant with the highest fitness represents the optimal schedule. The computation begins with an initialization process, followed by three search mechanisms, which are described below.

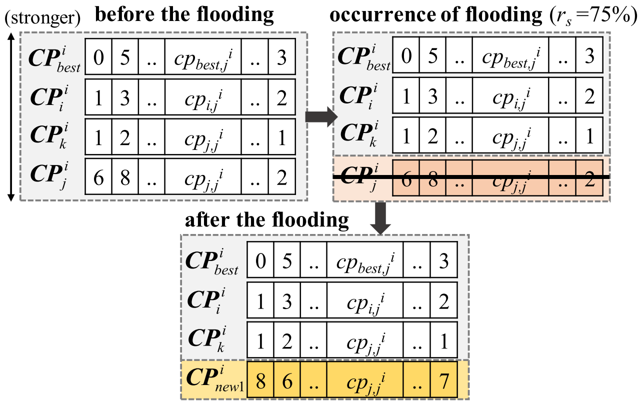


FIGURE 6. Search mechanism with consideration of flooding event.

Unlike traditional algorithms such as genetic algorithm and particle swarm optimization, the proposed method utilizes a grouping process for initialization after randomly generating the initial populations. The grouping process divides the large population into several smaller groups to improve the computing efficiency. A population of n plants is randomly generated and dispersed in a swamp as shown below:

$$\boldsymbol{S} = \begin{bmatrix} \boldsymbol{CP}_1 \\ \vdots \\ \boldsymbol{CP}_i \\ \vdots \\ \boldsymbol{CP}_n \end{bmatrix} = \begin{bmatrix} cp_{1,1} & \cdots & cp_{1,i} & \cdots & cp_{1,m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ cp_{i,1} & \cdots & cp_{i,i} & \cdots & cp_{k,m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ cp_{n,1} & \cdots & cp_{n,i} & \cdots & cp_{n,m} \end{bmatrix} \tag{16}$$

where $\boldsymbol{S}$ represents the initial swamp consisting of n feasible plants, $\boldsymbol{CP}_i$ denotes the i-th plant or feasible solution, $cp_{i,j}$ is the j-th control variable of the i-th feasible solution, and m represents the total number of control variables. Each variable of $cp_{i,j}$ is initialized by the following equation:

$$cp_{i,j} = b_{lw,j} + \left(b_{up,j} - b_{lw,j}\right) \cdot rand \tag{17}$$

where $b_{up,j}$ and $b_{lw,j}$ represent the upper and lower bounds, of the j-th control variable, and $rand$ denotes a random value generated between 0 and 1.

The evaluation of each generated plant is performed using the following objective function:

$$\begin{aligned} &\boldsymbol{f}_{obj}(\boldsymbol{S}) \\ &= \left[f_{obj}\left(\boldsymbol{CP}_1\right) f_{obj}\left(\boldsymbol{CP}_2\right) \cdots f_{obj}\left(\boldsymbol{CP}_i\right) \cdots f_{obj}\left(\boldsymbol{CP}_n\right)\right]^T \end{aligned} \tag{18}$$

The objective function value of each plant is then calculated, and the plants are sorted in ascending order based on this value. It is noted that the first carnivorous plant, $\boldsymbol{CP}_1$, corresponds to the strongest plant with the smallest objective function value. All plants are then divided into k groups, where each group contains n/k plants. The grouping rule is given below:

$$\boldsymbol{CP}_i \in \boldsymbol{G}_j, j = \mathrm{MOD}\left(i/k\right) \tag{19}$$

The whole solution space of swamp is hence formed as

$$\begin{aligned} \boldsymbol{S} &= \begin{bmatrix} \boldsymbol{G_1} \\ \vdots \\ \boldsymbol{G_i} \\ \vdots \\ \boldsymbol{G_k} \end{bmatrix} = \begin{bmatrix} \boldsymbol{CP_1} & \boldsymbol{CP_{k+1}} & \cdots & \boldsymbol{CP_{n-k+1}} \\ \vdots & \vdots & \cdots & \vdots \\ \boldsymbol{CP_i} & \boldsymbol{CP_{k+i}} & \ldots & \boldsymbol{CP_{n-k+i}} \\ \vdots & \vdots & \cdots & \vdots \\ \boldsymbol{CP_k} & \boldsymbol{CP_{2k}} & \ldots & \boldsymbol{CP_n} \end{bmatrix} \\ &= \begin{bmatrix} \boldsymbol{CP}^1_{best} & \boldsymbol{CP}^1_2 & \cdots & \boldsymbol{CP}^1_{n/k} \\ \vdots & \vdots & \ldots & \vdots \\ \boldsymbol{CP}^i_{best} & \boldsymbol{CP}^i_2 & \ldots & \boldsymbol{CP}^i_{n/k} \\ \vdots & \vdots & \ldots & \vdots \\ \boldsymbol{CP}^k_{best} & \boldsymbol{CP}^k_2 & \ldots & \boldsymbol{CP}^k_{n/k} \end{bmatrix} \end{aligned} \tag{20}$$

Note that this grouping process adopts a fair allocation method, which can disperse all individuals according to their quality. In this way, the search efficiency can be better ensured especially when there is a large number of feasible solutions [21]. Subsequently, the plant growth mechanism is expressed below:

$$\boldsymbol{CP}^{p,new}_i = \boldsymbol{CP}^p_i + c_g \cdot \left(\boldsymbol{b}_{up} - \boldsymbol{b}_{lw}\right) \cdot \frac{1}{\sigma\sqrt{2\pi}} e^{-rand^2/2\sigma^2} \tag{21}$$

where $\boldsymbol{CP}^p_i$ and $\boldsymbol{CP}^{p,new}_i$ represent the p-th carnivorous plant in the group $\boldsymbol{G}_p$ before and after the plant growth, $\boldsymbol{b}_{up}$ and $\boldsymbol{b}_{lw}$ denote the upper and lower bound vectors, c_g is the growth parameter, and σ is the standard deviation. Fig. 5 illustrates this growth process. The figure shows that if the objective value improves, the plant will be replaced; otherwise, it will be kept for further nutrient enrichment. Through this mechanism, the plant will achieve a higher fitness and facilitate a more effective local search.

Next, considering that carnivorous plant may spread their pollen through wind or insects, the study mimics the behavior of pollination delivery. With a random generated number of ε that is larger than a predefined threshold of c_{pol}, the insect pollination is performed; whereas if ε is smaller than c_{pol}, wind pollination is executed. The mathematical form of wind and insect pollination is expressed individually below:

$$\boldsymbol{CP}^{p,new}_i = \boldsymbol{CP}^p_i \cdot c_{pol} \cdot rand + \left(1 - c_{pol}\right) \cdot \boldsymbol{CP}^p_j, \ if\ \varepsilon \geq c_{pol} \tag{22}$$

where $\boldsymbol{CP}^{p,new}_i, \boldsymbol{CP}^p_i, \boldsymbol{CP}^p_j \in \boldsymbol{G}_p$

$$\boldsymbol{CP}^{p,new}_i = \boldsymbol{CP}^p_i \cdot c_{pol} \cdot rand + \left(1 - c_{pol}\right) \cdot \boldsymbol{CP}^q_{best}, \ if\ \varepsilon < c_{pol} \tag{23}$$

where $\boldsymbol{CP}^{p,new}_i, \boldsymbol{CP}^p_i \in \boldsymbol{G}_p$, $\boldsymbol{CP}^q_{best} \in \boldsymbol{G}_q$ where $\boldsymbol{CP}^p_j$ represents the j-th plant in the group $\boldsymbol{G}_p$. $\boldsymbol{CP}^q_{best}$ represents the strongest plant in the group $\boldsymbol{G}_q$. Note that each plant in group $\boldsymbol{G}_p$ spreads pollen to other plants, generating offspring or new feasible solutions. This pollination mechanism is considered as the global search since it searches the entire solution space.

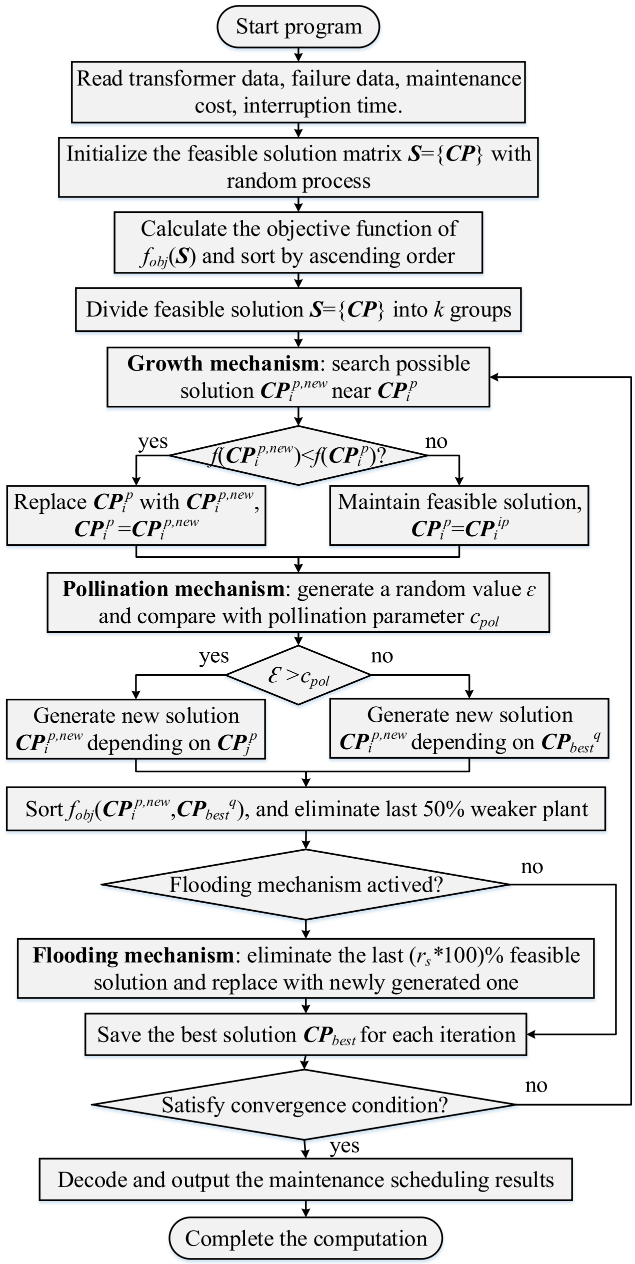


FIGURE 7. Computation procedure of the proposed method.

The pseudocode form of the pollination process is detailed as follows.

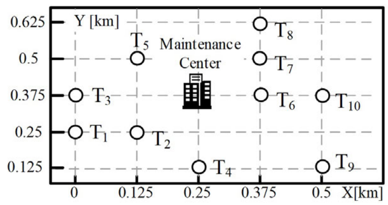
function ***Pollination***{
Assign $\varepsilon \leftarrow rand()$
for i from 1 *to n*
if $\varepsilon > c_{pol}$
$$CP_i^{p,new} = CP_i^p \times c_{pol} \times rand() + (1\text{-}\ c_{pol}) \times (\text{random } j\text{-}th \text{ plant } CP_i^p)$$
else
$$CP_i^{p,new} = CP_i^p \times c_{pol} \times rand() + (1\text{-}\ c_{pol}) \times (\text{best plant in random group } q)$$
end
end

TABLE 2. Parameter for evaluating the method.

Parameters	values
Inspection cost C_{ip}	1 \$NTD /m
Replacement cost C_f	6,000 \$NTD/per DTR
Electricity price C_e	2.63 \$NTD/kWh
Average blackout time T_b	1.5 hours each time
Rated life of insulation material	20.55 years

TABLE 3. Test data of DTRs.

Tr. No.	kVA	User	Age (year)	Peak Load	Tr. No.	kVA	User	Age (year)	Peak Load
1	50	21	8	0.89	6	100	45	11	1.02
2	100	42	18	1.11	7	50	25	19	0.64
3	50	19	5	0.75	8	25	11	5	0.51
4	50	22	6	0.77	9	25	9	8	0.57
5	50	20	12	0.88	10	50	20	2	0.86



Distance to Maintenance Center(m)			
#1	280	#6	125
#2	177	#7	177
#3	250	#8	280
#4	250	#9	354
#5	177	#10	250

FIGURE 8. Location of each transformer and the maintenance center.

sort $f_{obj}(CP_i^p,\ CP_i^{p,new})$ *in ascend or descend*;
abandon last half weaker plant;}

Along with the growth and pollen spread mechanisms described above, the method incorporates a flooding mechanism that simulates the occurrence of flooding events during the search process. This is necessary because swamps may occasionally experience flooding, and plants with insufficient fitness may be replaced by new budding seeds. Fig. 6 depicts the search mechanism that considers the possibility of flooding events. This approach is designed to prevent the algorithm from being stuck in local minimums. During numerical implementations, a survival rate of r_s is incorporated to enhance the algorithm's ability to survive when encountering flooding events. A smaller value of r_s indicates that a larger number of plants must be removed. This search mechanism is designed to introduce more diversity, thereby increasing the chances of finding a better solution. The pseudocode function of flooding event is detailed as follows:

*function****Flooding_event***{
Assign *counter*, r_s *a suitable value*
if counter> threshold value
sort $f_{obj}(S)$ *in ascend or descend*;
$S(last\ r_s\ CP) = b_{lw} + (b_{up} - b_{lw}) \times rand()$;
counter←0;
else
counter = *counter* +1;
end}

The above mechanisms of grouping, growing, and flooding are repetitively performed for a predefined number of iterations. Through this mechanism, the information contained in the carnivorous plant represents the possible solutions to the

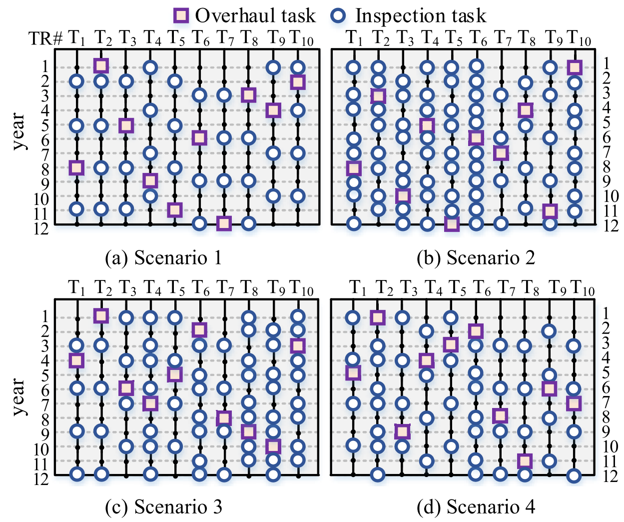


FIGURE 9. Inspection and overhaul schedule of 10 transformers.

TABLE 4. Scheduled results of test 1.

	Scenarios			
	1	2	3	4
Weight (w_1,w_2,w_3)	(1,0,0)	(0,1,0)	(0,0,1)	(0.33,0.33, 0.34)
f_{obj} value	0	0	0	0.3466
Fault cost ($)	7600.2	5715	6412.5	6931.3
Inspection cost ($)	9739.4	16332.8	16039.9	11389.6
Mainten. cost ($)	17339.6	22047.8	22452.4	18320.9
SAIDI (hours/year)	0.0158	0.0114	0.0134	0.0139
Insul. life loss (%)	0.137	0.1469	0.1279	0.1286

TABLE 5. Operation data of DTRs in test 2.

Tr. No.	kVA	User	Age (year)	Peak Load	Tr. No.	kVA	User	Age (year)	Peak Load
1	25	14	19	0.92	19	50	22	1	0.54
2	100	52	4	0.72	20	100	54	10	0.98
3	167	49	2	0.66	21	100	67	5	0.99
4	100	69	6	0.9	22	100	39	5	0.71
5	100	61	10	0.92	23	100	41	5	0.73
6	50	3	10	0.55	24	50	28	20	0.59
7	167	70	6	1.01	25	50	15	12	0.48
8	50	12	15	0.62	26	25	8	3	0.76
9	50	36	1	0.86	27	50	19	13	0.57
10	25	12	16	0.87	28	100	52	17	1.01
11	25	8	6	0.85	29	167	68	3	0.62
12	167	85	18	1.07	30	25	15	4	1
13	167	72	2	0.61	31	25	5	1	0.55
14	167	67	17	0.87	32	167	72	2	1.02
15	50	37	12	0.96	33	167	67	13	0.82
16	100	49	10	0.91	34	167	58	16	0.73
17	50	23	19	0.69	35	167	67	5	0.91
18	100	49	17	0.56					

problem, representing the maintenance scheduling of DTRs. The following section describes the computation algorithm.

V. COMPUTATION PROCEDURE

Fig. 7 shows the flowchart of the proposed approach. The method begins by entering parameter and data of DTRs obtained from electric utilities, including the information consisting of capacity, years of use, connected load, and location, maintenance cost (C_f), interruption time (T_b), interruption loss ($p_{b,i}$), and electricity price (c_e), plant size (n), group number (k), parameters of c_g, c_{pol}, and survival rate (r_s).

At the beginning, n sets of viable solutions are generated for scheduling the maintenance of M DTRs, which can be seen as n plants are cultivated in a marshy area denoted as $\boldsymbol{S}$=[$\boldsymbol{CP}_1$ $\boldsymbol{CP}_2$...$\boldsymbol{CP}_i$...CP_N]^T, where $\boldsymbol{CP}_i$ = [$cp_{i,1}cp_{i,2}\ldots cp_{i,m}$]^T. It is important to note that the objective of this study is to plan the maintenance work for the

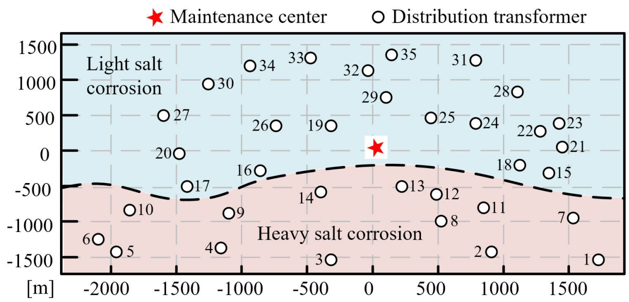


FIGURE 10. Locations of each distribution transformer in Test 2.

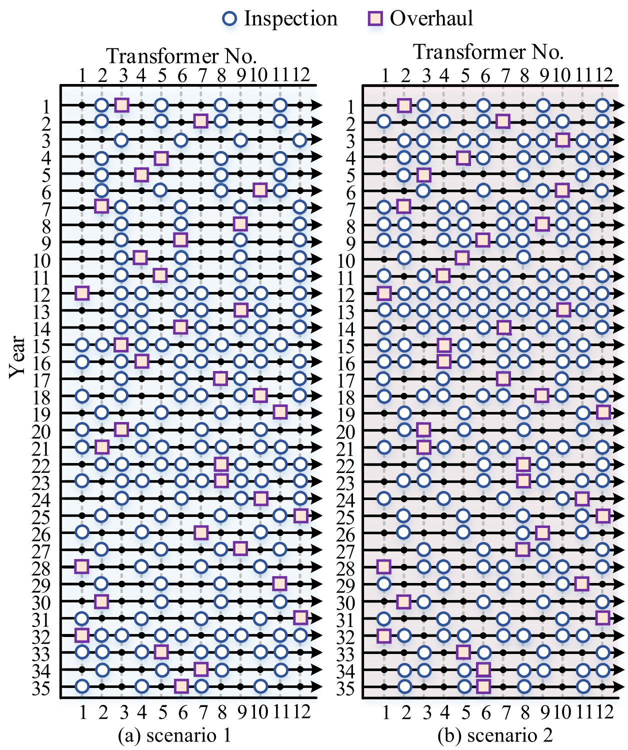


FIGURE 11. Inspection and overhaul schedule of 35 transformers.

TABLE 6. Scheduled results of test 2.

Item \ Value	Scenario 1	Scenario 2
Obj. func. value	0.4581	0.4055
Fault cost ($)	33093.29	31298.06
Inspection cost ($)	147527.35	160460.45
Maintenance cost ($)	180620.64	191758.5
SAIDI (hours/year)	0.01919	0.01823
Insulation life loss (%)	0.2385	0.2393

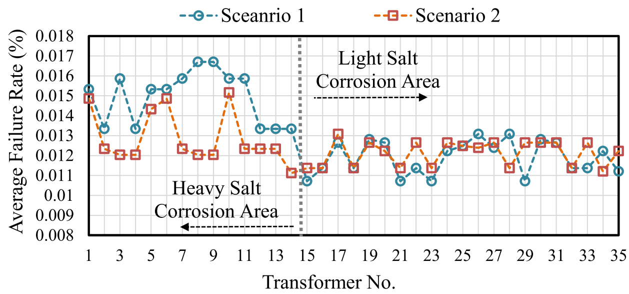


FIGURE 12. Averaged failure rate of DTRs in both areas.

TABLE 7. Comparison of methods in scenario 2.

Item \ Value	Methods		Variation (%)
	Conventional	Proposed	
Fault cost ($)	16,683.22	24,235.1	+45.27
Inspection cost ($)	245,386.64	155,779.2	-36.52
Maintenance cost ($)	262,069.86	180,014.3	-31.31
SAIDI (hours/year)	0.0119	0.0138	+15.97
Insulation life loss (%)	0.3109	0.2406	-22.61

TABLE 8. Test outcome of method 1 under various parameter combinations.

Experiment #	Parameter		Avg. obj. value
	Crossover p_c	Mutation p_m	
1	0.9~0.7*	0.3~0.2	0.3957
2		0.2~0.005	0.3472
3		0.005~0.001	0.3891
4	0.7 to 05	0.3~0.2	0.3785
5		0.2~0.005	0.3692
6		0.005~0.001	0.3566
7	0.5 to 03	0.3~0.2	0.3965
8		0.2~0.005	0.3849
9		0.005~0.001	0.3721

* indicate the parameter decreases from 0.9 to 0.7

TABLE 9. Test outcome of method 2 under various parameter combinations.

Experiment #	Parameter			Avg. obj. value
	w	c_1	c_2	
1	0.8	0.5	0	0.3512
2			0.5	0.3692
3		1.5	0	0.3663
4			0.5	0.3482
5	1	0.5	0	0.3566
6			0.5	0.3481
7		1	0	0.3512
8			0.5	0.3641
9	1.2	0.5	0	0.3739
10			0.5	0.3844
11		2	0	0.395
12			0.5	0.3962

TABLE 10. Test outcome of method 3 under various parameter combinations.

Experiment #	Parameter				Avg. obj. value
	k	c_g	c_{pol}	r_s	
1	5	0.3	0.4	0.75	0.3512
2			0.6	0.5	0.3692
3		0.5	0.4	0.75	0.3481
4			0.6	0.5	0.3512
5		0.7	0.4	0.75	0.3660
6	10	0.5	0.4	0.75	0.3471
7			0.6	0.5	0.3596
8		0.7	0.4	0.75	0.3471
9			0.6	0.75	0.3481
10		0.3	0.6	0.75	0.3660
11	15	0.5	0.4	0.5	0.3512
12			0.6	0.5	0.3663
13		0.7	0.4	0.75	0.3582
14			0.6	0.75	0.3696
15		0.3	0.4	0.75	0.3926

next 12 years. After consulting with utility engineers, it was determined that inspections should be conducted every three years with a frequency of four times, and overhauls should be performed every 12 years. As a result, each control vector in $\boldsymbol{CP}_i$ consists of one overhaul variable and three inspection variables, resulting in a total of $4M$ control variables. For instance, in the i-th solution, the control vector $\boldsymbol{cp}_{ij} = [1,0,0,6]$ specifies that the j-th DTR is due for inspection in the first year, and subsequently at the 4th, 7th, and 10th years. In addition, the DTRs is scheduled for overhaul in the 6th year.

Based on the above initialization, the fitness of each plant is evaluated based on their corresponding objective functions of $f_{obj}(\boldsymbol{CP_i})$. Each plant is arranged in ascending order and then divided into k groups, forming the set $\boldsymbol{S}$=$[\boldsymbol{G_1}G_2\ldots G_i\ldots \boldsymbol{G_k}]^T$ with each group represented as $\boldsymbol{G_i}$=$[\boldsymbol{CP_i}CP_{i+k}\ldots \boldsymbol{CP}_{n-k+i}]^T$. The next phase involves the exploration of feasible solutions, where each plant undergoes growth proportional to its fitness, analogous to the conversion of prey into nutrients. Should a plant exhibit improved fitness, it supersedes its predecessor in the ongoing process.

Subsequently, an ε is randomly generated and compared with c_{pol} to ascertain the mode of pollination. To sustain a set of solutions characterized by elevated average fitness, the objective values of the latter 50% of weaker plant are discarded. A counter is used to keep track of the number of epochs in which the objective function value of the best solution remains unchanged. If the counter exceeds a predetermined threshold, it signals the occurrence of flooding event and the survival rate r_s is meanwhile applied to eliminate weaker solutions. Note that for each iteration, the fitness of carnivorous plant is updated using the aforementioned computational procedures until the convergence criterion is satisfied.

VI. NUMERICAL TESTS

To evaluate the effectiveness of this proposed approach, the study applies the method to a sample system of 10 DTRs as well as a real system of 35 DTRs in a city located in southern Taiwan. The program is executed on an Intel Core i7-9700 @4.7 GHz with 16 GB of memory. Test 2 lists the parameters for evaluating the method, where the new Taiwan

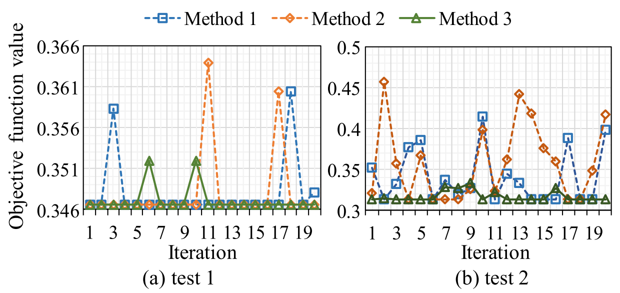


FIGURE 13. Results during 20 times of simulation.

TABLE 11. Test outcome of method 3 under various parameter combinations.

Test case	Test 1			Test 2		
Method / value	1	2	3	1	2	3
Max. obj. value	0.3602	0.3641	0.3522	0.4153	0.4592	0.3336
Min. obj. value	0.3466	0.3466	0.3466	0.3125	0.3125	0.3125
Avg. obj. value	0.3472	0.3481	0.3471	0.3608	0.3849	0.3227
Avg. comp. time (s)	39.2	41.3	40.5	391.7	445.1	428.4

dollar is abbreviated as NTD. These values were obtained from an existing database and validated through discussions with utility engineers, yet they may vary depending on the location.

A. TEST 1

In this case, the proposed method is evaluated on a 11.4 kV test system consisting of 10 DTRs. Table 3 shows the test data of DTRs, and Fig. 8 depicts the location of each DTR and maintenance center. Due to the considerable number of load data, this study only lists the peak load that affects the insulation life with the highest degree.

Based on aforementioned data, four scenarios are examined. Scenario 1 considers the maintenance cost, scenario 2 concerns the service reliability, scenario 3 observes the insulation life loss, and scenario 4 takes all of them into considerations. In this case, a total of 3-6 DTRs are allowed to inspect while only one DTR can be overhauled per year. For all tested scenarios, the maximum number of iterations is set to 1000. The results of all test systems have been discussed with utility engineers to confirm their suitability. The initial population of the method is set at 200 and divided into 10 groups.

Fig. 9 shows the inspection and maintenance schedule result. By setting $w_2 = w_3 = 0$, scenario 1 focuses on the maintenance cost, and each DTR is inspected every three years. Then, by considering the service reliability in scenario 2, the frequency of inspection task is seen increased. Next, as scenario 3 primarily examines the insulation life loss, the DTR #2 and #6 are overhauled earlier since they are operated at a larger peak load with a longer hour of operation. Finally, as the scheduled results of scenario 4 indicates, the number of inspections for each DTR is set to be 1 or 2 times per year, reducing the maintenance cost and keeping the reliability at an acceptable level. For this scenario 4, the DTR #2 is overhauled at the first year since the high peak load, the long operating time and the last inspection time occurred back to 3 years ago. It is also worth noting that the next inspection time for DTR #10 is arranged at the third year since the DTR #10 can be inspected simultaneously with DTR # 6, #7 and #8 nearby such that the overall inspection route can be reduced.

Table 4 shows the scheduled results of scenario 1-4. It is seen that the schedule obtained under scenario 1 comes with the lowest maintenance cost, scenario 2 reaches the lowest value of SAIDI, scenario 3 presents the lowest insulation life loss, and scenario 4 exhibits a balance in each objective function.

B. TEST 2

In this case, the maintenance scheduling including the effect of salt corrosion is investigated. A 11.4 kV distribution system consisting of 35 DTRs is served as the test sample. Fig. 10 shows the location of DTRs and Table 5 shows the operation data. The map is divided into severe and light salt corrosion area depending on their equivalent salt deposit density (ESDD) [39]. For this test, a total number of 12-18 DTRs is inspected, while that of 2-3 DTRs is overhauled each year. It is also noted that the overhaul task needs to be finished within 12 years, and each DTR should be inspected at least once every three years. There are two scenarios for the arrangement of maintenance schedule. While scenario 1 neglects the impact of salt corrosion, the scenario 2 takes the salt corrosion into consideration.

Fig. 11 shows the inspection and overhaul schedule of 35 DTRs. The inspection frequency of DTRs in severe salt corrosion area in scenario 2 is higher than that in scenario 1. This figure also indicates that the inspection could be performed every year for scenario 2, and twice per three years for scenario 1. Table 6 lists the scheduled results of scenario 1 and 2. The inspection cost of scenario 2 is higher than that of scenario 1 since a higher inspection frequency is required for the DTR allocated in the salt corrosion area. Fig.12 shows the averaged failure rate of each DTR. This simulation result confirms the feasibility of the approach for the maintenance scheduling of DTRs at different levels of salt-corrosion areas.

Table 7 lists the comparison of methods based on the inspection of DTR annually and overhauls it every 12 years. While the proposed method has a 15.97% higher value of SAIDI compared to the conventional method, it also offers a 36.52% reduction in inspection cost and a 22.61% reduction in insulation life loss. These results reveal that the proposed method reduces the burden of inspection labor at a limited decrease in reliability.

Continuing with the performance comparison of algorithms, the study refers to the accumulated experience in the research process, selects several feasible parameter ranges, and conducts combination verification [9]. Each combination of parameters undergoes 20 simulations by taking the scenario 4 in test 1 as the common reference. Table 8-10 lists the averaged objective values under various combination of parameters. As listed in Table 8 for Method 1 (genetic algorithm), its smallest objective value occurs when the initial crossover rate decreases from 0.9 to 0.7 while the mutation probability reduces from 0.2 to 0.005. Then, for the performance evaluation of Method 2 (particle swarm optimization) as listed in Table 9, the smallest objective value takes place when the weight parameter w, acceleration parameter c_1 and c_2 are set at 1, 0.5 and 0.5. Next, based on the outcome of Method 3 (proposed method) as listed in Table 10, the smallest objective value appears when the group number k is set at 10, the growth parameter c_g is 0.5, the pollination parameter c_{pol} is 0.4, and the survival rate r_s is 0.75.

Fig. 13 presents the comparison results of methods. Each method runs 20 times, with a maximum of 1000 epochs. Table 11 summarizes a summary of the simulation results. In Test 1, there is an insignificant variation of objective values among the methods. However, in Test 2, the difference between the maximum and minimum objective values of Method 1 and 2 is larger than that of Method 3. It is concluded that although Method 3 is not the fastest, it offers a relatively stable solution search compared to the other methods, confirming the robustness of the method.

VII. CONCLUSION

This paper proposes a novel approach of maintenance scheduling of distribution transformers using the carnivorous plant growth-based optimization approach. The method incorporates local search, global search, and local escape to further enhance its effectiveness. The approach was tested on two systems with different numbers of transformers and compared with other methods under various scenarios. The test results of this study can serve as useful decision support for transformer maintenance planning and development, offering a promising new alternative for power grid applications.

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