Optimal Placement of Fault Indicators Using the Immune Algorithm

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***Abstract*—This paper examines the application of the immune algorithm for the problem of optimal placement of fault indicators to minimize the total cost of customer service outage and investment cost of fault indicators. The reliability index of each service zone is derived to solve the expected energy not served due to fault contingency, and the customer interruption cost is then determined according to the customer type and power consumption within the service zone. To demonstrate the effectiveness of the proposed IA methodology and solve the optimal placement of fault indicators, a practical distribution feeder of Taiwan Power Company is selected for computer simulation to explore the cost benefit of fault indicator placement.**

***Index Terms*—Distribution automation system, fault indicator, immune algorithm.**

I. Introduction

WITH economic development and increasing computer applications, power quality has become a more and more critical concern for utility customers. Power companies have to improve overall customer satisfaction through enhancing service quality to maximize customer retention. Therefore, distribution automation systems have been implemented at Taiwan Power Company (Taipower) as an intelligent technology to strengthen the reliability and operation efficiency of distribution systems.

Among all functions to be achieved by the distribution automation system (DAS), the fault detection, isolation, and restoration (FDIR) is considered to be the most important with the objective of reducing service restoration time from an average of 58 min to less than 20 s for the permanent fault contingency of distribution feeders. However, the experience of Taipower distribution network operations has indicated a large amount of distribution network outages occurred in the laterals of distribution feeders not monitored in the current design of Taipower's DAS. Table I illustrates the average of the feeder and lateral outages for the 24 of Taipower's business districts in 2008. Most of the outages are from laterals for overhead and underground conductor types. Due to the larger number of branches, to include feeder laterals into the DAS will require a large capital investment in the automatic switches and communication devices. Installing high voltage and customer side fault indicators (FIs) with communication capability is a solution to minimize the fault detection and identification time at the feeder and lateral levels. The fault indicator trips when it senses an inrush of fault current, then communicates back to the distribution dispatching control center (DDCC) of Taipower through the mesh network. The DDCC personnel monitoring the master station receive the fault information and dispatch a troubleshooting crew to the fault location. This significant decrease in response time allows repair crews to react swiftly to restore power to Taipower customers.

TABLE I
AVERAGE OF FEEDER AND LATERAL OUTAGES OF TAIPOWER IN 2008

Feeder types	Customer types	Average feeder outage number (Including lateral outages)	Average lateral outage (%)
Overhead	Residential	153.23	70.12
	Commercial	32.33	55.44
	Industrial	20.56	65.74
Underground	Residential	76.30	76.46
	Commercial	15.13	77.34
	Industrial	4.22	57.74

*feeder outages include primary feeder and lateral outages

It is neither economical nor necessary to install an FI at each line segment of a wide-area distribution system. With so many line segments of a feeder in the Taipower distribution system, the placement of FIs becomes a very difficult and tedious problem to be solved by conventional optimization techniques because of the voluminous combinations to be examined. With the installation of FIs in the distribution system, the reliability indices of customer service zones can therefore be evaluated according to the installation locations of FIs. As a result, the problem of optimal FI placement (OFP) is concerned with where and how many FIs should be implemented in the distribution systems to heighten reliability at a minimum number of FIs.

A genetic algorithm (GA) based procedure for solving the OFP problem was presented in [1]. The method makes it possible to select the optimal placement by knowing the characteristics of the distribution systems. The impact of FIs on the reliability of distribution systems was examined in [2]. The proposed model and evaluation technique was applied to a real Iranian distribution network.

The effectiveness of the immune algorithm (IA) to solve complicated optimization problems has been illustrated in many previous case studies [3]–[8]. In this paper, an economically based fitness function is used for the IA to determine the optimal locations of FIs with communications capability for the existing

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distribution system to illustrate the simulation process. To alleviate the degeneration phenomenon in the original GA and increase convergence speed, the proposed IA uses the prior knowledge of the problem in the search process. This notion is applied to the OFP problem since some line segments that are or are not required to install FI can be initially determined. Three effective vaccines are abstracted using the rules associated with Taipower's FI installation rules and the levels of the priority customers. By comparing to the genetic algorithm, the IA provides the following advantages to solve the optimization problems.

1) The memory cell is maintained without applying operators such as recombination, selection, etc. to the population.
2) It operates on the memory cell, guaranteeing rapid convergence.
3) The diversity of the immune system is embedded using an affinity calculation.
4) The injection of vaccines into the individuals of generations reveals a remarkably increased convergence process.

In this paper, the objective function for the OFP is expressed as the antigen inputs. The feasible solutions are represented as the antibody for the IA to solve the optimization problem. The genetic operators including crossover and mutation are then processed for producing antibodies in a feasible space. Through operating IA on the memory cell, a very rapid convergence will be obtained during the searching process by applying the information entropy as a measure of diversity for the population to avoid falling into a local optimal solution. The effectiveness of the proposed IA to solve FI placement is then verified by comparing to the GA.

This paper is organized as follows. Section II describes the FI placement problem description and formulation. Section III provides a brief overview of the optimization algorithm and its applications in the paper. Simulation results for the practical Taipower distribution system are provided in Section IV. Discussion and conclusion are presented in Section V to explain the effectiveness of the obtained results by the proposed method.

II. Technical Work Preparation Problem Description and Formulation

To evaluate the service reliability of the Taipower distribution system, the number of customers affected and outage duration time for each fault contingency is generated in the data logging of the outage management system (OMS). By performing the statistical analysis of service outage, the customer interruption cost (CIC) of a distribution system is expressed as follows:

$$CIC = \sum_{i=1}^{n} IC_i = \sum_{i=1}^{n} \lambda_i l_i \left(\sum_{j=1}^{n} C_{ij} L_j \right) \tag{1}$$

where

n	total number of line segments;
IC_i	interruption cost per year due to outages in line *Segment* i;
λ_i	outage rate (failure per year/Km) of line *Segment* i;
l_i	length of line *Segment* i;
C_{ij}	interruption cost of load at *Segment* j due to an outage at *Segment* i;
L_j	total load of line Segment j.

The C_{ij} in (1) represents the integrated interruption costs of different types of customers derived for the residential, commercial, and industrial customers, respectively [9]. Besides, three different categories of key customers with high service priority levels are considered in this paper. The higher hierarchy level of customers indicates the power service is more critical to them.

Level 1) the customers with power outage could be affected by inconvenience or public concern (schools, supermarkets, sport and entertainment facilities, etc.)

Level 2) the customers with power outage could result in serious financial damage (banks, oil refinery plants, high technology plants, etc.)

Level 3) the customers with power outage could jeopardize public security (hospitals, police stations, fire stations, important telecommunications, etc.)

$$C_{ij} = \Big(\mathrm{Res}_j \cdot f_R(r_{ij}) + Com_j \cdot f_C(r_{ij}) + Ind_j \cdot f_I(r_{ij}) + \sum_{l=1}^{3} \mathrm{Pri}_j^l \cdot f_p^l(r_{ij})\Big) \tag{2}$$

where

Res, Com, Ind, Pri	load percentage of residential, commercial, industrial, and key customers;
f_r, f_c, f_i, f_p	interruption cost function of residential, commercial, industrial, and key customers;
r_{ij}	duration of service interruption of *Segment* j due to a outage at *Segment* i;
l	hierarchy level of key customers.

To solve the load percentages of residential, commercial, industrial, and key customers within each service zone, the customer-to-transformer mapping is retrieved from the facility database of OMS. Besides, the daily load patterns of different customer classes are derived by load survey study [10], and the energy consumption of each customer is retrieved from the customer information system (CIS) database. The hourly loading of each service zone is then obtained by integrating the power profiles of all customers served. Fig. 1 shows the overall structure of reliability assessment for the distribution systems.

As described previously, the objective of service reliability improvement is to reduce customer service outage cost by proper placement of FIs. To solve the problem, FIs have to be installed at the feeder and lateral levels to improve distribution system reliability. In this paper, the total cost of reliability (TCR) to be minimized is defined as (3):

$$\text{Minimize } TCR = CIC + INVC \tag{3}$$

where CIC is customer interruption cost and $INVC$ is the investment cost of FIs.

To reduce the search space and provide the installation knowledge for the abstraction of vaccines of IA, the following

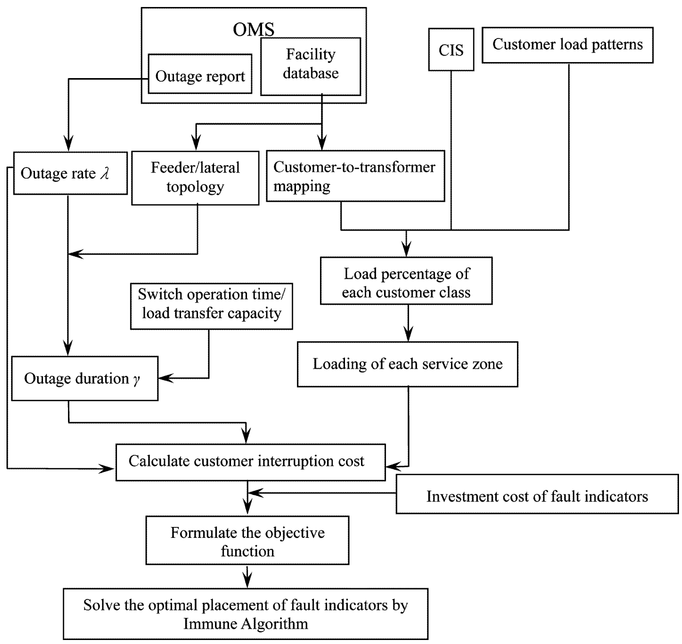

Fig. 1. Reliability assessment for distribution systems.

Taipower's FI installation rules are considered in the proposed IA.

1) The feeders or laterals serving high technology plants, industrial areas, business metropolises, and outage frequently service zones have higher priority to install FIs.
2) The FIs must be installed on the non-automatic switches, three-phase, four-way sectionalizing cabinets, or three-phase, feed-through, pad-mounted transformers.
3) The FIs are not required to be installed on the normally open-tie nodes.

III. Immune Algorithm

The immune algorithm (IA) has been widely used to solve optimization problems by applying the same operating principle as the human immune system. The capability of IA method for pattern recognition and memorization does provide a more efficient way to solve the optimization problem compared to the genetic algorithm. The objective function is represented as antigen inputs, while the solution process is simulated by the antibody production in the feasible space through the genetic operation mechanism (i.e., crossover and mutation). During the actual operation, IA prevents the degenerative phenomena arising from the crossover and mutation processes, thus making the fitness of population increase steadily [11]. The immune operators including vaccine injection and immune selection are performed in the IA process, as shown in Fig. 2. The vaccine is used for increasing fitness and the immune selection is for preventing deterioration. The calculation of affinity between antibodies is embedded within the immune selection to determine the promotion and suppression of antibody production. Through the IA computation, the antibody best fitting the antigen is considered the solution to the optimization problem.

An immune algorithm based decision making [12] is proposed in this study to find the optimal FI number and their placement for distribution systems. The population of memory cells

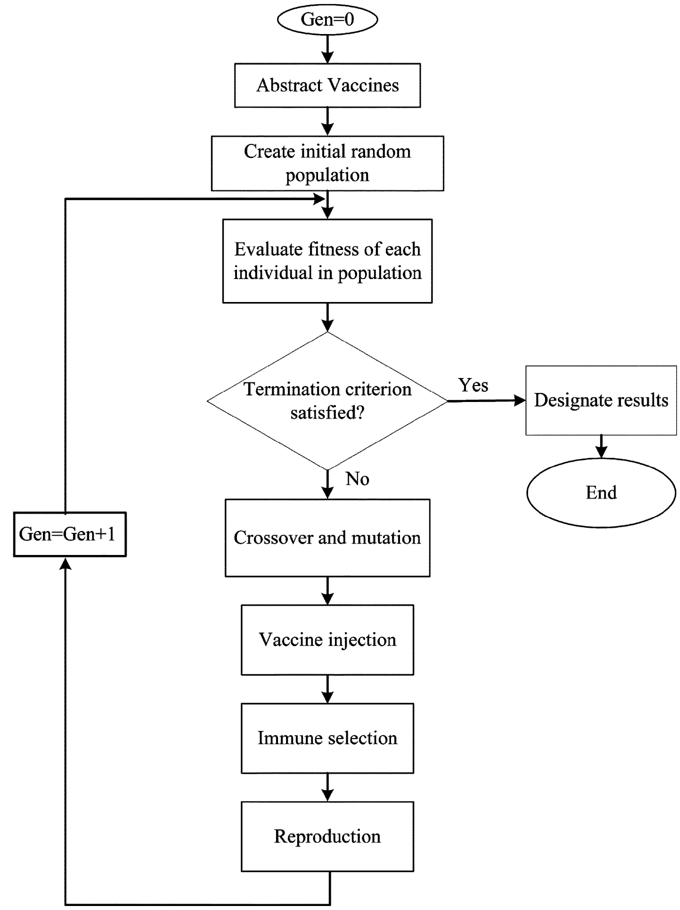

Fig. 2. Flowchart to find the optimal solution by IA.

TABLE II
Binary Structure and Corresponding Description for Each Gene

Bit	Bit type	Value	Description
1	binary	0	without FI installation
		1	with FI installation
2	binary	0	FI only
		1	manual switch with FI

is a collection of the antibodies (feasible solutions) accessible toward the optimality, which is the key factor to achieve rapid convergence for global optimization. In this paper, the genetic coding structure for the immune algorithm is adopted and the diversity and affinity of the antibodies are calculated during the decision making process to discover the FI placement. By applying the immune algorithm to solve the optimal placement of FIs, the attributes of each gene $FI(i)$ represent installation status (with/without FI) and type (FI only/manual switch with FI) at the candidate installing locations, as illustrated in Table II. The data structure of the genes is represented as two bits with binary coding in each gene structure. For a feeder with N possible strategies of FI placement with M FIs, it will generate N antibodies having M genes in the antibody pool as shown in Fig. 3.

A. Abstraction of Vaccines

As mentioned earlier, vaccines are abstracted from prior knowledge or local information of the problem. According

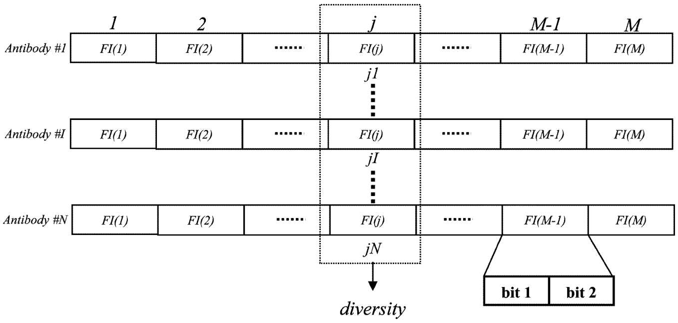

Fig. 3. Data structure of genes and corresponding information entropy for optimal fault indicator placement process.

to the Taipower's FI installation rules, some types of prior knowledge can be extracted as discussed in the following.

Vaccine 1: The nodes which are automatic switches (with remote access) or normally open-tie points should have no FI. The FIs should not be installed at the same locations with automatic switches because of the existing FDIR function of automatic switches. It is important to point out the abstraction knowledge of vaccine 1 is always true. This vaccine should be injected in the entire individuals with probability one.

Vaccine 2: The node serving priority customers and frequently experiencing outage in service zones should be assigned an FI location. Similar to vaccine 1, the knowledge behind vaccine 2 is always true. This vaccine should be injected into all the individuals with probability one.

Vaccine 3: The nodes located in the non-automatic switches, four-way sectionalizing cabinets, or feed-through distribution transformers may not need to have FIs due to the high penetration of these facilities in Taipower distribution systems. It is neither economical nor necessary to install FIs in all these facilities. In contrast with vaccines 1 and 2, the idea behind vaccine 3 is not true all the time and for all cases. To find the global optimum, vaccine 3 should not be injected into all the entire individuals. Assume N_p is the number of individuals in the population, $N_{v3} = \alpha \cdot N_p$ will be the number of individuals randomly selected to be injected by vaccine 3, where α is the vaccine rate and it is assumed to be 0.5 in the simulated cases.

B. Diversity

The diversity is measured between the antibodies and is increased to prevent local optimization during the optimal FI placement search. For each evolving generation, the new antibodies are generated to strengthen the diversity of antibody population in the memory cell. With the data structure of genes in Fig. 3, the entropy E_j of the jth gene $(j = 1, 2, \ldots, M)$ is defined as [13]

$$E_j = -\sum_{i=1}^{N} P_{ij} \log P_{ij} \tag{4}$$

where N is the quantity of antibodies and P_{ij} is the probability the jth allele comes out at the jth gene. If all alleles at the jth gene are the same, the entropy of the jth becomes zero. From (4), the diversity of all genes is calculated as the mean value of informative entropy:

$$\bar{E} = \frac{1}{M} \sum_{j=1}^{M} E_j. \tag{5}$$

C. Affinity

The affinity of antibodies is an important index to select the optimal antibodies to the memory cell during the optimization process. If the affinity of some antibodies is the same during the immune process, it will influence the search efficiency of optimization for planning FI placement. Two types of affinity are calculated for the proposed IA in this paper. One is the affinity between antibodies:

$$(Ab)_{ij} = \frac{1}{1 + E(2)} \tag{6}$$

where $E(2)$ is the information entropy of these two antibodies. The genes of the ith antibody and the jth antibody will be the same when $E(2)$ equals zero. The affinity between the ith antibody and the jth antibody, $(AB)_{ij}$, will be within the range $[0, 1]$.

The other is the affinity between the antibody (candidate of optimal FI placement) and the antigen (the objective function):

$$(Ag)_i = \frac{1}{1 + TCR_i} \tag{7}$$

where TCR_i is the total cost of reliability evaluated by (3) to represent the connection between the antigen and antibody i. The antigen with the maximum affinity $(Ag)_i$ will be the optimal FI placement within the feasible space.

D. Immune Selection

The process consists of two steps: immune test and annealing selection. The immune test is to test the vaccinated antibodies. If the fitness increases, then go to the next step; or else make the parent take part in the competition of selection instead of the offspring. The second is the probabilistic process to select an individual x_i in the present offspring to join in the new parents with probability as follows:

$$P(x_i) = \frac{e^{f(x_i)/T_k}}{\sum_{j=1}^{n} e^{f(x_j)/T_k}} \tag{8}$$

where n is the number of present offspring, $f(x_i)$ is the fitness of individual i, and T_k is the annealing temperature approaching zero with the progress of generations. The annealing temperature can be computed as follows:

$$T_k = \ln\left(\frac{T_0}{k} + 1\right), \quad T_0 = 100 \tag{9}$$

where k is the generation number.

E. Computation Procedures

The process to solve the objective function for optimal FI placement is simulated by the interaction of antibody and antigen in the immune algorithm. During the evolution of genes, vaccination and immune selection are performed in the

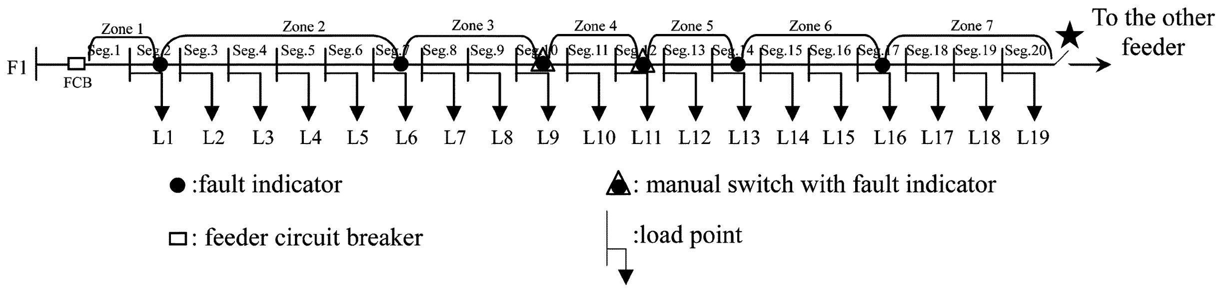

Fig. 4. Optimal placement of FIs for the test feeder.

proposed IA process to overcome the blindness in the action of the crossover and mutation. The candidates of FI placement planning with high affinity are selected and included in the memory cells, which will be used to generate new candidate planning. The computation procedure of IA method is executed as follows.

Step 1) Recognition of antigens
To solve the optimal FI placement planning, the total cost of the reliability of each possible solution is calculated in this step. The binary coding is adopted for the antigen pattern to represent the relationship of genes and physical FI placement planning in the objective function for the computation process.

Step 2) Production of initial antibody population
A random number generator is applied to generate the antibodies in the feasible space. All antibodies and a group of genes are considered to form the antibody pool. Some of the antibodies will be from the memory cells with higher affinity during the search process to generate a new set of antibodies. Each antibody represents a possible solution for the optimal FI placement in a feeder.

Step 3) Calculation of affinity
In this step, the affinity between antibodies $(Ab)_{ij}$ and the affinity between the antibodies and antigens $(Ag)_i$ are calculated by (6) and (7), respectively, as the references in the following evaluation process.

Step 4) Evaluation fitness of each individual in the population
The antibody having high affinity with the antigen is added to the new memory cells. To maintain the size of the memory cells and ensure the speed of convergence, the diversity of memory cells is calculated and the antibody with high affinity (namely, $(Ab)_{ij}$ close 1) is removed so the violation of size constraint of memory cells can be prevented. Since most of the selected antibodies have higher affinities with the antigen, the average affinity of the new population pool will be higher than that of the original pool to obtain better evolution during the IA optimization process.

Step 5) Crossover and mutation
After selection of the antibody generation, the operations of crossover and mutation for the new generated antibodies are performed. The crossover operation is performed by applying the one-cut-point method, which randomly selects the mating point and exchanges the gene arrays of the right-hand portion of the mating points between two antibodies. The mating operation will prevent the search process from local optimization by increasing the diversity of the antibody population. According to the predefined mutation rate, mutation is executed to perform the occasional random alteration of the value for an antibody.

Step 6) Vaccination and immune selection
According to the abstraction knowledge of the vaccines, Vaccines 1 and 2 should be injected in all the entire individuals and Vaccine 3 should be injected in one half of the individuals which are randomly selected. The immune test and the annealing selection are then executed to perform the immune selection in this step.

Step 7) Decision of optimal fault indicator placement
During the immune process, the antibody having high affinities with the antigen will be added to the new memory cell, which will be maintained after applying the operation of crossover, mutation, vaccination, and immune selection for the population. The search process of optimization continues until no further improvement in relative affinity can be obtained, and the antibody with the highest affinity in the memory cell will be the optimal strategy for FI placement.

IV. Numerical Analysis

In this study, the proposed immune algorithm is implemented with Matlab on a Pentium-IV personal computer. Like other statistical methods, the IA method has several parameters that must be selected before use. These include the antibody pool size, the number of the generation, the crossover rate, and the mutation rate. Based on the simulation tests and the programming experience, the antibody pool, crossover rate, and mutation rate are determined as 100, 0.8, and 0.1, respectively, to achieve rapid convergence for the optimization of FI placement by the IA algorithm. A sample distribution feeder and one Taipower feeder are selected for computer simulation in this study.

A. Case 1: Simulation of a Sample Distribution Feeder

Fig. 4 depicts the one-line diagram of a test feeder with 20 line segments and 19 load points. There are three manual switches on the line segments Seg.10, Seg.12, and Seg.20. Besides, one

TABLE III
RELIABILITY DATA AND SYSTEM DATA FOR THE SAMPLE TEST SYSTEM

Parameters	Rate/Duration time
Average feeder failure rate	0.132 failures/year-km
Average lateral failure rate	0.149 failures/year-km
Average repair time	60 min.
Fault detection (with communication capability)	5 min.
Service restoration (unfaulted but out of service zones)	20 min.

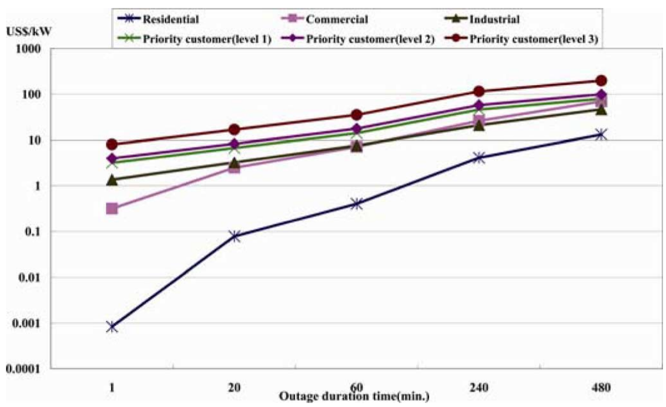

Fig. 5. Service interruption costs of customer classes and key customers.

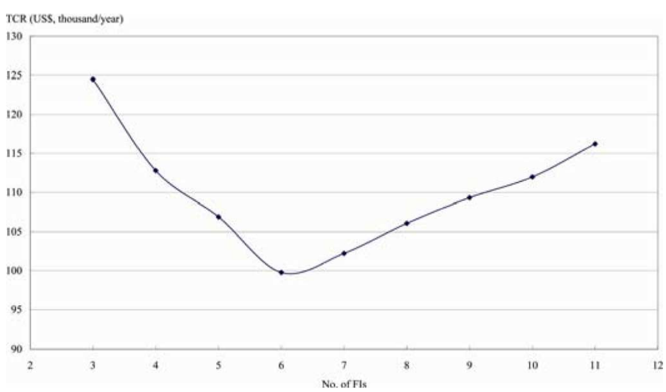

Fig. 6. Total reliability cost versus various number of FIs.

key customer is served at LP10. Each line segment of the feeder is a candidate location for FI placement. The failure rate, repair rate, and time required to complete load transfer were derived by statistical analysis according to the customer outage information retrieved from the OMS system in Table III. The investment cost of three-phase FIs with remote access (GSM/PSTN) to the master station is US$960 [14] with a life cycle of ten years. The cost of communication equipment has also been added to the FIs as the auxiliary equipment for the test system.

According to the interruption cost in [9], the outage cost functions of the residential, commercial, and industrial customers were derived by assuming an inflation rate of 3% in Fig. 5. Here, the interruption costs of key customers are determined based on the field survey in Taipower.

For the sample feeder in Fig. 4, the total reliability cost (TCR) for the distribution system by installing different number of three-phase FIs is solved and illustrated in Fig. 6. It is found the TCR can be minimized by placing of six FIs for the test feeder. Table IV shows the reliability indices of SAIDI and the expected customer interruption cost (ECOST). The SAIDI of

TABLE IV
RELIABILITY INDICES AND CUSTOMER INTERRUPTION COST OF THE TEST FEEDER

Zones	Load points	Load (kW)	Total customers/ key customers	SAIDI (min./cus.yr)	ECOST ($/yr.)
1	L1	70	38/0	24.493	4892
2	L2	143	40/0	24.416	5832
	L3	168	39/0		4460
	L4	113	25/0		4918
	L5	100	5/0		4670
	L6	265	20/0		5971
3	L7	251	17/0	24.382	5857
	L8	331	13/0		6011
	L9	188	10/0		5667
4	L10	1205	25/2	21.022	20131
	L11	210	26/0		6113
5	L12	989	17/0	24.270	5692
	L13	43	22/0		3904
6	L14	96	22/0	24.152	4773
	L15	129	20/0		4972
	L16	44	10/0		3855
7	L17	80	22/0	24.053	4525
	L18	75	12/0		4701
	L19	115	10/0		4809

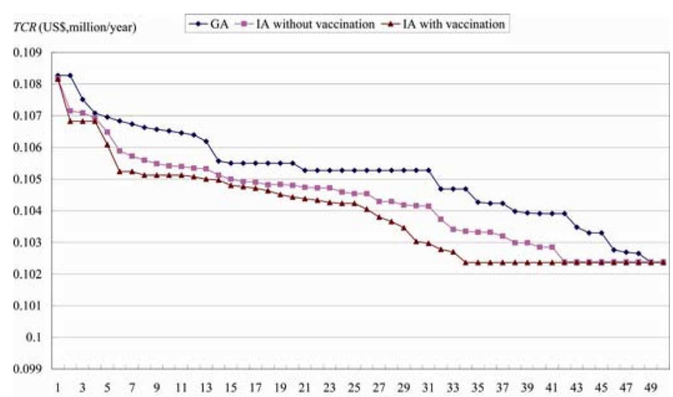

Fig. 7. Comparison between GA and IA with/without vaccinations.

Zone 4 is smaller than that of the other zones when two manual switches with fault indicators are installed on Segments 10 and 12, respectively. Besides, the ECOST of L10 is larger than other load points because of the larger interruption cost of the key customer served.

Fig. 7 depicts the variation in TCR with respect to the generations for conventional GA and IA with and without vaccinations. All specifications including the crossover rate and mutation rate of GA are the same with those of IA. Evaluations of these methods were made based on the average of ten runs. All simulations were performed under the same computer and tested with the same system. It is found that all methods find the best solution. There is a minimum TCR cost of 102 364 ($/year) in this study. However, the IA with vaccinations converges at the 34th generation while IA without vaccinations and GA converge at the 42nd and 49th generation, respectively.

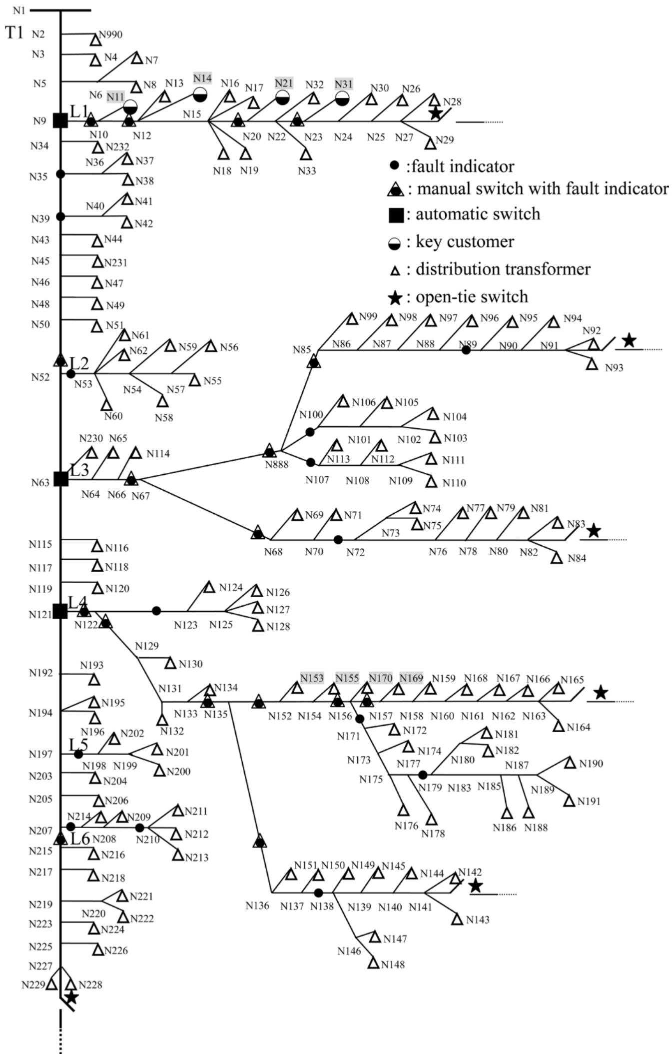

Fig. 8. Taipower distribution system after optimal placement of fault indicators.

B. Case 2: Simulation of Taipower Distribution System

To demonstrate the effectiveness of the proposed methodology to solve the optimal placement of FIs for an actual distribution system, the test feeder BC34 in the Fengshan District of Taipower has been selected for computer simulation. Fig. 8 shows the system one-line diagram of the test feeder, including six laterals (L1–6), 105 segments, and 123 load points to serve the mixture load of residential and commercial customers with several key customers in the suburban area. There are four automatic switches and 22 manual switches in the system. To improve the reliability of the distribution systems, the optimal placement of FIs has to be derived to reduce customer interruption cost while achieving cost effectiveness for the investment in FIs.

After solving the optimal FI placement by the proposed IA algorithm to enhance customer service reliability, Fig. 8 shows the Taipower distribution system with the proposed placement of FIs. It is found that four and 27 FIs are installed at the primary feeder and lateral levels, respectively. Seventeen of these FIs are installed to coordinate with manual switches.

Fig. 9 shows the reduction in annual customer expected interruption cost (ECOST) of different load points after applying the OFP. The interruption cost of the key customers (such as N11, N14, N21, and N31) and commercial customers (such as N153, N155, N170, and N169) were significantly reduced because of the enhanced service reliability of the proposed fault indicator placement.

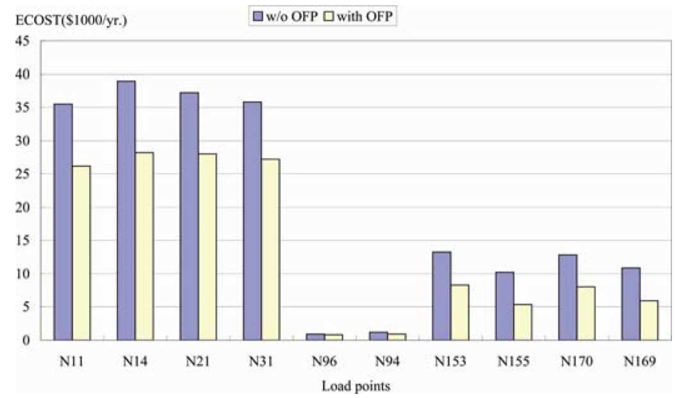

Fig. 9. Annual customer interruption cost of Taipower distribution system.

TABLE V
ENHANCEMENT OF RELIABILITY INDICES BY OPTIMAL FAULT INDICATOR PLACEMENT

Primary feeder/Laterals	SAIDI (minute/customer-year)	
	before OFP	after OFP
T1	21.3	20.6
L1	35.7	29.8
L2	46.7	36.7
L3	36.4	30.6
L4	35.9	30.4
L5	45.3	37.2
L6	45.1	36.9
System	35.5	29.8

Table V lists the primary feeder, laterals, and system reliability index (SAIDI) of the test feeder before and after the optimal placement of fault indicators. The system average interruption duration, SAIDI, decreased from 35.5 to 29.8 min/customer-year. The SAIDI of the primary feeder T1 is less than that of laterals due to the application of the FDIR function with the automatic line switches. Note that the improved service reliability obtained by OFP is sensitive to the number and locations of FIs to be installed. For example, with four new FIs added in segments N9-N10, N10-N12, N15-N20, and N22-N23, the SAIDI of the lateral L1 improved from 35.7 to 29.8 min/customer-year, implying that the customer interruption time decreased by 17% with the proposed FI placement.

Table VI illustrates the annual total cost of reliability (TCR) of the distribution system before and after applying the proposed OFP. The total cost of reliability decreased from \$123 826/year to \$87 436/year. With the installation of automatic line switches at the proposed locations of distribution feeders, the customer interruption cost is dramatically reduced from \$123 826/year to

TABLE VI
TCR OF THE TESTED TAIPOWER DISTRIBUTION SYSTEM

Scenario	w/o OFP	OFP with IA (with vaccines)	OFP with IA (w/o vaccines)	OFP with GA
TCR ($/year) (CIC/INVC)	123826 (123826/----)	87436 (83980/3456)	87436 (83980/3456)	87488 (83936/3552)
CPU time (sec)	----	37	46	76

CIC: customer interruption cost, INVC: investment cost

$83 980/year. Although almost the same results were obtained by both algorithms, higher efficiency of the IA algorithm with vaccines to solve the optimization problem has been illustrated. It is noted that the vaccination operator has some overhead computation in each generation, so the execution time of a generation in IA with vaccines is a little longer than that in IA without vaccines. However, the efficiency of IA with vaccines is still superior to that of IA without vaccines while the required generations decrease to achieve an acceptable solution.

V. CONCLUSIONS

In this paper, the application of the IA method to solve the optimal placement of FIs for distribution systems is presented. The main idea of the proposed IA is to utilize prior knowledge to associate with the considered problem. The *a priori* knowledge of the OFP problem is abstracted as some vaccines based on the Taipower's FI installation rules and the levels of the priority customers. Rapid convergence is obtained during search process by injecting these vaccines into the individuals of generations. With the proposed placement of FIs, the customer interruption time has been reduced very effectively with enhanced of service reliability.

To demonstrate the effectiveness of the proposed immune algorithm to solve the OFP problem, one Taipower feeder within the service area of Fengshan DAS project was selected for computer simulation. The number and installation locations of FIs were determined after solving the optimization problem by the proposed IA algorithm. It is found that four and 27 FIs are installed at the primary feeder/lateral levels, and four FIs corresponding with manual switches are added for a lateral with key customers. The expected customer interruption cost due to service outage was derived to examine the effect of the proposed OFP on system service reliability. It is found the customer interruption cost of the test feeder decreased by 32% or $38 846 per year with an annualized investment of $3456 for the proposed placement of FIs. It is concluded that the optimal placement of FIs by the proposed immune algorithm can therefore strengthen the FDIR function of distribution systems to reduce customer interruption cost for fault contingency in a very cost-effective way.

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