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THESIS

MULTI-OBJECTIVE OPTIMAL PLACEMENT OF SWITCHES AND PROTECTIVE DEVICES IN ELECTRICAL DISTRIBUTION SYSTEMS USING ANT COLONY OPTIMIZATION

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A Thesis Submitted in Partial Fulfillment of
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The purpose of this research is to develop an optimal placement methodology of switches and protective devices in electrical distribution systems based on multi-objective optimization. The objective functions are to minimize the System Average Interruption Frequency index (SAIFI), to minimize System Interruption Duration Index (SAIDI) and to minimize the total cost (including customer interruption cost and utility investment cost).
The type and location of basic devices in electrical distribution systems (switches, fuses and reclosers) are optimally identified. The multiple ant colony system (MACS) has been improved and applied to solve this problem because it has characteristics of positive feedback, distributed computation, and the use of a constructive greedy heuristic. The standard benchmark instances are used to evaluate performance of MACS compared with the Non-dominated Sorting Genetic Algorithm version II (NSGA-II). The RBTS Bus 2 and 4 and a real 22 kV distribution feeder of Provincial Electricity Authority of Thailand (PEA) are modeled as the test systems. The test results are simulated using Matlab program. The results of placement of switches and protective devices in the electrical distribution systems for both double objective functions and triple objective functions show that the algorithm can successfully determine the sets of optimal non-dominated solutions for all cases. It allows the electric utility to obtain the optimal type and location of devices to achieve the best system reliability with the lowest cost.

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LIST OF ABBREVIATIONS

ACO	=	Ant Colony Optimization
ACS	=	Ant Colony System
AS	=	Ant System
CCDF	=	Composite Customer Damage Function
CDF	=	Customer Damage Functions
CIC	=	Customer Interruption Costs
GA	=	Genetic Algorithm
IA	=	Immune Algorithm
MACS	=	Multiple Ant Colony System
MAIFI	=	Momentary Average Interruption Frequency Index
NMTS	=	New Multi-objective Tabu Search
NSGA-II	=	Non-dominated Sorting Genetic Algorithm version II
PEA	=	Provincial Electricity Authority of Thailand
SAIDI	=	System Average Interruption Duration Index
SAIFI	=	System Average Interruption Frequency Index
TC	=	Total Cost
TSP	=	Traveling Salesman Problem

MULTI-OBJECTIVE OPTIMAL PLACEMENT OF SWITCHES AND PROTECTIVE DEVICES IN ELECTRICAL DISTRIBUTION SYSTEMS USING ANT COLONY OPTIMIZATION

INTRODUCTION

The main objective of planning and operation of electrical distribution systems is to satisfy the system load and energy requirements as economically as possible with a reasonable assurance of continuity and quality. The two aspects of obtaining relatively low cost electrical energy at a high level of reliability are often in direct conflict due to the fact that providing a higher level of reliability will cost utilities more in capital and operational expenditures. This has become justification to emphasize on the optimization of system costs and reliability.

In electrical distribution system planning, the optimal placement of switches and protective devices in distribution networks allows better operation and improvement on the reliability indices of the systems. This optimization is considered a very difficult task because it is a combinatorial constrained problem described by a nonlinear and non-differential objective function. Several researches have solved the problems using intelligent algorithms. However, most of the approaches are the optimization of a single objective (mono-objective) function such as minimizing economic cost or one of reliability indices. In fact, taking into consideration only single objective function by neglecting the other objectives or turning them to constraints causes the loss of the best results. For this reason, this research develops the procedure for multi-objective optimal placement of switches and protective devices to minimize the total cost, and the reliability indices in electrical distribution systems.

This research considers optimal placement of basic switches and protective devices installed in general electric distribution systems. They are disconnecting switches, fuses and reclosers. The three objective functions for optimal placement of switches and protective devices in electrical power distribution systems are simultaneously proposed. The objectives are to simultaneously minimize SAIFI, minimize SAIDI and minimize total cost (including customer interruption cost and utility investment cost). This research develops the model and method for calculating the reliability indices of electrical distribution systems by using set theory, and improves the MACS to handle the tri-objective function. The MACS, which possesses the characteristics of positive feedback, distributed computation, and the use of a constructive greedy heuristic, is employed to find a set of good solutions that covers the various regions of the Pareto front in the best way.

To illustrate the improved MACS performance, the standard benchmark instances (traveling salesman problem or TSP) are used for testing its performance by comparison to the well known multi-objective genetic algorithm named as Non-dominated Sorting Genetic Algorithm version II (NSGA-II). The results of performance evaluation show that the MACS can effectively solve the bi-criteria and tri-criteria TSP problems. After that, the algorithm is applied to the bus 2 and bus 4 of Roy Billinton test systems (RBTS) and a real 22 kV distribution feeder of Provincial Electricity Authority of Thailand (PEA) to illustrate the effectiveness. Additionally, the results of the double and triple objective optimization obtained by the MACS give the optimal types and locations of switches and protective devices by balancing all objective functions. The proposed procedure can be used for typical electrical distribution systems for improving the reliability with reasonable cost.

OBJECTIVES

To develop the effective procedure for multi-objective optimal placement of switches and protective devices in electrical distribution system to improve the system reliability and minimizing cost simultaneously.

LITERATURE REVIEW

This research concentrates on the multi-objective optimization to place switches and protective devices in electrical distribution systems by ant colony optimization. Therefore, this chapter presents the main ideas of pervious researches in the area of optimal placement of switches and protective devices, and after that it presents the evolution of ant colony optimization.

1. Optimal placement of switches and protective devices

Electrical distribution system reliability has been measured by many reliability indices. The most common indices used by electrical utilities are the System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI), to measure the impact of power interruptions, in terms of the number of interrupted customers and interruption durations respectively (Bupasiri 2002). In addition, as more customers become sensitive to a short outage, there is increasing interest in the quantitative analysis of distribution system reliability worth and its applications, such as value-based reliability optimization (Sohn *et al*., 2006).

A typical radial electrical distribution system consists of a number of single-feeders, tree-like networks interconnected through tie-lines. Tie-lines contain switches that are usually open and are used to provide restoration or line reconfiguration. The single-feeder network consists of a series of lines and cables connecting any load point to the single supply source. These lines and cables are divided into sections by connection nodes and load points. Each section has its individual failure rate which depends on the type of line construction, section length, and environmental conditions. Usually, failure rates are found to be approximately proportional to section lengths (Levitin *et al*., 1995).

The switches and protective devices play a major role for reliability improvement of the electrical distribution systems. As they are installed at the beginning of line sections in the main feeder or lateral line sections, they can reduce the failure rate and average outage duration of load points in electrical distribution system. The basic protective equipments used in a radial distribution system consist of a circuit breaker at the substation with line reclosers, sectionalizers, automatic or manual isolating switches and fuses. Each type of devices has a unique set of functionalities (Soudi and Tomsivic, 1998).

A feeder circuit breaker located at the substation is the major protective device for protecting violent faults. Its protection scheme consists of phase, ground and automatic reclosing relays. Such a circuit breaker also has fault interruption and automatic reclosing capabilities.

A line recloser that has fault sensing, fault interrupting, and automatic reclosing capabilities can automatically test a line downstream from the recloser. The automatic scheme can be set to test energize the line once or twice at very high speed with several additional tests at a lower speed. The high speed tests are designed to enable the line recloser to check for a temporary fault without blowing load side fuses, thereby avoiding any unnecessary permanent outages for the customers downstream of the fuse. This capability is called a fuse saving scheme. Line reclosers are installed on the main overhead feeder and on heavily loaded or long laterals.

A sectionalizer is a device designed to automatically isolate a faulted line section after the number of operations of an upstream breaker or line recloser has reached a pre-determined value. A sectionalizer does not have fault interruption or automatic reclosing capability, but it can be used to switch load currents that fall within its continuous current rating. Sectionalizers are overhead line devices which must be used in conjunction with a line recloser or a breaker. If there is a location for which a line recloser should be installed, but coordination can not be achieved (with load and source side protection devices), then a sectionalizer can be used instead.

Automatic or manual isolating switch does not have a protective function. They can reduce down time by isolating only the faulted part from the rest of the system after the circuit is opened by a breaker or recloser. Hence, the upstream and downstream sections of the faulted section can be restored.

A fuse is a low cost automatic sectionalizing device. It has fault sensing and interruption capabilities, but obviously lacks automatic reclosing capability so that momentary faults are treated the same as permanent faults. A fuse is used on both overhead and underground circuits. It is important to insure that fuses will coordinate with source and load side protective devices. Miscoordination between these devices may cause a fuse to blow for a fault outside its protection zone which will delay identifying the trouble section and hence increase outage duration.

Selecting types and locating of switches and protective devices can significantly influence the reliability indices. There are many researches demonstrating the optimal placement of switches and protective devices to minimize reliability indices or minimize cost of reliability. Levitin *et al.* (1995) pointed out that the allocation of sectionalizers and tie-line switches affected the distribution system's reliability. Two types of optimization problems to minimize the system average interruption duration index (SAIDI) were addressed. The first type was the optimal allocation of a specified number of sectionalizers in a radial system with a given allocation of tie-lines. The other was the optimal allocation of a specified number of tie-lines and sectionalizers in a given radial system. The basic genetic operator (GA) and its modified version were developed to solve the specific problem. A modification of the GA outperformed the original version when applied to the considered problem. The computational example illustrated that the optimal allocation of sectionalizers and tie-line switches given by GA successfully reduced the reliability index.

Billinton and Jonnavithula (1996) proposed a problem formulation for sectionalizing device placement taking into consideration outage, maintenance and investment costs. They introduced that the formulation of sectionalizing switches was a combinatorial constrained optimization problem with a non-linear, non-differentiable objective function. A solution methodology based on the optimization technique of simulated annealing was proposed to determine (i) the number of sectionalizing switches and (ii) the locations of the switches. The proposed solution methodology offered a global optimal solution for the sectionalizing device placement problem which included the reliability, investment and maintenance costs.

Brown *et al*. (1997) showed automated design tools for placement of switches and protection devices in distribution systems after distribution substations had been located and primary feeders had been routed. An automated distribution system design method capable of identifying reliable and low-cost designs was developed. The total cost of reliability was equal to the sum of the utility cost of reliability and the customer cost of reliability. The total cost of reliability as a design criterion was examined by several discrete optimization methods such as integer programming, genetic algorithms, and simulated annealing. The automated design to a utility distribution system was applied to the areas of protection, switch placement, automation, and undergrounding. Implementing this optimization technique on a personal computer provided an automated design tool which helped engineers design reliable distribution systems while minimizing costs.

Teng and Lu (2002) concluded that due to the continuous requirement of providing better service to its customers, the Taiwan Power Company found that switch rearrangement was a cost-effective method for reducing customer outage costs. They pointed out that in feeder-switch planning, the size, number, and locations of the sectionalizers were determined based on some estimations of feeder load growth and distribution. Since the feeder configuration and land usage evolved, after a long-term service, the spatial distribution of feeder loads might be different from that used in the original design. Thus, the locations of feeder sectionalizers had to be adapted to the changes in order to achieve the best result. To solve the feeder-switch relocation problem, a heuristic approach in conjunction with simple numerical computation was proposed. In order to enhance the reliability in the distribution systems, a value-based method was proposed to take load distribution changes into account and searched for new locations of feeder sectionalizers such that the customer interruption costs (CIC) were reduced.

Teng and Liu (2003) showed a cooperative agent algorithm ,the ant colony system (ACS), for optimum switch relocation. The ACS had the characteristics of positive feedback, distributed computation, and the use of a constructive greedy heuristic. The applicability of the ACS-based algorithm in the power system optimization problems was investigated. Test results shown that the proposed ACS-based algorithm offered a near-optimum solution for switch relocation. The comparisons of the proposed method with a genetic-algorithm (GA)-based method were also shown in the test results to demonstrate the values of the proposed method.

Silva *et al*. (2004) presented a mathematical formulation for the problem of optimal allocation of protective devices in distribution systems, aiming at improving the system average interruption frequency index (SAIFI). The allocation problem was formulated by a nonlinear objective function that mathematically modeled the benefits and inconveniences of allocating protective devices in the main feeder and in all branches of the distribution circuit. The permanent and temporary fault indices in each section of the circuit, and number of customers were considered. The considered constraints contemplated technical and economical limitations, such as coordination problems of protective devices in series, number of pieces of equipment available for allocation, importance of the feeder under analysis and the topology of the circuit. The result of this type of analysis was a mathematical programming problem with binary variables, which was composed of a nonlinear objective function regulated by a linear constraint set. The use of a dedicated genetic algorithm (GA) to solve this problem was proposed. A 134-bus real circuit was analyzed and the results were compared to that of the present protection system.

Teng and Lu (2006) employed network reliability data and the customer interruption costs for a value-based planning method to find the optimal number and location of switches in feeder automation systems. The proposed method took reliability costs, maintenance and investment costs into account to obtain a feeder automation plan that had a maximum benefit and the properly met system reliability requirement. Numerical processing procedure was described, and the solution efficiency and results were compared with those obtained from the genetic algorithms.

Chen *et al*. (2006) illustrated the effectiveness of the proposed immune algorithm (IA) to find the optimal line switch placement, a Taipower distribution system was selected for computer simulation. The number and installation locations of automatic and manual switches were determined after solving the optimization problem using the proposed IA algorithm. It was found that the customer interruption cost of the Taipower distribution system had been reduced for the proposed placement of line switches. It was concluded that the optimal placement of line switches by the proposed immune algorithm enhanced the fault detection, isolation, and restoration functions of the distribution automation system to reduce customer interruption cost for fault contingency in a very cost-effective way.

Sohn *et al*. (2006) presented a method for identifying the types and locations for protection devices and switches on pre-routed distribution systems using value-based optimization. The lateral taps were divided into three categories for identifying the types and locations of protection devices and isolating switches. The optimization technique used in this research was binary linear integer programming. The objective function in this research was expressed as a sum of linear combination over control variables and their product terms. Any product terms were replaced with a new variable by adding only two constraints while maintaining linearity. The efficiency and validity were demonstrated in the case study. The proposed method was an effective tool for radial distribution system planning and design.

Silva *et al*. (2008) showed a novel approach for an integrated placement and replacement of control and protective devices in distribution network feeders. The problem was modeled as a mixed integer non-linear programming. This model considered the main actual physical aspects of the problem that directly affected the investment costs and improvement of reliability indices. The reactive tabu search algorithm proposed for solving the mixed integer non-linear programming was developed through a codification system and neighbourhood structure that considered the actual physical structure of problem under analysis. The obtained results for a practical feeder showed the excellent performance of the algorithm. The proposed technique found good-quality solutions, which fulfilled the imposed physical and operational constraints.

Most of the approaches presented above are the optimization of a single objective (mono-objective) function such as minimizing economic costs or reliability indices. Nevertheless, there are some papers that propose the multi-objective optimization for design problems of power distribution system planning. Rosado and Agustín (2001) presented a multi-objective optimization methodology for finding out the best distribution network reliability while simultaneously minimizing the system expansion costs. Hsiao (2004) proposed a multi-objective evolution programming method for distribution feeder reconfiguration in a practical system. Rosado and Navarro (2004) presented a new possibilistic (fuzzy) model for the multi-objective optimal planning of power distribution networks that determined the non-dominated multi-objective solutions corresponding to the simultaneous optimization of the fuzzy economic cost, level of fuzzy reliability, and exposure (optimization of robustness) of such networks, using an original and powerful meta-heuristic algorithm based on Tabu Search. Rosado and Navarro (2006) presented a new multi-objective Tabu search (NMTS) algorithm to solve a multi-objective fuzzy model for optimal planning of distribution systems.

However, in these papers, they are limited in scope to the multi-objective routing of primary feeders. In electrical distribution system design, after primary feeders have been routed, the system needs to be designed in detail-switches and protection devices must be placed. All of these design decisions effect reliability and cost. Therefore, this research proposes the multi-objective optimal placement of switches and protective devices for improve reliability while minimizing cost of the system.

2. Ant colony optimization (ACO)

Ant colony optimization (ACO) is a metaheuristic inspired by the foraging behavior of real ant colonies (Dorigo *et al*., 1996). In many ant species, ants walking to and from a food source deposit on the ground a substance called pheromone. Other ants perceive the presence of pheromone, and tend to follow paths where pheromone concentration is higher. Through this mechanism, ants are able to transport food to their nest in an extremely effective way. In this example, ants coordinate their activities via stigmergy, a form of indirect communication mediated by modifications of the environment. The ant algorithm uses this idea to form the artificial stigmergy to coordinate societies of artificial ants (Darigo and Stutzle, 2004).

The ACO algorithms are essentially construction algorithms. For each iteration, every ant constructs a solution to the problem by traveling on a construction graph. Each edge of the graph, representing the possible steps the ant can make, has associated two kinds of information that guide the ant movement. The first is Heuristic information, as denoted by η_{ij}. It measures the heuristic preference of moving from node i to node j, i.e., of traveling the edge a_{ij}. This information is not modified by the ants during the process. The other is artificial pheromone trail information, which measures the ‘‘learned desirability’’ of the movement and mimics the real pheromone that natural ants deposit. This information is modified during the process depending on the solutions found by the ants. It is denoted by τ_{ij}.

Several researchers have further developed different ACO algorithms such as the Ant System (Dorigo *et al*., 1996), the ant colony system (Dorigo and Gambardella, 1997), the Max–Min ant system (Stutzle amd Hoos, 1997), the rank-based ant system (Bullnheimer *et al*., 1999), and the best–worst ant system (Cordon *et al*., 2000). The two basic ant algorithms are briefly reviewed as follows.

2.1. Ant system

Ant system (AS), developed by Dorigo *et al*. (1996), was the first ACO algorithm. The AS is characterized by the fact that the pheromone update is triggered once all ants have completed their solutions and it is done as follows. First, all pheromone trails are reduced by a constant factor, implementing in this way the pheromone evaporation. Second, every ant of the colony deposits an amount of pheromone on its path which is a function of the quality of its solution. Initially, the AS did not use any centralized daemon actions (actions not performed by the ants but by an external agent, which have not got any natural counterpart, but are just additional procedures to improve the metaheuristic performance). It is very straightforward to add a local search procedure to refine the solutions generated by the ants.

Solutions provided by the AS are constructed as follows. At each construction step, an ant h in the AS chooses to go to a next node with a probability that is computed by equation (1).

$$P_{ij}^{h} = \begin{cases} \dfrac{\left[\tau_{ij}\right]^{\alpha} \cdot \left[\eta_{ij}\right]^{\beta}}{\sum_{u \in N_i^h} \left[\tau_{iu}\right]^{\alpha} \cdot \left[\eta_{iu}\right]^{\beta}}, & if\ j \in N_{h(i)}\ , \\ 0, & \text{otherwise}, \end{cases} \tag{1}$$

Where $N_h(i)$ is the feasible neighborhood of ant h when located at node i, and α, β are two parameters that weight the relative importance of the pheromone trail and the heuristic information. Each ant h stores the sequence it has followed so far, and this memory L_h is exploited to determine $N_h(i)$ in each construction step.

As mentioned above, the pheromone deposit is made once all ants have finished constructing their solutions. First, the pheromone trail associated to every edge is evaporated by reducing all pheromones by a constant factor, as expressed by equation (2).

$$\tau_{ij} = (1-\rho)\cdot\tau_{ij} \qquad (2)$$

Where $\rho \in$ (0, 1] is the evaporation rate. Next, each ant retraces the path it has followed (stored in its local memory L_h) and deposits an amount of pheromone $\Delta\tau_{ij}^h$ on each traversed connection (global update) described in equation (3).

$$\tau_{ij} \leftarrow \tau_{ij} + \Delta\tau_{ij}^h, \quad \forall a_{ij} \in S_h, \qquad (3)$$

Where $\Delta\tau_{ij}^h = f(C(S_h)),$ i.e., the amount of pheromone released is function of the quality $C(S_h)$ of the solution S_h of ant h. For example, in the TSP, $f(x)$ is usually equal to x^{-1}.

The extended version of this algorithm, called elitist AS (Dorigo *et al*., 1996), proposed a better performance. In the elitist AS, once the ants have released pheromone on the connections associated to their generated solutions, the daemon performs an additional pheromone deposit on the edges belonging to the best solution found until that moment in the search process (this solution is called global-best solution in the following). The amount of pheromone deposited, which depends on the quality of that global best solution, is weighted by the number of elitist ants considered, *e*, as shown in equation (4).

$$\tau_{ij} \leftarrow \tau_{ij} + e \cdot f(C(S_{global-best})), \quad \forall a_{ij} \in S_{global-best}. \qquad (4)$$

2.2. Ant colony system

Ant colony system (ACS) (Dorigo and Gambardella, 1997) is one of the first successors of AS. It introduces three major modifications into the AS:

2.2.1. ACS uses a different transition rule, which is called pseudo-random proportional rule: Let *h* be an ant located at node i, $q_0 \in$ [0, 1] be a parameter, and q

a random value in [0, 1]. The next node j to be visited is randomly chosen according to the probability distribution described in equation (5).

• If $q \le q_0$:

$$P_{ij}^{h} = \begin{cases} 1, & if\ j = \arg\max_{u \in N_h(i)} \left\{ \tau_{iu}^{\alpha} \cdot \eta_{iu}^{\beta} \right\}, \\ 0, & otherwise, \end{cases}$$

• else $q > q_0$: (5)

$$P_{ij}^{h} = \begin{cases} \dfrac{\left[\tau_{ij}\right]^{\alpha} \cdot \left[\eta_{ij}\right]^{\beta}}{\sum u \in N_i^{h[\tau_{iu}]^{\alpha} \cdot [\eta_{iu}]^{\beta}}}, & if\ j \in N_h(i), \\ 0, & \text{otherwise}, \end{cases}$$

As given above, the rule has two aims: when $q \le q_0$, it exploits the available knowledge, choosing the best option with respect to the heuristic information and the pheromone trail. However, if $q > q_0$, it applies a controlled exploration, as done in the AS. In summary, the rule establishes a trade-off between the exploration of new connections and the exploitation of the information available at that moment.

2.2.2. Only the daemon (and not the individual ants) triggers the global pheromone update. To do so, ACS only considers a single ant, the one who generated the global best solution, $S_{global-best\cdot}$. The pheromone update is done by first evaporating the pheromone trails on all the connections used by the global-best ant. It is important to notice that, in the ACS, pheromone evaporation is only applied to the connections of the solution that is also used to deposit pheromone as shown in equation (6).

$$\tau_{ij} = (1-\rho) \cdot \tau_{ij}, \quad \forall a_{ij} \in S_{global-best\cdot} \tag{6}$$

Next, the daemon deposits the pheromone by the rule described in equation (7).

$$\tau_{ij} = \tau_{ij} + \rho \cdot f(C(S_{global-best})), \quad \forall a_{ij} \in S_{global-best}. \qquad (7)$$

Additionally, the daemon can apply a local search algorithm to improve the ants' solutions before updating the pheromone trails.

2.2.3. Ants apply the local pheromone update that encourages the generation of different solutions to those yet found. Each time an ant travels an edge a_{ij}, it applies the rule calculated by equation (8).

$$\tau_{ij} \leftarrow (1-\varphi) \cdot \tau_{ij} + \varphi \cdot \tau_0 \qquad (8)$$

Where $\varphi \in$ (0, 1] is a second pheromone decay parameter. As shown above, the local pheromone update rule includes both pheromone evaporation and deposit. Because the amount of pheromone deposited is very small (in fact, τ_0 is the initial pheromone trail value which is chosen in such a way that, in practice, it corresponds to a lower pheromone trail limit. That is by the choice of the ACS pheromone update rules, no pheromone trail value can fall below τ_0), the application of this rule makes the pheromone trail on the connections traversed by an ant decrease. Hence, it results in an additional exploration technique of the ACS by making the connections traversed by an ant less attractive to the following ants, and helps to avoid that every ant follows the same path.

3. Multi-objective ant colony optimization

For multi-objective optimization problems, an excellent review and analysis on this subject are found in (Martinez *et al.*, 2007). The paper compares the characteristics of two state-of-the-art genetic algorithms (the good combination of the selection and replacement mechanism with the crossover and mutation operators) with the characteristics of eight major ant-inspired algorithms (the good management of problem specific and learned information). The ant-inspired algorithms have performed very well for the particular test cases such as a bi-criteria TSP. As an algorithm, in particular, the multiple ant colony system (MACS), presented in (Baran *et al.*, 2003), results in high quality solutions and the best distribution of solutions in the front.

The MACS is based on the ACS but, contrary to its predecessor, it uses a single pheromone matrix, τ, and two heuristic information functions, η^0 and η^1. In this way, an ant moves from node i to node j by applying the equation (9).

$$j = \begin{cases} \arg\max_{j \in \Omega}(\tau_{ij} \cdot \left[\eta_{ij}^0\right]^{\lambda\beta} \cdot \left[\eta_{ij}^1\right]^{(1-\lambda)\beta}), & if\ q \le q_0 \\ \hat{i} & otherwise, \end{cases} \tag{9}$$

Where β weights the relative importance of the objectives with respect to the pheromone trail, λ is computed for each ant h as $\lambda = h/m$, with m being the number of ants, and $\hat{i}$ is a node selected according to the following probability distribution described in equation (10):

$$P(j) = \begin{cases} \dfrac{\tau_{ij} \cdot \left[\eta_{ij}^0\right]^{\lambda\beta} \cdot \left[\eta_{ij}^1\right]^{(1-\lambda)\beta}}{\sum_{u \in \Omega} \tau_{iu} \cdot \left[\eta_{iu}^0\right]^{\lambda\beta} \cdot \left[\eta_{iu}^1\right]^{(1-\lambda)\beta}}, & if\ j \in \Omega, \\ 0, & \text{otherwise}, \end{cases} \tag{10}$$

Every time an ant crosses the edge a_{ij}, it performs the local pheromone update as calculated according to equation (11).

$$\tau_{ij} = (1-\rho) \cdot \tau_{ij} + \rho \cdot \tau_0. \tag{11}$$

Initially, τ_0 is calculated from a set of heuristic solutions by taking their average costs in each of the two objective functions, f^0 and f^1, by applying equation (12)

$$\tau_0 = 1/(\hat{f}^0 \cdot \hat{f}^1) \tag{12}$$

However, the value of τ_0 is not fixed during the run of algorithm, as usual in the ACS, but it undergoes adaptation. Every time an ant h builds a complete solution, it is compared to the Pareto set *P* generated till now to check if the former is a non-dominated solution. At the end of each iteration, τ_0' is calculated by applying the previous equation with the average values of each objective function taken from the solutions currently included in the Pareto set.

Then, if $\tau_0' > \tau_0$, the current initial pheromone value, the pheromone trails are reinitialized to the new value $\tau_0 \leftarrow \tau_0'$.

Otherwise, the global update is performed with each solution *S* of the current Pareto optimal set *P* by applying the equation (13) on its composing edges a_{ij}:

$$\tau_{ij} = (1-\rho)\cdot\tau_{ij} + \rho / (f^0(S)\cdot f^1(S)) \tag{13}$$

In this research, the MACS is improved from only solving the bi-criteria problems to effectively solving the tri-criteria problems for optimal placement of switches and protective devices in electrical distribution systems.

MATERIALS AND METHODS

Materials

1. Computer Intel® Pentium® 4 CPU 2.6 GHz 1 GB of RAM
2. Matlab® software

Method

This research develops the procedure of multi-objective placement of switches and protective devices for a balance between minimizing reliability indices and minimizing reliability cost. The electrical distribution systems are modeled in a form of sets of section paths and load point paths to identify the location of each section and load point. The devices installed in the system are also represented by a set of the position of them. The mathematical equations for calculating the reliability indices and cost of reliability are presented by using set theory. The MACS is improved by extending the ability of solving bi-objective function problems to solve tri-objective function problems. The search space of ant colony is developed for finding the optimal placement of several types of devices.

This research uses standard benchmark data sets known as traveling salesman problem (TSP) for evaluating performance of the MACS. The TSP is the problem of finding the cheapest way of visiting all the cities once and returning to the starting point. The K-objective symmetric TSP instance is the combination of the single objective symmetric TSP having the same number of towns and having K different cost factors that are defined between each pair of towns. In practical applications, the cost factors may for example correspond to cost, length, and travel time or tourist attractiveness.

The single objective TSP instances used in this research are presented in Appendix A that consists of Kroa100, Krob100 and Kroc100 instances. They are subsequently combined in terms of both bi-criteria and tri-criteria TSP instances for testing the performance of the MACS and the NSGA-II. The bi-criteria TSP instances consist of Kroab100, Kroac100 and Krobc100 instances, and the tri-criteria TSP instance is Kroabc100 instance. The MACS and the NSGA-II procedures compute the same TSP instances for maximum run time of 900 seconds and the number of runs for each algorithm is 10. The results that are non-dominated sets of bi-criteria and tri-criteria are verified by the two well known performance metrics, C metric and SP metric.

After the results are verified, the MACS algorithm is applied for the application in electrical distribution systems. This research selects three electrical distribution systems that including the two well known Roy Billinton test system (RBTS), bus 2 and bus 4, and a real electrical distribution system of the Provincial Electricity Authority of Thailand (PEA) as the case studies. The MACS are employed to solve the optimal placement and replacement of switches and protective devices for minimizing the two reliability indices and the total cost simultaneously. The experiments of the placement of switches and protective devices in the electrical distribution systems include of single, double and triple objective optimizations. The solutions of single objective optimizations (minimizing SAIFI or SAIDI or total cost) are calculated by the single objective ACS. The double objective problems (minimizing SAIFI or SAIDI and total cost) are computed by the double objective MACS. Finally, the triple objective MACS is applied to solve the triple objective problem (minimizing SAIFI, SAIDI and total cost simultaneously). The results of the multi-objective problems are presented as the non-dominated set. The engineer can select one of all best solutions. Nevertheless, there is the method to select a fine single solution from the non-dominated set, presented in the following section.

The rest of this chapter consists of explanation of the Pareto optimality concepts in section 1, the distribution feeder model in section 2, the mathematic model of three objective functions in section 3, the MACS algorithm in section 4, the

NSGA algorithm in section 5, the performance metrics in section 6, and finally the selection method for the final solution in section 7.

1. Parato optimality concepts

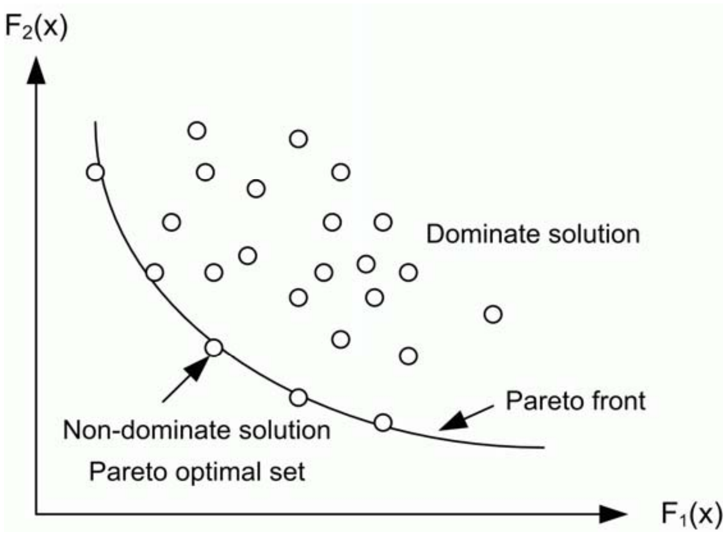

Figure 1 The concept of Pareto front for a multi-objective optimization problem

Source: Mendoza *et al*. (2006)

In many real-life optimization problems, there can be several objectives to be optimized simultaneously. Therefore, multi-objective optimization techniques have been used to solve this kind of problems. A general multi-objective problem could be expressed by equation (14).

$$\begin{aligned} &\min F(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), ..., f_k(\mathbf{x}))^T \\ &x \in S \\ &\mathbf{x} = (x_1, x_2, ..., x_n)^T \end{aligned} \tag{14}$$

where $f_1(\mathbf{x}), f_2(\mathbf{x}), ..., f_k(\mathbf{x})$ are the *k* objective functions, $(x_1, x_2, ..., x_n)$ are the *n* optimization parameters, and $S \in R^n$ is the solution or parameter space.

To obtain the optimal solution of multi-objective problems, some objectives are usually turned into constraints, or the objective vector may be reduced to a scalar optimization problem, for example, objective weighting, distance functions, Min–Max formulation and Lexicographic approach. However, all of the classical techniques used to solve multi-objective problems have serious drawbacks (Martinez *et al.*, 2007). Another approach is to search the solution space for a set of Pareto optimal solutions (Andersson 2000), from which the decision-maker may choose the final design. When a minimization problem and two solution vectors **x**, **y** $\in$ S are considered, **x** is said to dominate **y**, as denoted $\mathbf{x} \succ \mathbf{y}$, if:

$$\begin{aligned} \forall i \in 1,2,...,K \mid f_i(\mathbf{x}) \leq f_i(\mathbf{y}) \wedge \\ \exists j \in 1,2,...,K \mid f_j(\mathbf{x}) < f_j(\mathbf{y}). \end{aligned} \qquad (15)$$

The solution set of a multi-objective optimization problem consists of all non-dominated solutions, and is known as Pareto optimal set or Pareto optimal front. Figure 1 shows the concept of Pareto optimization.

2. Distribution feeder model

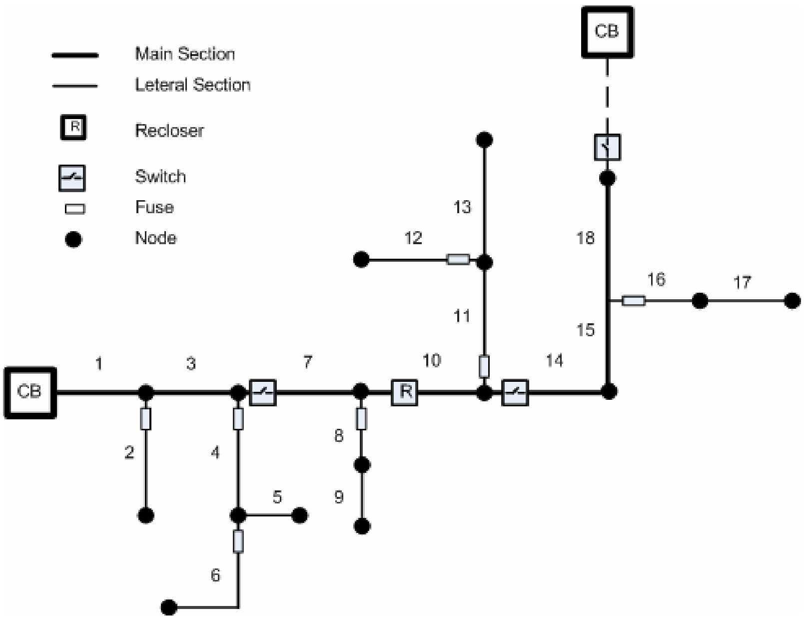

Figure 2 A simple distribution feeder.

This section presents the model of an electrical distribution feeder to be used in computer computation. Figure 2 shows a simple feeder of a distribution system consisting of several main and lateral sections, and the feeder load can be partially supplied by an interconnection of neighboring feeders. The distribution feeder can be represented by a tree graph G in which node o_i corresponds to tap connections or load points (Levitin *et al.*, 1995). Since each edge has a unique end node in the tree graph, the edge $(o_i,\ o_j)$ can be denoted as edge j. It corresponds to section j of the distribution system. Let $s(i)$ be the immediate predecessor of edge i, if graph G contains edge $(o_{s(i)},\ o_i)$. The set of predecessors for edge i is defined as equation (16).

$$S_i = \{i, s(i), s(s(i)), s(s(s(i))), ...\} \qquad (16)$$

S_i , the section path, contains all sections belonging to the path that connects section i to the energy source. For a simple distribution feeder in Figure 2, the paths connecting sections 10, 13 and 16 to the source are described as follows:

$$\begin{aligned} S_{10} &= \{1,3,7,10\} \\ S_{13} &= \{1,3,7,10,11,13\} \\ S_{16} &= \{1,3,7,10,14,15,16\} \end{aligned} \qquad (17)$$

The load point path, the set of sections which includes a section that connects loads or customers, can be defined similar to the section path. L_i is the load point path containing all sections belonging to the path from the initial section to the load section i. The examples of the load point path in Figure 2 are shown as follows:

$$\begin{aligned} L_2 &= \{1,2\} \\ L_5 &= \{1,3,4,5\} \\ L_6 &= \{1,3,4,6\} \end{aligned} \qquad (18)$$

The switches and protective devices as shown in Figure 2 play a major role for reliability improvement of the distribution system. They help reduce the failure rate and average outage duration of load points. Each type of devices has a unique set of functionalities.This study defines R , F , and D as sets of reclosers, fuses and switches that are installed in the distribution feeder. For example, in Figure 2, they are defined as

$$
\begin{aligned}
R &= \{10\} \\
F &= \{2,4,6,8,11,12,16\} \\
D &= \{7,14\} \,.
\end{aligned}
\tag{19}
$$

Sets of section paths, load point paths, switches and protective devices presented here will be used in calculating the objective functions as described in the next section.

3. Objective function model

The aim of the multi-objective optimization focused on this research is to achieve the best distribution network reliability while simultaneously minimizing the system costs. The most common indices used by electric utilities are system average interruption frequency index (SAIFI) and system average interruption duration index (SAIDI). They are used to measure the impact of power outages in terms of the number of interruptions and interruption durations respectively. Therefore, we selected three objectives to be minimized including SAIFI, SAIDI and total cost. The total cost consists of the average cost of interruptions (both temporary and permanent) and fixed cost associated with the investment for the purchase and installation of switches and protective devices. Mathematical models of the three objective functions can be established as follows:

3.1 SAIFI, $f_1(\mathbf{x})$: the system average interruption frequency index (sustained interruptions) is used to present the average frequency of sustained interruptions per customer. To calculate the index, use the equation (20).

$$SAIFI = \frac{\sum_{i=1}^{n}\left(\sum_{s=1}^{m}\lambda_{is}\right)N_i}{\sum_{i=1}^{n}N_i} \tag{20}$$

where λ_{is} is permanent failure rate of load point i due to outages in section s. It depends on the circuit topology and location of protective devices. From the characteristics of protective devices, the λ_{is} can be determined by equation (21).

$$\lambda_{is} = \begin{cases} \lambda_s & \text{if } S_s \cap (R \cup F) - L_i \cap (R \cup F) = \varnothing \\ 0 & \text{otherwise} \end{cases} \tag{21}$$

where λ_s is permanent failure rate of section s. N_i is number of customers at load point i, n and m represent number of load points and sections respectively.

3.2 SAIDI, $f_2(\mathbf{x})$: the system average interruption duration index is commonly referred as customer minutes of interruptions, and is established to present the average time that a customer is interrupted during a year. To calculate the index, use the equation (22).

$$SAIDI = \frac{\sum_{i=1}^{n}\left(\sum_{s=1}^{m}\lambda_{is}r_{is}\right)N_i}{\sum_{i=1}^{n}N_i} \tag{22}$$

where r_{is} is average outage time per interruption of load point i due to outages in section s, λ_{is} is permanent failure rate as defined in equation (21). Similar to λ_{is}, the r_{is} depends on the circuit topology and location of switches. From the characteristics of switches, the outage time of the faulted part of the circuit is equal to the repair time. On the other hand, the outage time of the upstream and downstream sections of the faulted part is equal to the switching time, usually shorter than the repair time. The r_{is} can be determined by equation (23).

$$r_{is} = \begin{cases} r_{rs} & \text{if } S_s \cap D \text{-} L_i \cap D = \varnothing \\ & or\ S_s^{'} \cap D \text{-} L_i^{'} \cap D = \varnothing \\ r_{ws} & \text{otherwise} \end{cases} \qquad (23)$$

where $S_i^{'}$ and $L_i^{'}$ are complement of S_i and L_i respectively. The r_{rs} and r_{ws} are repair time and switching time.

3.3 Total cost (TC), $f_3(\mathbf{x})$: This objective function is the sum of the fixed cost associated with capital investment on switches and protective devices, and the cost of interruptions. This cost is described by equation (24).

$$TC = FC + \sum_{i=1}^{n} \sum_{s=1}^{m} (CIP_{is} + CIT_{is}) \qquad (24)$$

where FC is the fixed cost including the investment for purchase and installation of switches and/or protective devices. The interruption costs for each load point i due to outages in section s consist of both cost of interruptions due to the permanent faults (CIP_{is}), and cost of interruptions due to temporary faults (CIT_{is}). They are defined in equation (25).

$$CIP_{is} = C_{is}(r_{is})\tilde{L}_i \lambda_{is} \qquad (25)$$
$$CIT_{is} = C_t \tilde{L}_i \gamma_{is}$$

where $\tilde{L}_i$ is average load at load point i. γ_{is} is temporary failure rate of load point i due to outages in section s, as described by equation (26).

$$\gamma_{is} = \begin{cases} \gamma_s & \text{if } S_s \cap R \text{ - } L_i \cap R = \varnothing \\ 0 & \text{otherwise} \end{cases} \tag{26}$$

where γ_s is temporary failure rate of section s. C_t is interruption cost per kilowatt ($US/kW) of temporary outages. $C_{is}(r_{is})$ is permanent interruption cost per kilowatt of load point i due to outages in section s with duration of r_{is}, as expressed by equation (27).

$$C_{is}(r_{is}) = (Res_s(\%) * f_r(r_{is}) + Com_s(\%) * f_c(r_{is}) + Ind_s(\%) * f_i(r_{is})) \tag{27}$$

where $Res_s(\%)$, $Com_s(\%)$, and $Ind_s(\%)$ are load percentage of each type of customers in section s. Also, $f_r(r_{is})$, $f_c(r_{is})$, and $f_i(r_{is})$ are interruption cost functions of residential, commercial, and industrial customers respectively.

3.4 Constraints: The coordination and selection of protective devices are considered as constraints in the formulation of this problem. Those constraints are described as only reclosers and switches are allowed to be installed on the main feeders, fuses cannot be placed upstream of a recloser and the maximum number of fuses placed in series is set to 3.

4. The multiple ant colony system (MACS)

The ant colony optimization technigues are briefly mentioned in the chapter of literature review. In this research, the MACS is improved from only solving the bi-criteria problems to effectively solving the tri-criteria problems for optimal placement of switches and protective devices in electrical distribution systems. The MACS was proposed as a variation of the MACS-VRPTW algorithm (Baran and Schaerer, 2003). So, it is also based on the ACS. Contrary to its predecessor, the MACS uses a single pheromone matrix, τ, and several heuristic information functions, η_k.

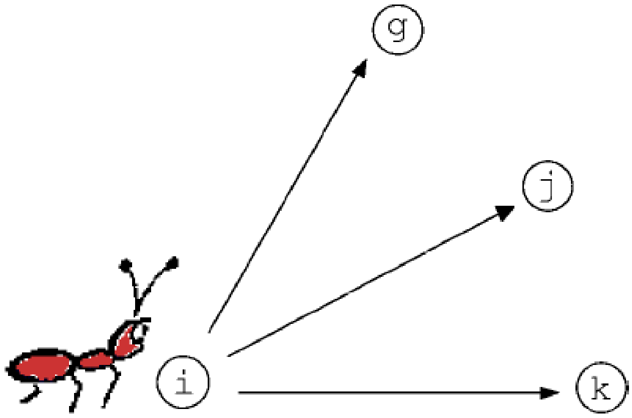

Figure 3 An ant in node i chooses the next node to visit via a stochastic mechanism

Source: Dorigo *et al*. (2006)

Each ant will start its tour from the home colony, and stop at the destination. In each stage, an ant chooses only one node to go to. Figure 3 shows an ant in node i chooses the next node by a stochastic mechanism. The decision will depend on a probability that is a function of the amount of pheromones present and the visibilities on the connecting edges of each state. An ant moves from node i to node j by applying the pseudo-random proportional rule as given in equation (28).

$$j = \begin{cases} \arg\max_{j \in \Omega} \tau_{ij} \cdot (\eta_{ij}^{1})^{\lambda_1 \beta} \cdot (\eta_{ij}^{2})^{\lambda_2 \beta} \cdot (\eta_{ij}^{3})^{\lambda_3 \beta} & \text{if } q \leq q0 \\ \hat{j}, & \textit{otherwise} \end{cases} \qquad (28)$$

where i is position of the current node $i(x, y, z)$, j is position of the next node $j(x, y, z)$, β is parameter that weights the relative importance of the heuristic information, and Ω is the current feasible neighborhood of the ant. The parameter q_0 can be set from 0 to 1, and q is a random value in a range of [0,1]. The λ_1, λ_2 and λ_3 are computed using equation (29) for each ant h, in order to force the ants to search in different regions of the Pareto front, where $h \in \{1, \ldots, \tilde{m}\}$, and $\tilde{m}$ is the number of ants.

$$\begin{aligned} \lambda_1 &= \text{mod}(h / \tilde{m}, 1) \\ \lambda_2 &= \text{mod}(h / \tilde{m} + 1, 1) \\ \lambda_3 &= \text{mod}(h / \tilde{m} + 2, 1) \end{aligned} \tag{29}$$

$\hat{j}$ is a node to be selected according to the probability distribution described in equation (30).

$$P(\hat{j}) = \begin{cases} \dfrac{\tau_{ij} \cdot (\eta_{ij}^1)^{\lambda_1 \beta} \cdot (\eta_{ij}^2)^{\lambda_2 \beta} \cdot (\eta_{ij}^3)^{\lambda_3 \beta}}{\sum_{u \in \Omega} \tau_{iu} \cdot (\eta_{iu}^1)^{\lambda_1 \beta} \cdot (\eta_{iu}^2)^{\lambda_2 \beta} \cdot (\eta_{iu}^3)^{\lambda_3 \beta}}, & \text{if } j \in \Omega \\ 0, & \text{otherwise} \end{cases} \tag{30}$$

The selection process of the next node $\hat{j}$ is based on spinning the roulette wheel using the probability calculated in equation (17). The η_{ij}^1, η_{ij}^2 and η_{ij}^3 are the visibilities for the objective functions $f_1(\mathbf{x})$, $f_2(\mathbf{x})$ and $f_3(\mathbf{x})$ respectively. They are defined in equation (31).

$$\begin{aligned} \eta_{ij}^1 &= 1 / \hat{f}_1(\mathbf{x}) \\ \eta_{ij}^2 &= 1 / \hat{f}_2(\mathbf{x}) \\ \eta_{ij}^3 &= 1 / \hat{f}_3(\mathbf{x}) \end{aligned} \tag{31}$$

where $\hat{f}_1(\mathbf{x})$, $\hat{f}_2(\mathbf{x})$ and $\hat{f}_3(\mathbf{x})$ are the values of three objective functions when an ant arrives node j. Every time an ant crosses the edge a_{ij}, it performs the local pheromone update as shown in equation (32).

$$\tau_{ij} = (1 - \rho) \cdot \tau_{ij} + \rho \cdot \tau_0 \tag{32}$$

where $\rho \in (0,\ 1]$ is the evaporation rate, and τ_0 is initially calculated according to equation (33).

$$\tau_0 = 1/(\hat{f}_1(\mathbf{x})^0 \cdot \hat{f}_2(\mathbf{x})^0 \cdot \hat{f}_3(\mathbf{x})^0) \quad (33)$$

where $\hat{f}_1(\mathbf{x})^0$, $\hat{f}_2(\mathbf{x})^0$ and $\hat{f}_3(\mathbf{x})^0$ represent the initial estimation of $f_1(\mathbf{x})$, $f_2(\mathbf{x})$ and $f_3(\mathbf{x})$ respectively.

During a run of the algorithm, the value of τ_0 is not fixed, but it undergoes improvement. Every time an ant h builds a complete solution, it is compared to the Pareto set P generated up till now to check if the former is a non-dominated solution. At the end of each iteration, $\tau_0^{'}$ is calculated by applying the equation (34).

$$\tau_0^{'} = 1/(\hat{f}_1(\mathbf{x})^p \cdot \hat{f}_2(\mathbf{x})^p \cdot \hat{f}_3(\mathbf{x})^p) \quad (34)$$

where the $\hat{f}_1(\mathbf{x})^p$, $\hat{f}_2(\mathbf{x})^p$ and $\hat{f}_3(\mathbf{x})^p$ are average values of each objective function taken from the solutions currently included in the Pareto set.

Then, if $\tau_0^{'} > \tau_0$, the pheromone trails are reinitialized to the new value $\tau_0 \leftarrow \tau_0^{'}$. Otherwise, the global update is performed using each solution S of the current Pareto optimal set P by applying the equation (35) on its composing edges a_{ij}:

$$\tau_{ij} = (1-\rho)\cdot\tau_{ij} + \rho / \hat{f}_1(\mathbf{x})^p \cdot \hat{f}_2(\mathbf{x})^p \cdot \hat{f}_3(\mathbf{x})^p \quad (35)$$

Figure 4 shows the searching space of the optimal placement of tri-criteria MACS. All possible candidate locations and types of devices are represented by the states in the searching space in correspondence to stage. The number of stages (x) is equal to the number of devices. Each stage has the number of states equal to the possible candidate locations (y) multiplied by the number of types of devices (z). The position of each state can be represented by a three-dimensional point, for example, state $i(x, y, z)$. The detail of the MACS procedure is shown in Figure 5.

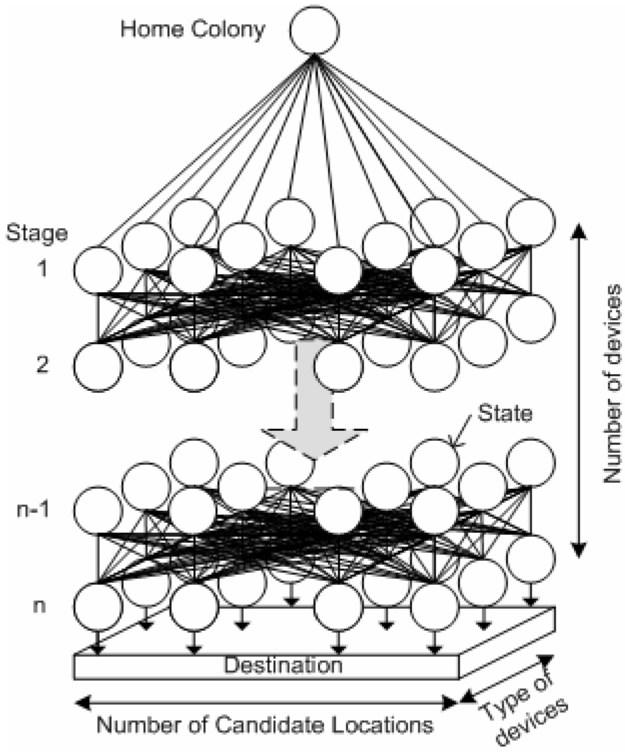

Figure 4 Search space of MACS for optimal placement of switches and protective devices.

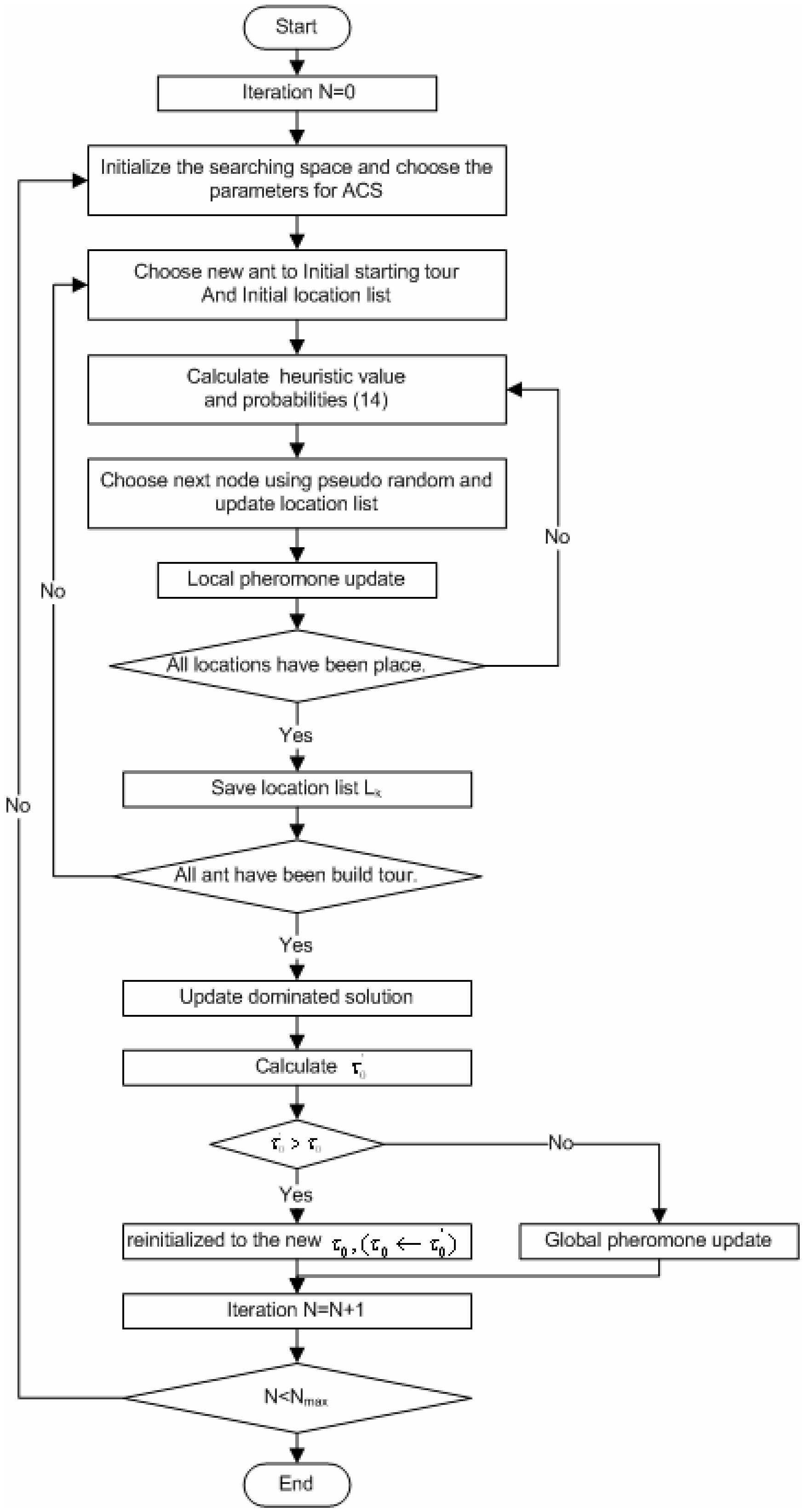

Figure 5 Computation procedure of MACS.

5. Non-dominated Sorting Genetic Algorithm (NSGA-II)

This approach was introduced in (Deb *et al*., 2002) as an improved version of the NSGA (Srinivas and Deb, 1994). In the NSGA-II, for each solution one has to determine how many solutions dominate it and the set of solutions to which it dominates. The NSGA-II estimates the density of solutions surrounding a particular solution in the population by computing the average distance of two points on either side of this point along each of the objectives of the problem. This value is the so-called crowding distance. During selection, the NSGA-II uses a crowded-comparison operator which takes into consideration both the non-domination rank of an individual in the population and its crowding distance. The steps of this algorithm are given as follows:

5.1 Create a random parent population (P_0) of size *N*, initially.

5.2 Sort the random parent population based on non-domination.

5.3 For each non-dominated solution, assign a fitness (rank) equal to its non-domination level (1 is the best level, 2 is the next best level, and so on).

5.4 Create a child population (Q_0) of size *N* using binary tournament selection, recombination, and mutation operators.

5.5 From the first generation onwards, creation of each new generation constitutes the following steps:

5.5.1 Create the mating pool (R_t) of size 2*N* by combining the parent population (P_t) and the child population (Q_t).

5.5.2 Sort the combined population (R_t) according to the fast non-dominated sorting procedure to identify all non-dominated fronts $(F_1, F_2, ..., F_l)$.

5.5.3 Generate the new parent population (P_{t+1}) of size *N* by adding non-dominated solutions starting from the first ranked non-dominated front (F_1) and proceeding with the subsequently ranked non-dominated fronts $(F_2, F_3, ..., F_l)$, till the size exceeds *N*. This means that the total count of the non-dominated solutions from the fronts $F_1, F_2, ..., F_l$, exceeds the population size *N*. Now, in order to make the total count of the non-dominated solutions equal to *N*, it is required to reject some of the lower ranked non-dominated solutions from the last (F_{lth}) front. This is achieved through a sorting done according to the crowded comparison operator $(\geq_n)$ based on the crowding distance assigned to each solution contained in the F_{lth} non-dominated front. Thus, the new parent population (p_{t+1}) of size *N* is constructed.

5.5.4 Perform the selection, crossover and mutation operations on the new generated parent population (p_{t+1}) to create the new child population (Q_{t+1}) of size *N*.

5.6 Repeat Step 5.5 until the maximum number of generations is reached.

The concept of the NSGA-II is shown in Figure 6, and the computation procedure is shown in Figure 7.

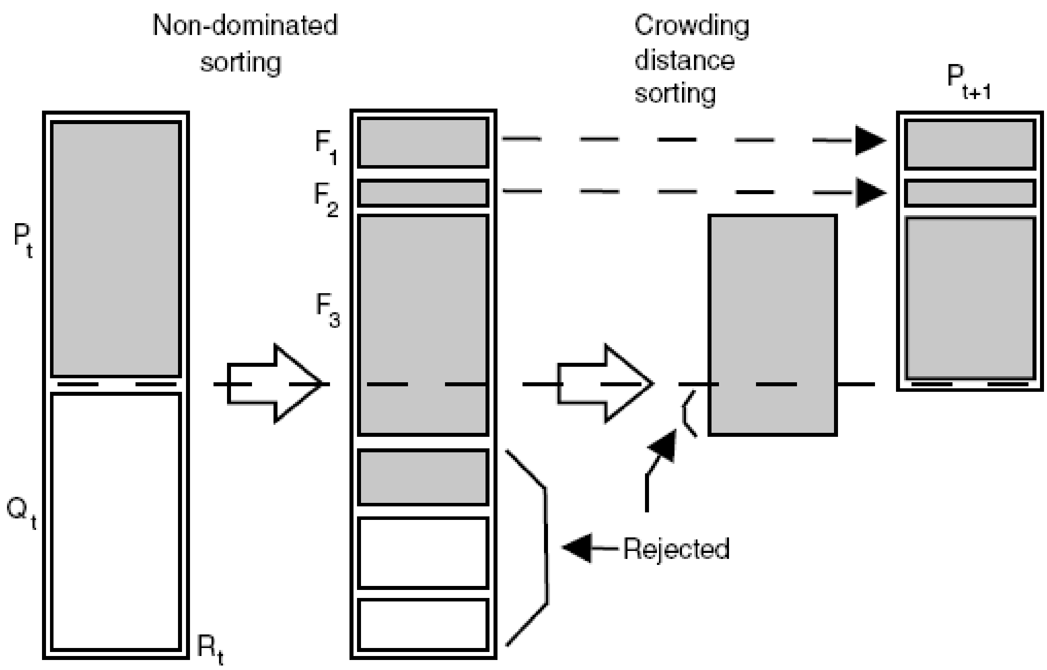

Figure 6 The concept of NSGA-II

Source: Martinez *et al*., (2007)

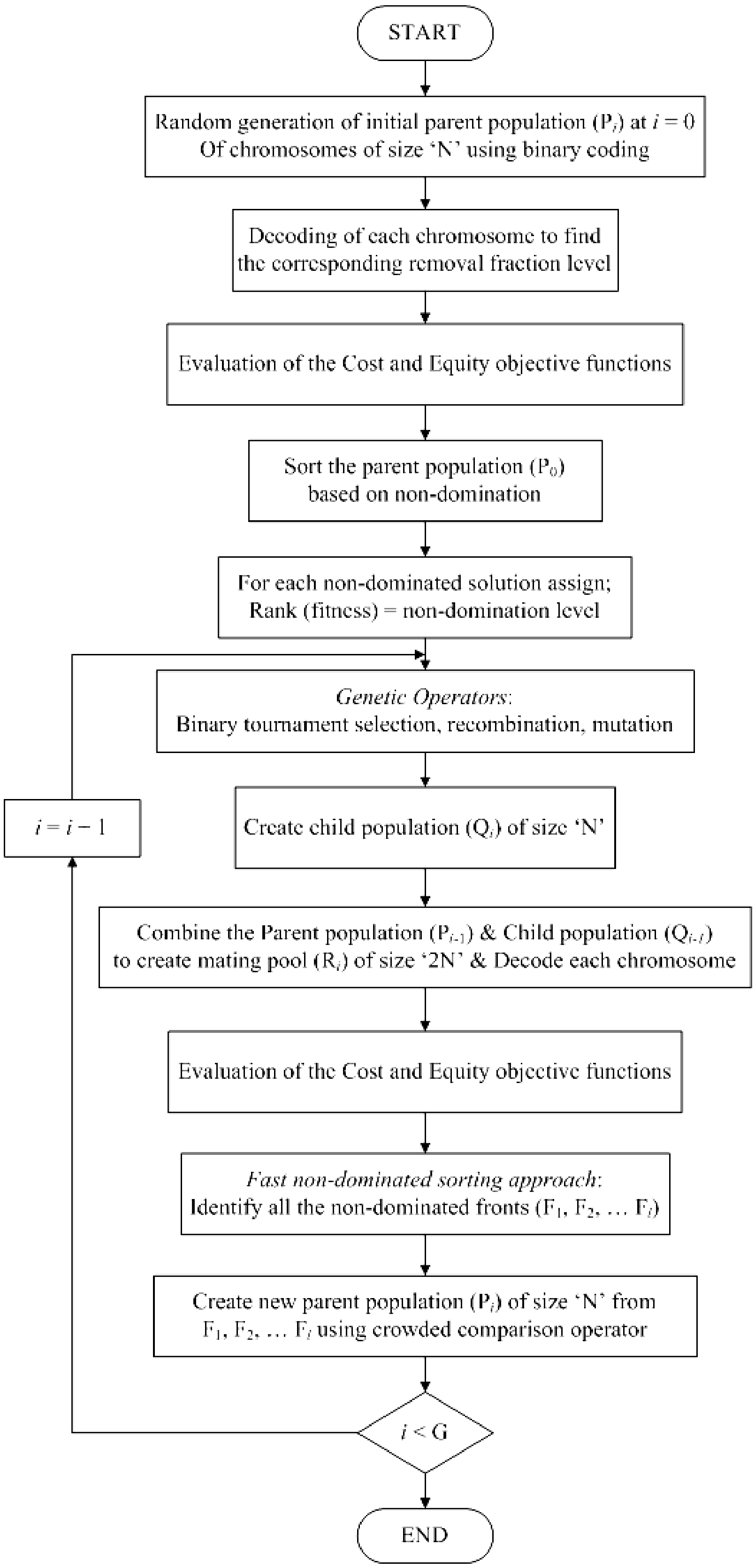

Figure 7 Computation procedure of NSGA-II.

6. Metrics of performance

To compare the performance of two different multi-objective algorithms this thesis selects two standard metrics for testing the performance of the MACS and the NSGA-II. First, the C metric, one of the most used metrics was proposed by Zitzler *et al*. (2000). This metric is utilized to compare a pair of non-dominated sets by computing the fraction of each set that is covered by the other, as shown in equation (36).

$$C(x', x'') = \left|\{a'' \in X''; \exists a' \in X' : a' \succ a''\}\right| / \left|X''\right| \qquad (36)$$

Where $a' \succ a''$ indicates that the solution a' dominates the solution a''
Hence, the value $C(X', X'') = 1$ means that all the solutions in X'' are dominated by or equal to solutions in X'. The opposite, $C(X', X'') = 0$, represents the situation where none of the solutions in X'' are covered by the set X'. Note that both $C(X', X'')$ and $C(X'', X')$ have to be considered, since $C(X', X'')$ is not necessarily equal to 1- $C(X'', X')$.

As the other, the spread (SP) metric is also an important one in comparison of evolutionary multi-objective optimization algorithms. One of its instances is introduced by Schott (1995), as shown in equation (37).

.

$$SP = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\bar{d} - d_i)^2} \qquad (37)$$

Where $d_i = \min_{j=1 \to N} \sum_{m=1}^{M} \left| f_m^i - f_m^j \right|$, f_m is objective function m, and N is the population size and M is the number of objectives. The interpretation of this metric is that the smaller the value of SP, the better the distribution in the set.

7. Selection of the final multi-objective results

After analyzing the set of non-dominated solutions, this research finds the final result by using the well-known max-min operator found in the literature by Rosado and Navarro (2004). A max-min approach is used to select the best (final) multi-objective planning solution. Each solution in the set of non-dominated solutions has an associated vector of values $\hat{f}_1(x), \hat{f}_2(x), \hat{f}_3(x)$ that can be normalized using the equation (38),

$$\left(\frac{\hat{f}_1(x)_{max}-\hat{f}_1(x)}{\hat{f}_1(x)_{max}-\hat{f}_1(x)_{min}},\frac{\hat{f}_2(x)_{max}-\hat{f}_2(x)}{\hat{f}_2(x)_{max}-\hat{f}_2(x)_{min}},\frac{\hat{f}_3(x)_{max}-\hat{f}_3(x)}{\hat{f}_3(x)_{max}-\hat{f}_3(x)_{min}}\right) \quad (38)$$

where $\hat{f}_1(x)_{max}$, $\hat{f}_2(x)_{max}$ and $\hat{f}_3(x)_{max}$ are of the maximum values obtained for the objective functions, and $\hat{f}_1(x)_{min}$, $\hat{f}_2(x)_{min}$ and $\hat{f}_3(x)_{min}$ are the minimum values. Note that the result of this normalization gives the vector (1, 1, 1) for the ideal point $(\hat{f}_1(x)_{min}, \hat{f}_2(x)_{min}, \hat{f}_3(x)_{min})$ and the vector (0, 0, 0) for the anti-ideal point $(\hat{f}_1(x)_{max}$, $\hat{f}_2(x)_{max}, \hat{f}_3(x)_{max})$. Thus, it can be used to represent the level of satisfaction for each objective function. Afterwards, a max-min approach, as shown in equation (39), is applied to select the best (final) multi-objective planning solution.

$$max\left\{min\left[\left(\frac{\hat{f}_1(x)_{max}-\hat{f}_1(x)}{\hat{f}_1(x)_{max}-\hat{f}_1(x)_{min}},\frac{\hat{f}_2(x)_{max}-\hat{f}_2(x)}{\hat{f}_2(x)_{max}-\hat{f}_2(x)_{min}},\frac{\hat{f}_3(x)_{max}-\hat{f}_3(x)}{\hat{f}_3(x)_{max}-\hat{f}_3(x)_{min}}\right)\right]\right\} \quad (39)$$

RESULTS AND DISCUSSION

Results

This chapter presents the results obtained from the experimentation divided into two sections. In the first section the results of performance evaluation of the MACS on TSP instances are given. The second section provides the results of the optimal placement of switches and protective devices in electrical distribution systems.

1. Performance Evaluation

To test the performance, the MACS and the NSGA-II procedures are examined through the TSP problems. They execute the same TSP instances in maximum run time of 900 second, and the number of runs for each algorithm is 10. Table 1 is the collection of the parameters for both algorithms. The results of the studies are illustrated in the graphical representation of the Pareto sets, the values for the C metric and the values of the SP metric.

Figure 8 is the comparison of non-dominated sets obtained by the bi-objective optimization, Kroab100 instance. In this Figure, the plot shows that the values of non-dominated set resulted from the MACS dominate those obtained from the NSGA-II. Similarly, the results of the bi-criteria TSP Kroac100 and Krobc100 instances are shown in Figure 9 and 10. They confirm that the results of the MACS dominate those of the NSGA-II. Figure 11 and 12, in the tri-criteria TSP instance, display the three dimensional non-dominated set achieved by the MACS and the NSGA-II respectively. Figure 13 makes it more obvious by showing the results of both algorithms together. It shows that the tri-criteria non-dominated set obtained from the MACS dominate the results of the NSGA-II again.

Afterwards, the values of the C metric of the two algorithms are compared by calculating the dominance degree of their respective Pareto sets. The box plots of the

C metric measurement of the MACS that is covered by the NSGA-II are shown in Figure 14. On the contrary, the box plots of C metric measurement of the NSGA-II that is covered by the MACS are shown in Figure 15. The values of the C metrics in Figure 14 show that the values in the bi-criteria and tri-criteria TSP instances are equal to 1. It means that the NSGA-II is strongly dominated by the MACS. Meanwhile, Figure 15 presents that the bi-criteria instances have the values of the C metrics equal to 0, and tri-criteria instance has it nearly 0. From the results, it means that the MACS is not dominated by the NSGA-II algorithm.

At last, the box plots of the SP metrics of the bi-criteria instances are shown in Figure 16, 17 and 18, and that of the tri-criteria instance is shown in Figure 19. The results of SP metrics, for the bi-criteria instances, show that the values of the MACS are above the NSGA-II. In opposition, the results from the tri-criteria instance show that the values of the MACS are lower than NSGA-II.

Table 1 The parameter values for performance evaluation of MACS and NSGA-II.

Parameter	**Value**
Number of runs for each algorithm	10
Maximum run time	900 seconds
Number of ants	100
α	1
β	2
ρ	0.2
q_0	0.98
NSGA-II population size	100
Crossover Probability	0.8
Mutation Probability	0.1
Computer specifications	Intel® Pentium® 2.6GHz with 1 GB RAM
Operation system	Windows XP Service Pack 2

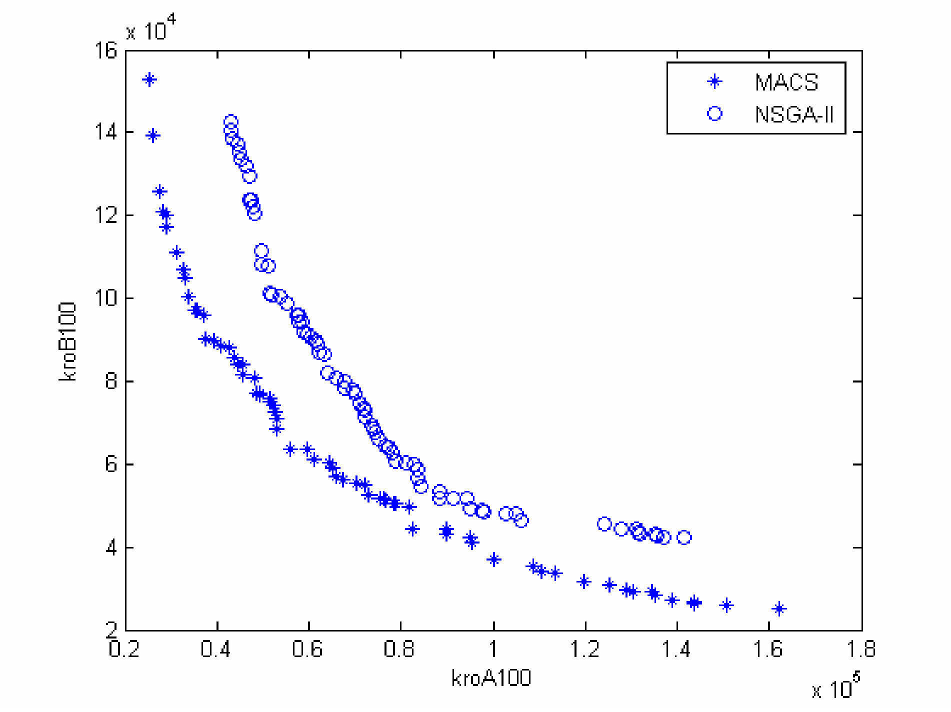

Figure 8 The non-dominated solution sets from a test for Kroab100 instance.

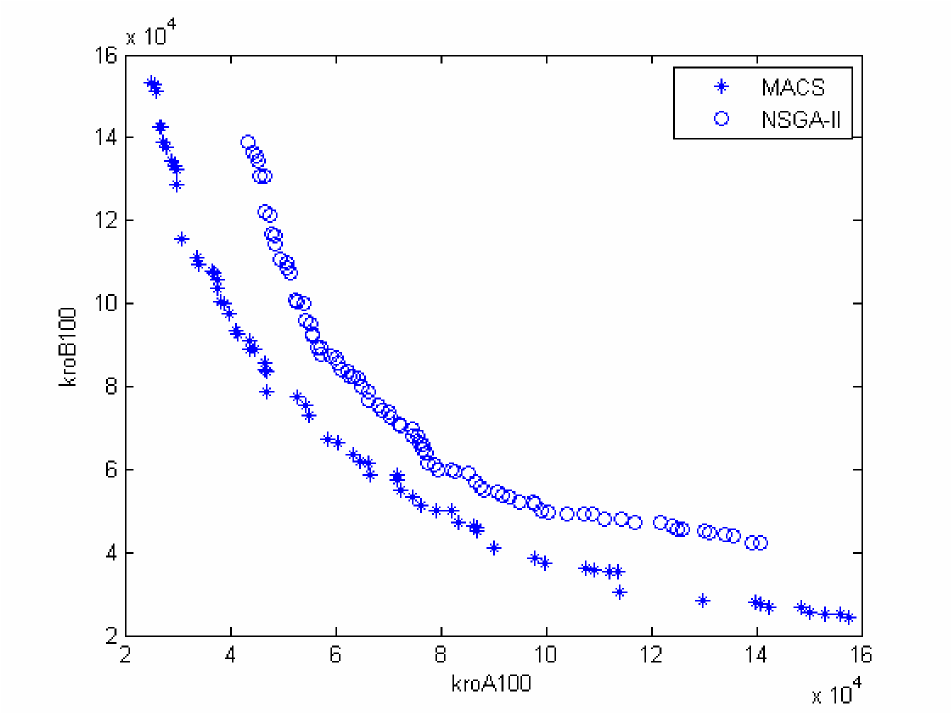

Figure 9 The non-dominated solution sets from a test for Kroac100 instance.

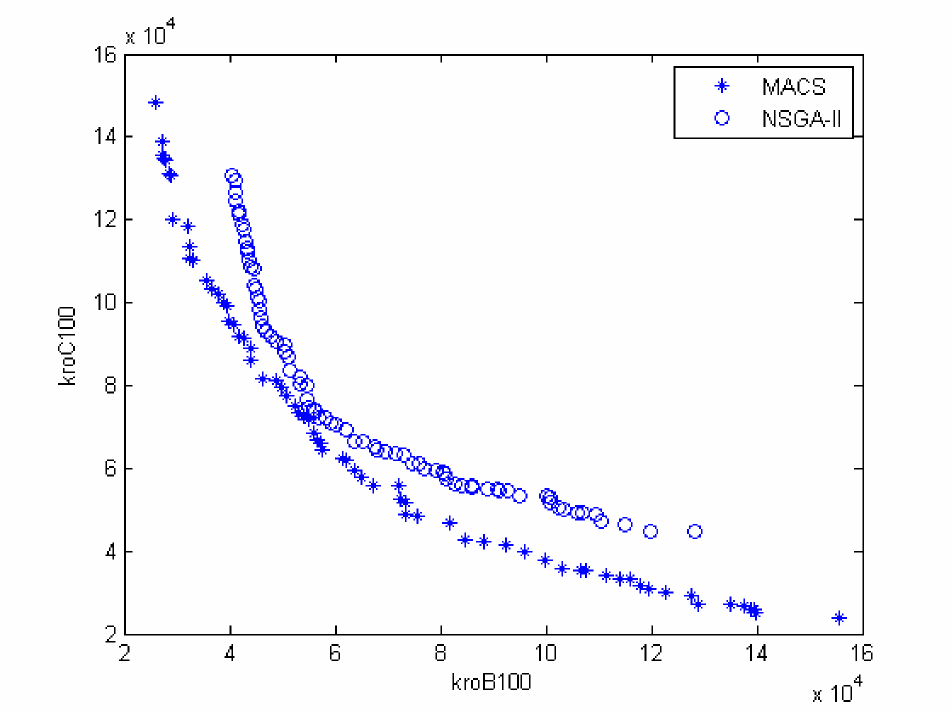

Figure 10 The non-dominated solution sets from a test for Krobc100 instance.

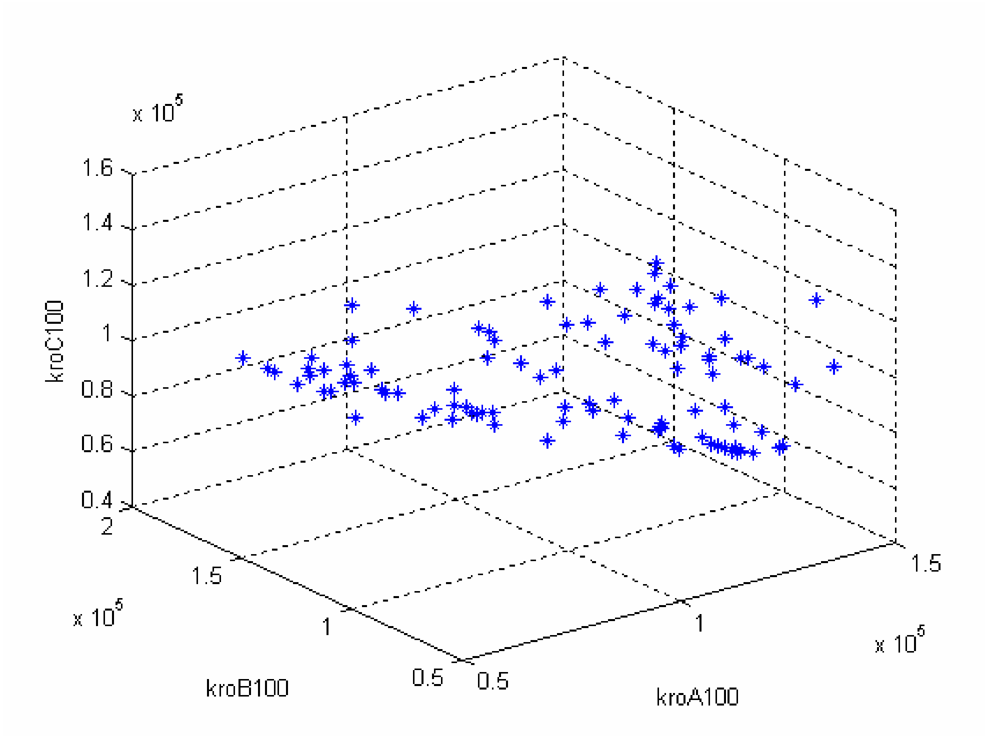

Figure 11 The non-dominated solution set from a test for Kroabc100 instance using MACS.

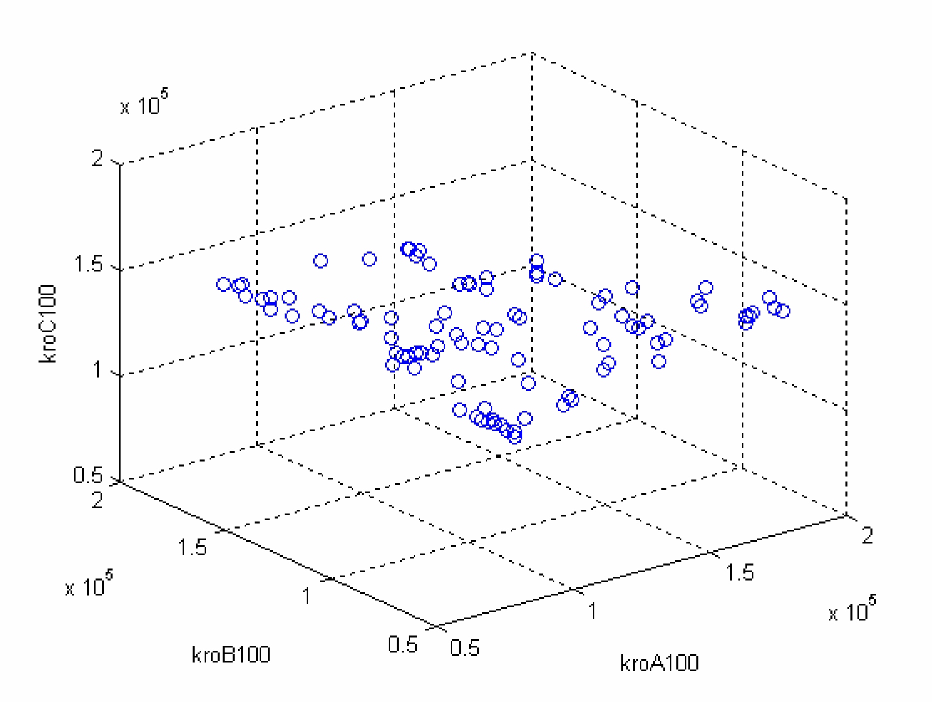

Figure 12 The non-dominated solution set from a test for Kroabc100 instance using NSGA-II.

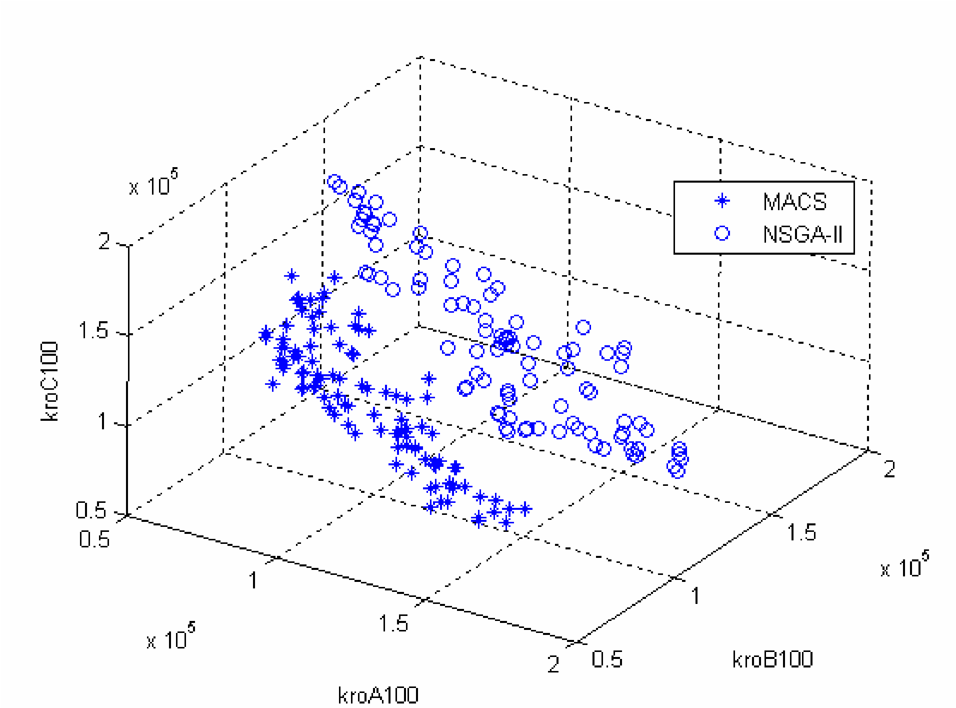

Figure 13 The non-dominated solution sets from a test for Kroabc100 using MACS and NSGA-II.

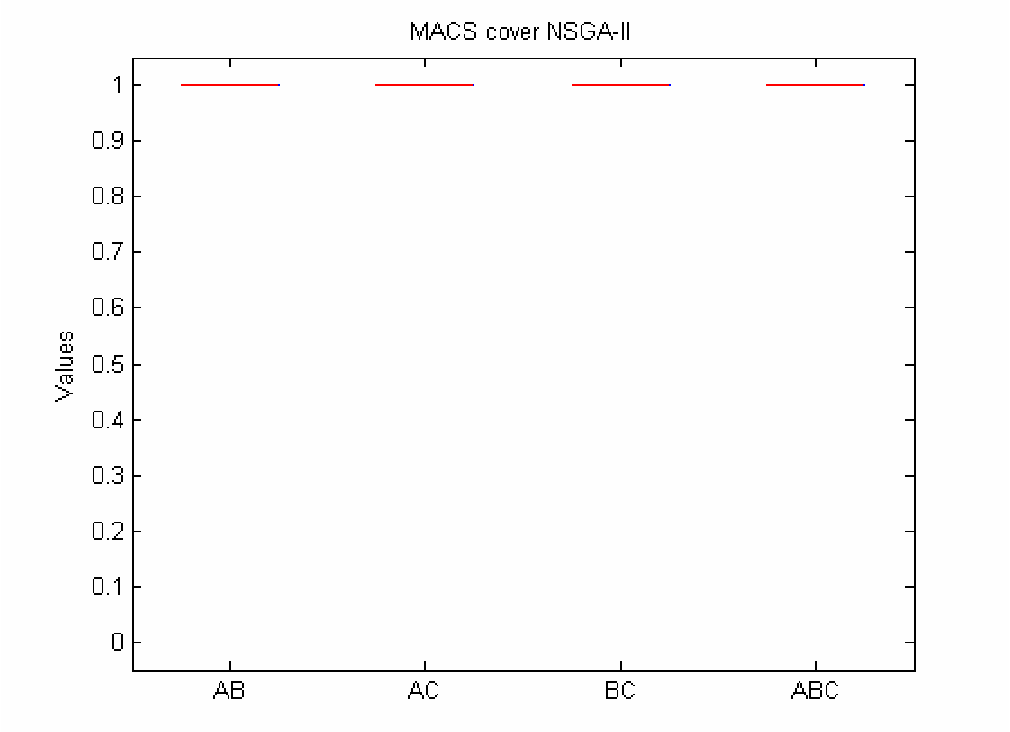

Figure 14 The Box-plots of the C metric considering NSGA-II covered by MACS.

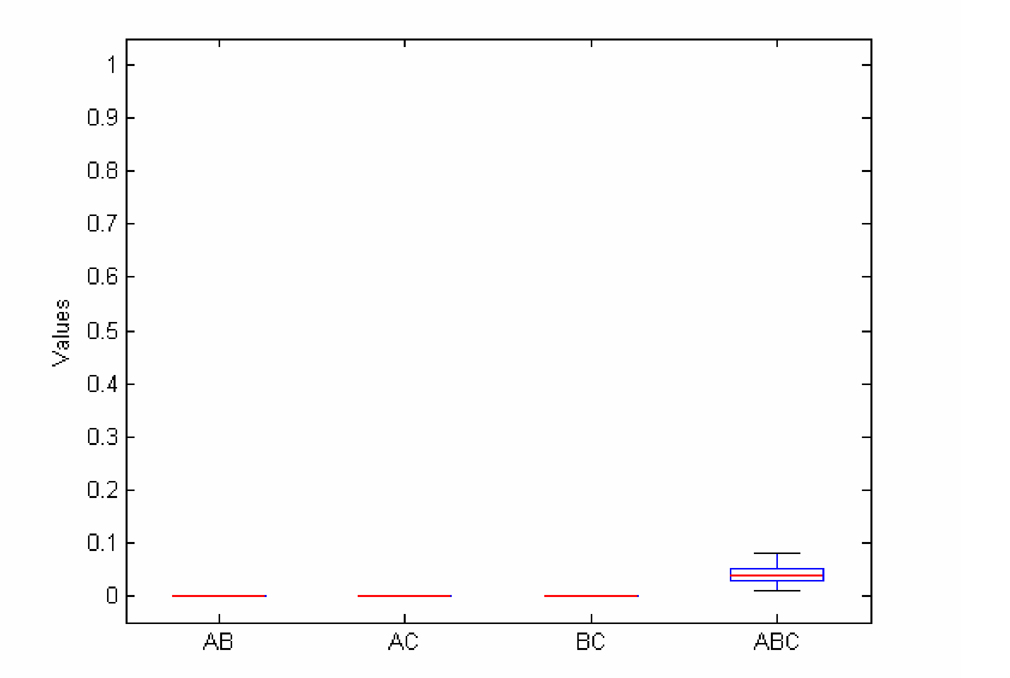

Figure 15 The Box-plots of the C metric considering MACS covered by NSGA-II.

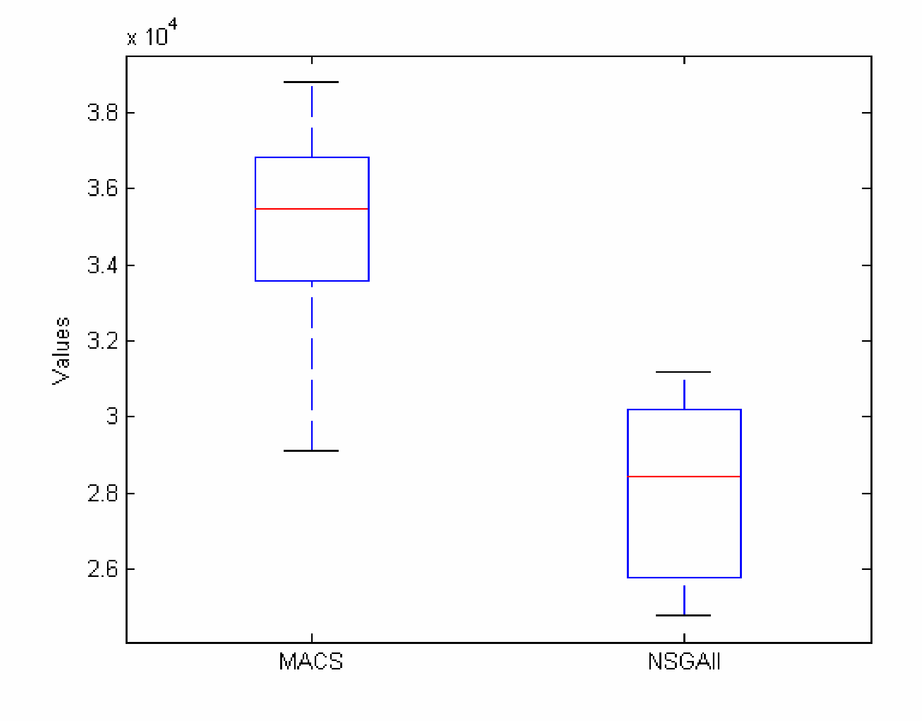

Figure 16 The Box-plots of the SP metric from a test for the Kroab100 instance.

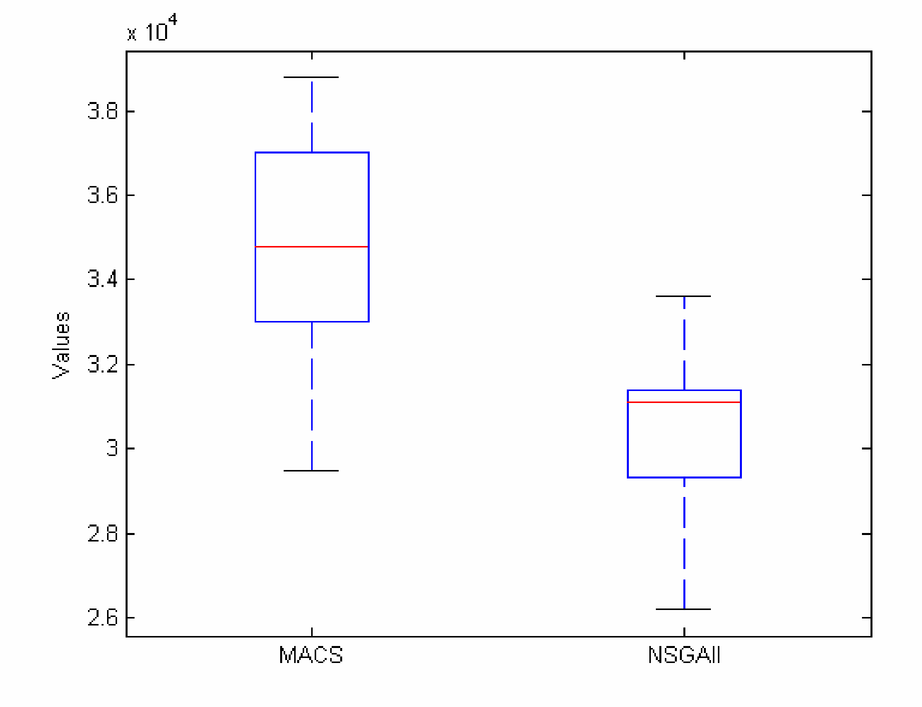

Figure 17 The Box-plots of the SP metric from a test for the Kroac100 instance.

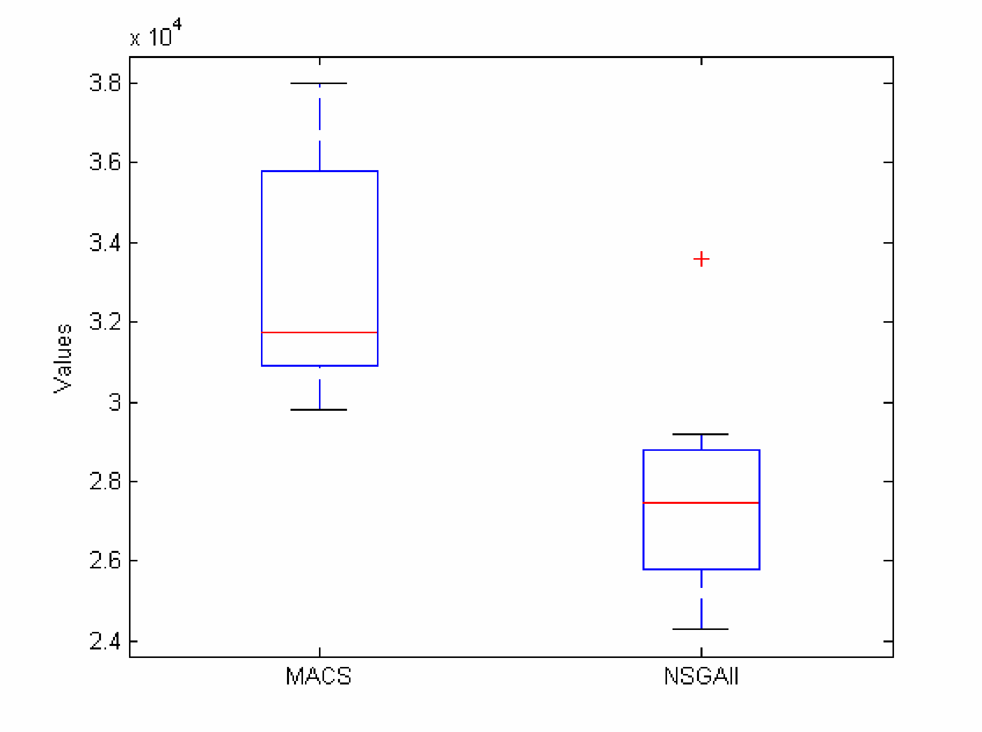

Figure 18 The Box-plots of the SP metric from a test for the Krobc100 instance.

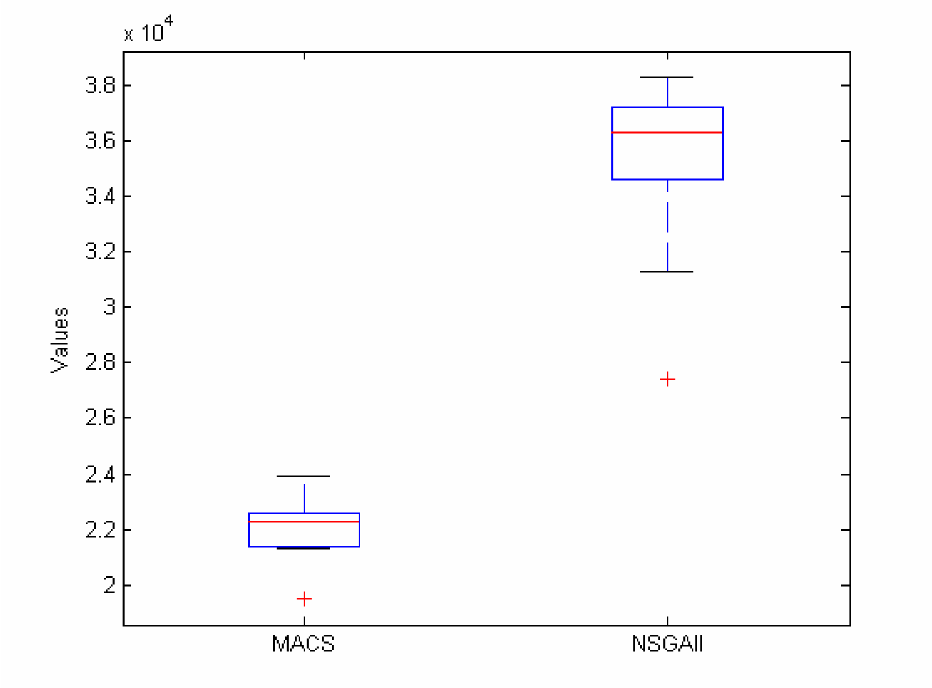

Figure 19 The Box-plots of the SP metric from a test for the Kroabc100 instance.

2. The results of case studies in electrical distribution systems

In this section, the proposed procedure is applied to the electrical distribution feeders for three case studies. The first is the RBTS bus 2 that it has the loading level of 20 MW and 36 sections. The second is the RBTS bus 4 that it has the loading level of 40 MW and 66 sections. At last, the real system of the Provincial Electricity Authority of Thailand (PEA) with 51 sections is selected. The objective functions are derived with the following basic assumptions.

1. The feeders is operated as a radial feeder but can be connected as a loop through a normally open switch.
2. The number and type of customers and amount of loads are known for each individual section.
3. Multiple faults are not considered and all failures are repaired before the next fault occurs.
4. A breaker is located at the substation and no fuses are allowed to be installed on the main feeder.
5. The protective equipment is perfectly coordinated, i.e., the device closest to the fault operates first.

2.1 The case study in RBTS bus 2

The single line diagram of the RBTS bus 2 (Alan al et., 1991) is shown in Figure 20. It has the residential, commercial, government/institution and small user loads. The loading level of BUS 2 (20 MW) only justifies a single supply point. In this case study, all the 11 kV feeders and lateral are considered as overhead lines. Each 11 kV feeder and lateral has one of three given the lengths, which are 0.6, 0.75 or 0.8 km. These are shown in Table 2. The customer types and the average loads are shown in Table 3. The reliability data used for 11 kV system components is shown in Table 4. Using the customer damage functions (CDF) in the paper written by Sohn et al. (2006), the composite customer damage function (CCDF) at the load points is shown in Table 5. Table 6 shows the fixed cost associated with switches and protective devices, consisting of costs of purchase, material and labors for installation. The parameter values of the MACS algorithm are summarized in Table 7. The proposed procedure is applied to find the optimal placement of switches and reclosers for ten candidate locations of the main feeders. It is assumed that fuses are installed in all of the lateral sections.

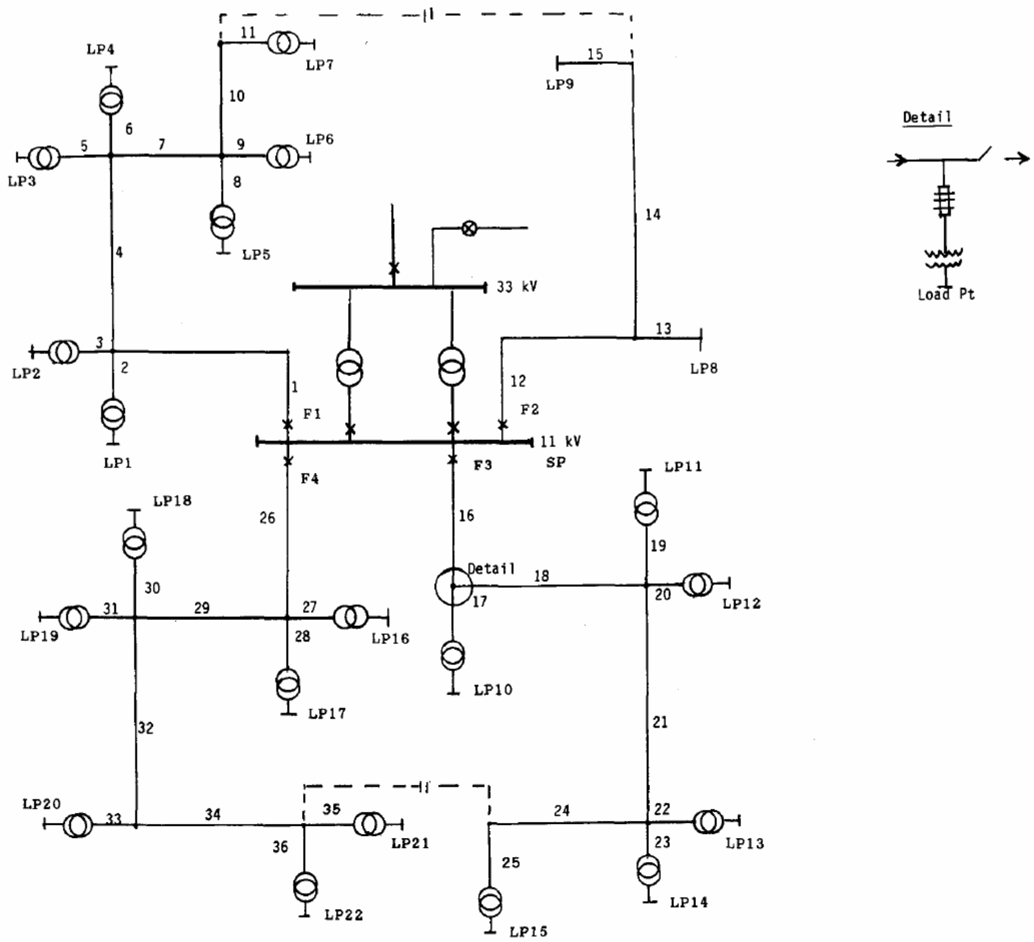

Figure 20 Single line diagram of RBTS Bus 2.

Table 8, 9 and 10 summarize types and location of devices obtained by minimizing each of single objectives. Table 17 shows the total cost (TC), in $US, the SAIFI in interruptions per customer per year, and the SAIDI in hours per customer per year. In case of double objective functions, the results show non-dominated sets in two dimensions. Figure 21 presents the set of results of minimizing SAIFI and total cost, and Figure 22 presents the set of results of minimizing SAIDI and total cost. The selection of the final result from the non-dominated set is achieved by using the method presented in the previous chapter. The final result including types and location of devices are shown in Table 11 and 13. The values of reliability indices and total cost are shown in Table 12 and 14. Figure 23 shows the non-dominated set in three dimensions resulted from minimizing the triple objective function. Table 15 shows types of devices and locations of them, and Table 16 shows the value of reliability indices and total cost of this triple objective problem. Table 17 shows the summation of the results for the RBTS bus 2.

Table 2 Feeder Types and Lengths of RBTS bus 2.

Feeder type	Length (km)	Feeder section numbers
1	0.60	2,6,10,14,17,21,25,28,30,34
2	0.75	1,4,7,9,12,16,19,22,24,27,29,32,35
3	0.80	3,5,8,11,13,15,18,20,23,26,31,33,36

Table 3 Customer Data of RBTS bus 2.

Number of load points	load points	customer type	load level per load point, MW		number of customers
			average	peak	
5	1-3,10,11	residential	0.535	0.8668	210
4	12,17-19	residential	0.450	0.7291	200
1	8	small user	1.00	1.6279	1
1	9	small user	1.15	1.8721	1
6	4,5,13,14,20, 21	govt/inst	0.566	0.9167	1
5	6,7,15,16, 22	commercial	0.454	0.7500	10
TOTALS			12.291	20.00	1908

Table 4 Reliability data of overhead line for RBTS system.

Reliability data	value
Permanent failure rate (f/yr.km)	0.065
Temporary failure rate (f/yr.km)	0.095
Repair time (hr)	5
Switching time (hr)	1

Table 5 Load point composite customer damage function (CCDF) for RBTS system.

Duration	CCDF ($US/kW)
temporary	0.67
1 hr	2.476
5 hr	16.457

Table 6 Fixed costs of switch and protection equipment.

Device	Cost ($US/year)
Recloser	6,000
Fuse	1,500
Switch	2,500

Table 7 Parameter values assigned for MACS.

Parameter	Value
β	2
ρ	0.2
q_0	0.98

Table 8 The best locations of devices in case of minimizing cost for RBTS bus 2.

Type	Location of devices
Fuse	2,3,5,6,8,9,11,13,15,17,19,20,22,23,25,27,28,30,31,33,35,36
Switch	7,21,32
Recloser	-

Table 9 The best locations of devices in case of minimizing SAIFI for RBTS bus 2.

Type	Location of devices
Fuse	2,3,5,6,8,9,11,13,15,17,19,20,22,23,25,27,28,30,31,33,35,36
Switch	-
Recloser	4,7,10,14,18,21,24,29,32,34

Table 10 The best locations of devices in case of minimizing SAIDI for RBTS bus 2.

Type	Location of devices
fuse	2,3,5,6,8,9,11,13,15,17,19,20,22,23,25,27,28,30,31,33,35,36
switch	-
recloser	4,7,10,14,18,21,24,29,32,34

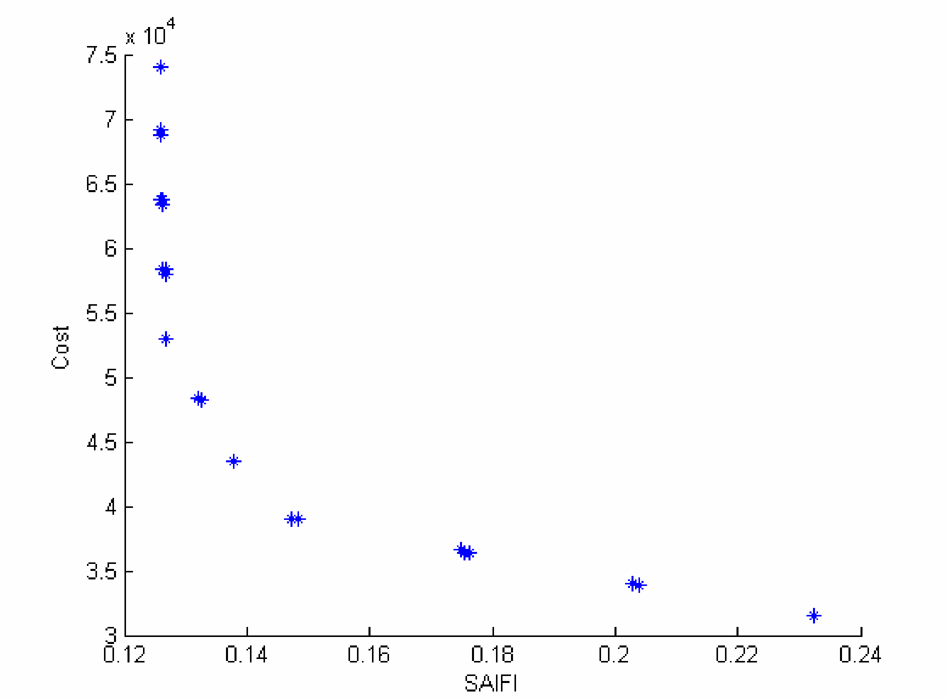

Figure 21 The non-dominated solution set from a case of minimizing SAIFI and cost for RBTS bus 2.

Table 11 The best locations of devices in case of minimizing SAIFI and cost for RBTS bus 2.

Type	Location of devices
fuse	2,3,5,6,8,9,11,13,15,17,19,20,22,23,25,27,28,30,31,33,35,36
switch	-
recloser	4,21,32

Table 12 The best reliability indices and cost in case of minimizing SAIFI and cost for RBTS bus 2.

Total cost ($US)	SAIFI index	SAIDI index
51313	0.1473	0.7014

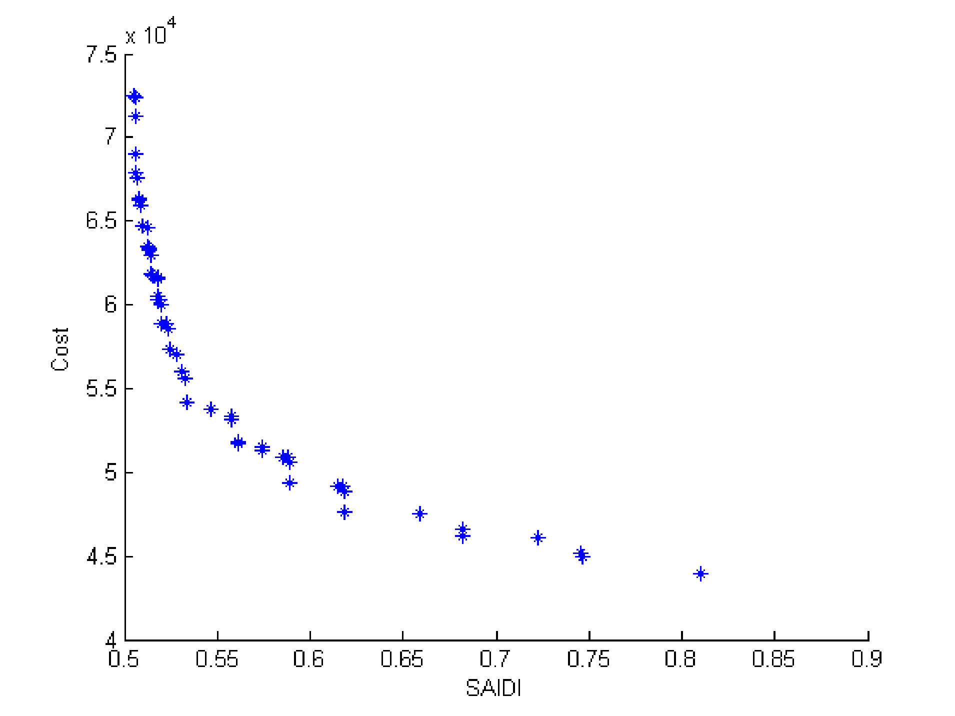

Figure 22 The non-dominated solution set from a case of minimizing SAIDI and cost for RBTS bus 2.

Table 13 The best locations of devices in case of minimizing SAIDI and cost for RBTS bus 2.

Type	Location of devices
fuse	2,3,5,6,8,9,11,13,15,17,19,20,22,23,25,27,28,30,31,33,35,36
switch	7,18,21,29,32,34
recloser	4

Table 14 The best reliability indices and cost in case of minimizing SAIDI and cost for RBTS bus 2.

Total cost ($US)	SAIFI index	SAIDI index
50,874	0.2029	0.5853

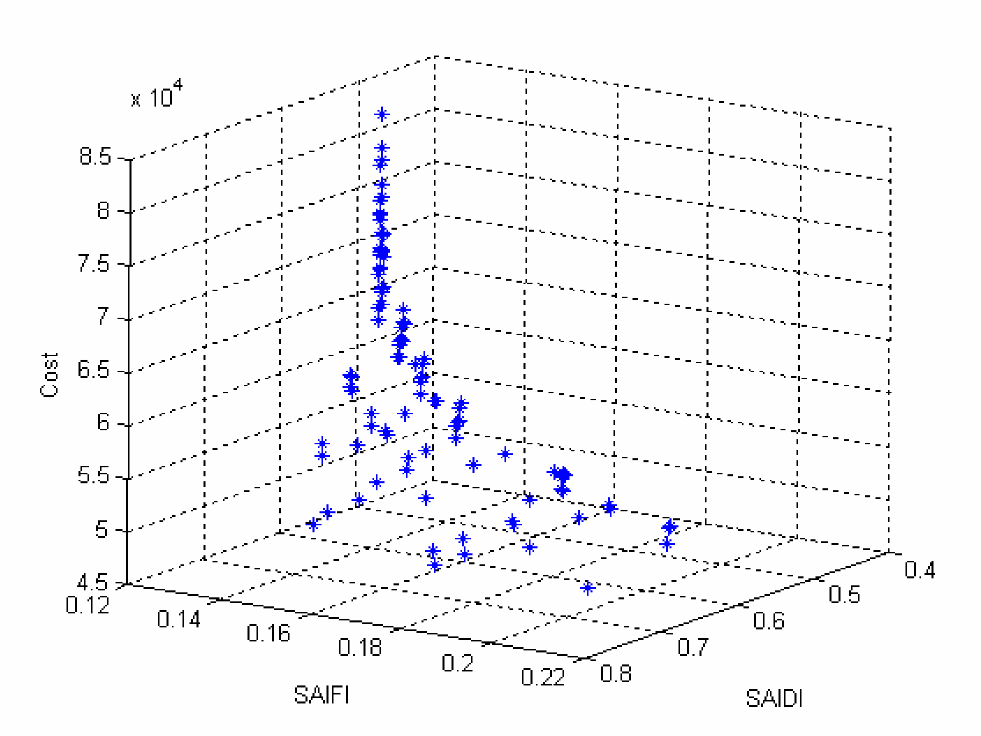

Figure 23 The non-dominated solution set from a case of minimizing SAIFI, SAIDI and cost for RBTS bus 2.

Table 15 The best locations of devices in case of minimizing SAIFI, SAIDI and cost for RBTS bus 2.

Type	Location of devices
fuse	2,3,5,6,8,9,11,13,15,17,19,20,22,23,25,27,28,30,31,33,35,36
switch	7,29
recloser	4,18,21,32

Table 16 The best reliability indices and cost in case of minimizing SAIFI, SAIDI and cost for RBTS bus 2.

Total cost ($US)	SAIFI index	SAIDI index
57,081	0.1417	0.5279

Table 17 Summary of the results for RBTS bus 2.

Method	Reliability indices		
	Total cost ($US)	SAIFI index	SAIDI index
Minimizing cost	43,943	0.2325	0.8097
Minimizing SAIFI	82,456	0.1259	0.5052
Minimizing SAIDI	82,456	0.1259	0.5052
Minimizing SAIFI&cost	51313	0.1473	0.7014
Minimizing SAIDI&cost	50,874	0.2029	0.5853
Three objective functions	57,081	0.1417	0.5279

2.2 The case study in RBTS bus 4

Figure 24 shows the single line diagram of the RBTS bus 4. Similar to the RBTS bus 2, it includes the residential, commercial and small user loads, but the government/institution loads are disappeared. The loading level of BUS 4 (40MW) is sufficient to justify higher reliability provided by a 33kV ring linking three supplies. The 11 kV feeders and laterals are considered as overhead lines. The data of sections lengths are shown in Table 18, and the customer types and the average loads are shown in Table 19. The data of reliability, the load point composite customer damage function (CCDF), the fixed cost of the devices and the parameter values of the MACS algorithm are the same as given in Table 4, 5, 6 and 7 respectively. In this case, assuming that all of laterals are equipped with fuses, the MACS is applied to find the optimal placement of switches and reclosers in 22 candidate locations of the main feeder sections.

Table 20, 21 and 22 summarize types and locations of devices obtained by minimizing each of single objectives. Table 29 shows the total cost (TC), in $US, the SAIFI in interruptions per customer per year, and the SAIDI in hours per customer per year. The results of the double objective functions show non-dominated sets in two dimensions. Figure 25 presents the set of results of minimizing SAIFI and total cost, and Figure 26 presents the set of results of minimizing SAIDI and total cost. The final result of types and locations of devices are shown in Table 23 and 25. The values of reliability indices and total cost are shown in Table 24 and 26. Figure 27 shows the non-dominated set in three dimensions resulted from minimizing the triple objective function. Table 27 shows types of devices and locations of them, and Table 28 shows the values of reliability indices and total cost of this triple objective problem. The summary of the results for RBTS bus 4 are shown in Table 28.

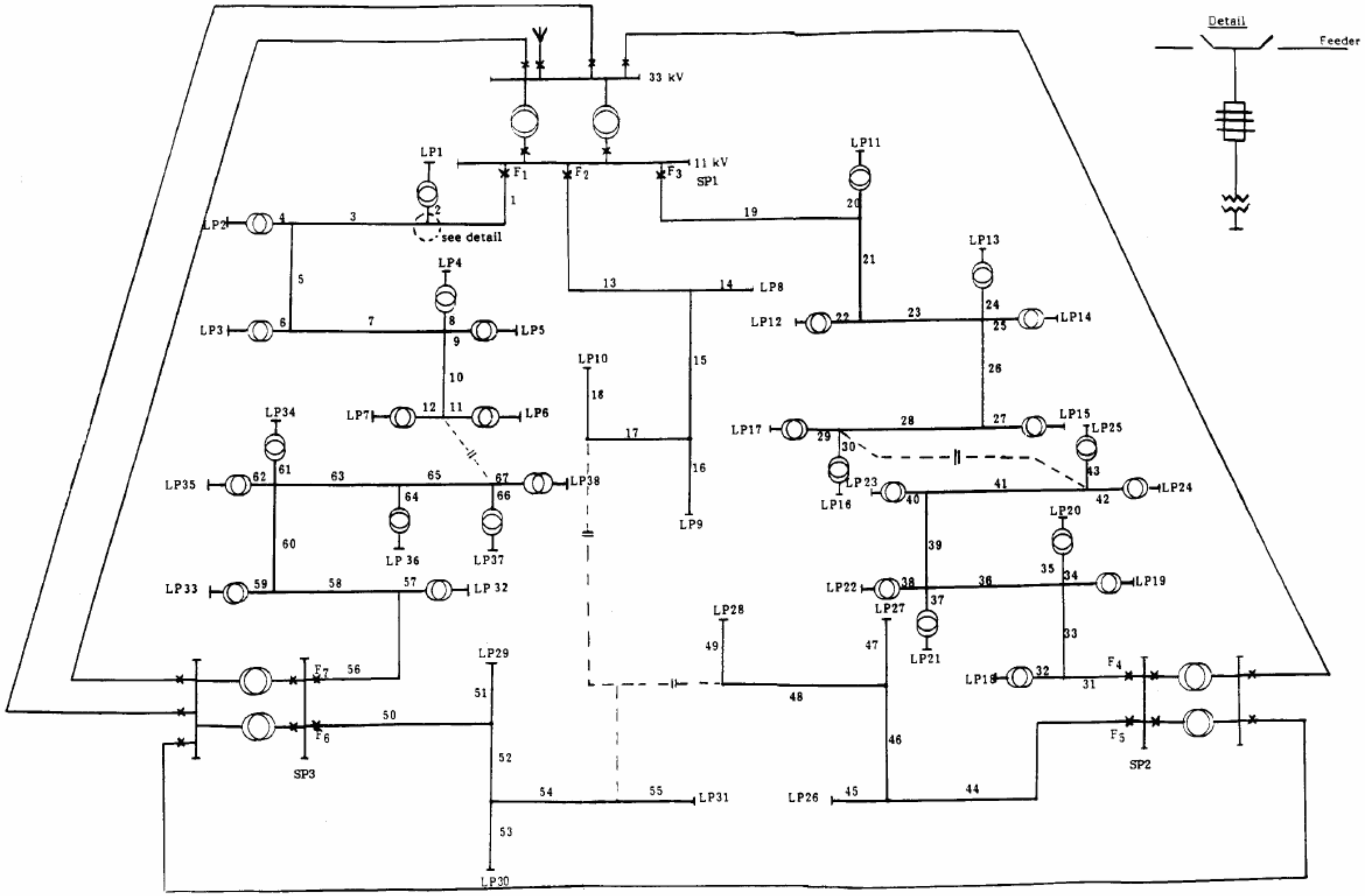

Figure 24 Single line diagram of RBTS Bus 4

Table 18 Feeder Types and Lengths of RBTS bus 4.

Feeder type	Length (km)	Feeder section numbers
1	0.60	2,6,10,14,17,21,25,28,30,34,38,41, 43,46,49,51,55,58,61,64,67
2	0.75	1,4,7,9,12,16,19,22,24,27,29,32,35, 37,40,42,45,48,50,53,56,60,63,65
3	0.80	3,5,8,11,13,15,18,20,23,26,31,33, 36,39,44,47,52,54,57,59,62,66

Table 19 Customer Data of RBTS bus 4.

Number of load points	load points	customer type	load level per load point, MW		number of customers
			average	peak	
15	1-4, 11-13, 18-21, 32-35	residential	0.545	19.00	220
7	5, 14, 15, 22, 23, 36, 37	residential	0.5	19.00	200
7	8, 10, 26-30	small user	1.00	16.30	1
2	9, 31	small user	1.50	16.30	1
7	6, 7, 16, 17, 24, 25, 38	commercial	0.415	4.70	10
TOTALS			24.58	40.00	4779

Table 20 The best locations of devices in case of minimizing cost for RBTS bus 4.

Type	Location of devices
Fuse	1,3,5,7,10,13,15,17,19,21,23,26,28,31,33,36,39,41,44,46,48, 50,52,54,56,58,60,63,65
Switch	7,15,26,36,46,54,63
Recloser	-

Table 21 The best locations of devices in case of minimizing SAIFI for RBTS bus 4.

Type	Location of devices
Fuse	1,3,5,7,10,13,15,17,19,21,23,26,28,31,33,36,39,41,44,46,48, 50,52,54,56,58,60,63,65
Switch	-
Recloser	3,5,7,10,15,17,21,23,26,28,33,36,39,41,46,48,52,54,58,60,63,65

Table 22 The best locations of devices in case of minimizing SAIDI for RBTS bus 4.

Type	Location of devices
fuse	1,3,5,7,10,13,15,17,19,21,23,26,28,31,33,36,39,41,44,46,48, 50,52,54,56,58,60,63,65
switch	-
recloser	3,5,7,10,15,17,21,23,26,28,33,36,39,41,46,48,52,54,58,60,63,65

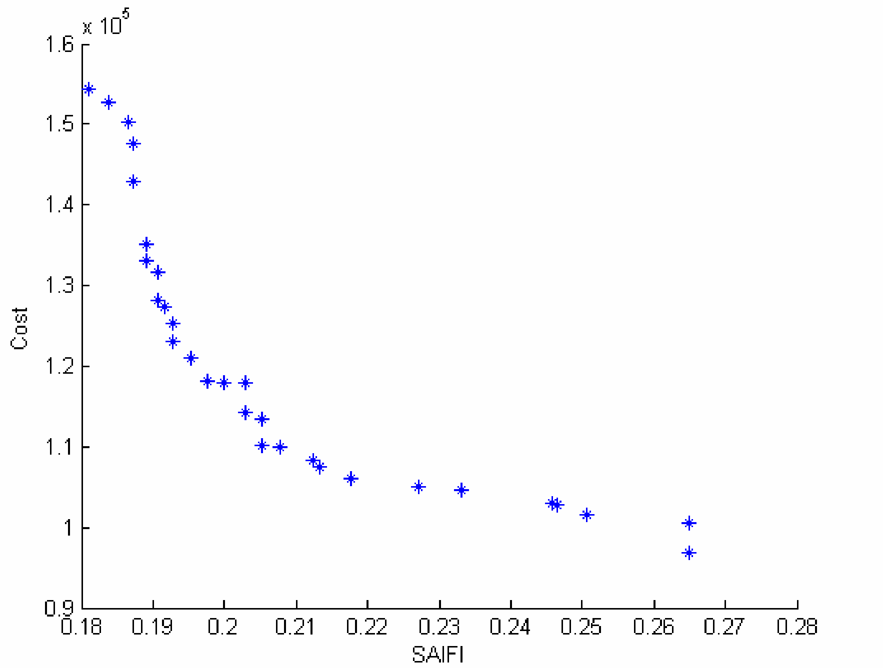

Figure 25 The non-dominated solution set from a case of minimizing SAIFI and cost for RBTS bus 4.

Table 23 The best locations of devices in case of minimizing SAIFI and cost for RBTS bus 4.

Type	Location of devices
fuse	1,3,5,7,10,13,15,17,19,21,23,26,28,31,33,36,39,41,44,46,48, 50,52,54,56,58,60,63,65
switch	15,46,54
recloser	5,26,36,39,60,63

Table 24 The best reliability indices and cost in case of minimizing SAIFI and cost for RBTS bus 4.

Total cost ($US)	SAIFI index	SAIDI index
110,140	0.2052	0.7999

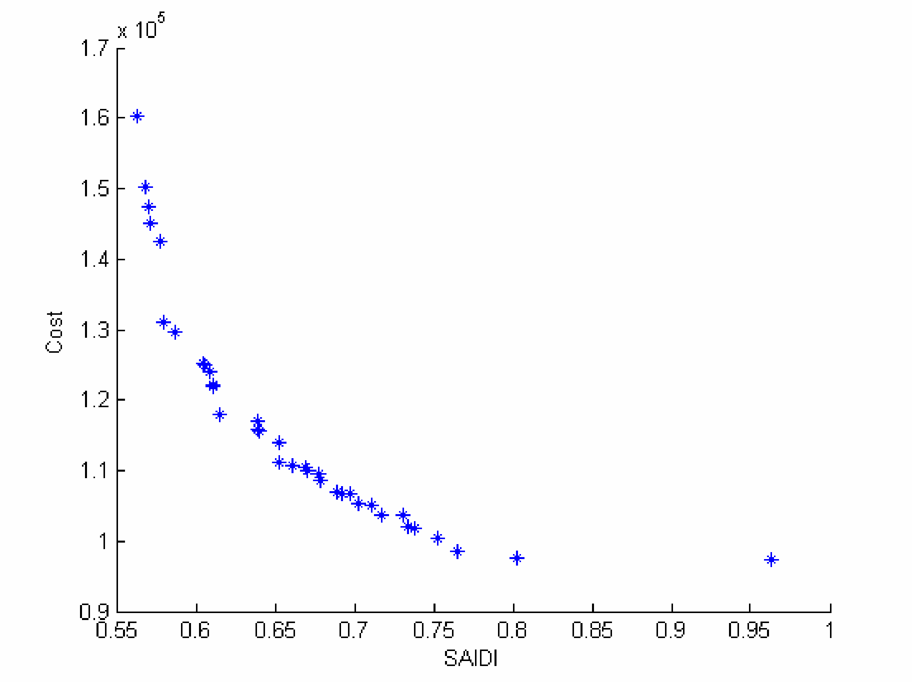

Figure 26 The non-dominated solution set from a case of minimizing SAIDI and cost for RBTS bus 4.

Table 25 The best locations of devices in case of minimizing SAIDI and cost for RBTS bus 4.

Type	Location of devices
fuse	1,3,5,7,10,13,15,17,19,21,23,26,28,31,33,36,39,41,44,46,48, 50,52,54,56,58,60,63,65
switch	3,5,7,15,21,23,28,33,39,46,54,60,65
recloser	26,36,63

Table 26 The best reliability indices and cost in case of minimizing SAIDI and cost for RBTS bus 4.

Total cost ($US)	SAIFI index	SAIDI index
111,160	0.2306	0.6524

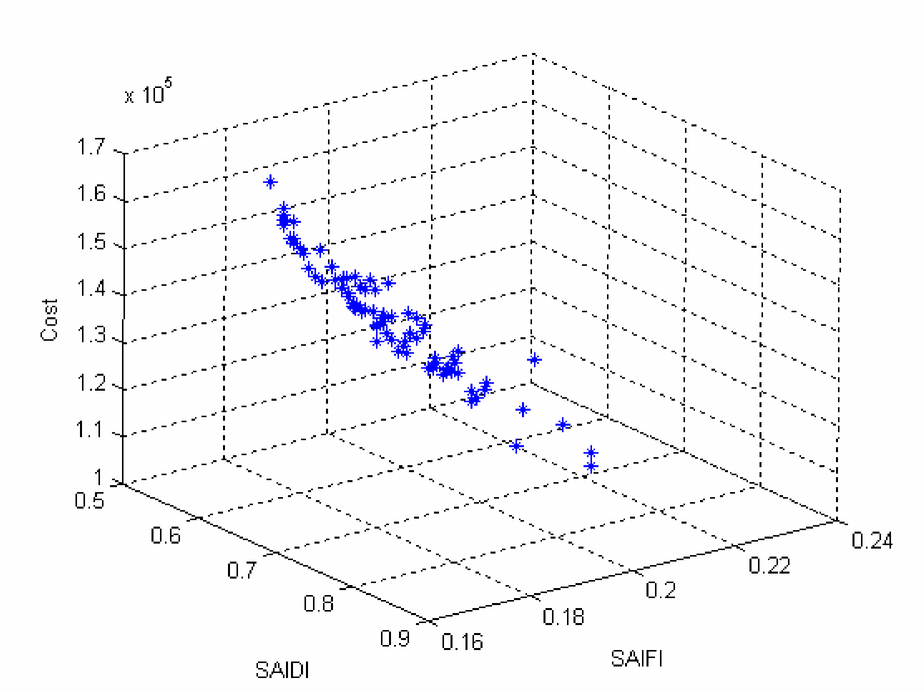

Figure 27 The non-dominated solution set from a case of minimizing SAIFI, SAIDI and cost for RBTS bus 4.

Table 27 The best locations of devices in case of minimizing SAIFI, SAIDI and cost for RBTS bus 4.

Type	Location of devices
fuse	1,3,5,7,10,13,15,17,19,21,23,26,28,31,33,36,39,41,44,46,48,50, 52,54,56,58,60,63,65
switch	5,15,23,33,46,52,60
recloser	3,10,21,26,36,39,58,63,65

Table 28 The best reliability indices and cost in case of minimizing SAIFI, SAIDI and cost for RBTS bus 4.

Total cost ($US)	SAIFI index	SAIDI index
141,410	0.2607	0.8507

Table 29 Summary values of the results for RBTS bus 4.

Method	Reliability indices		
	Total cost ($US)	SAIFI index	SAIDI index
Minimizing cost	95,315	0.2847	0.9736
Minimizing SAIFI	177,420	0.1792	0.5627
Minimizing SAIDI	177,420	0.1792	0.5627
Minimizing SAIFI&cost	110,140	0.2052	0.7999
Minimizing SAIDI&cost	111,160	0.2306	0.6524
Three objective functions	141,410	0.2607	0.8507

2.3 The case study in the real electrical distribution system

In this section, the proposed procedure is applied to an electrical distribution feeder of the Provincial Electricity Authority of Thailand (PEA). Figure 28 describes the practical one-line diagram of the feeder with 51 sections and 44 load points. This feeder has four interconnection neighboring feeders. Length of each section, the number of customers and the average load of each section are listed in Table 30.

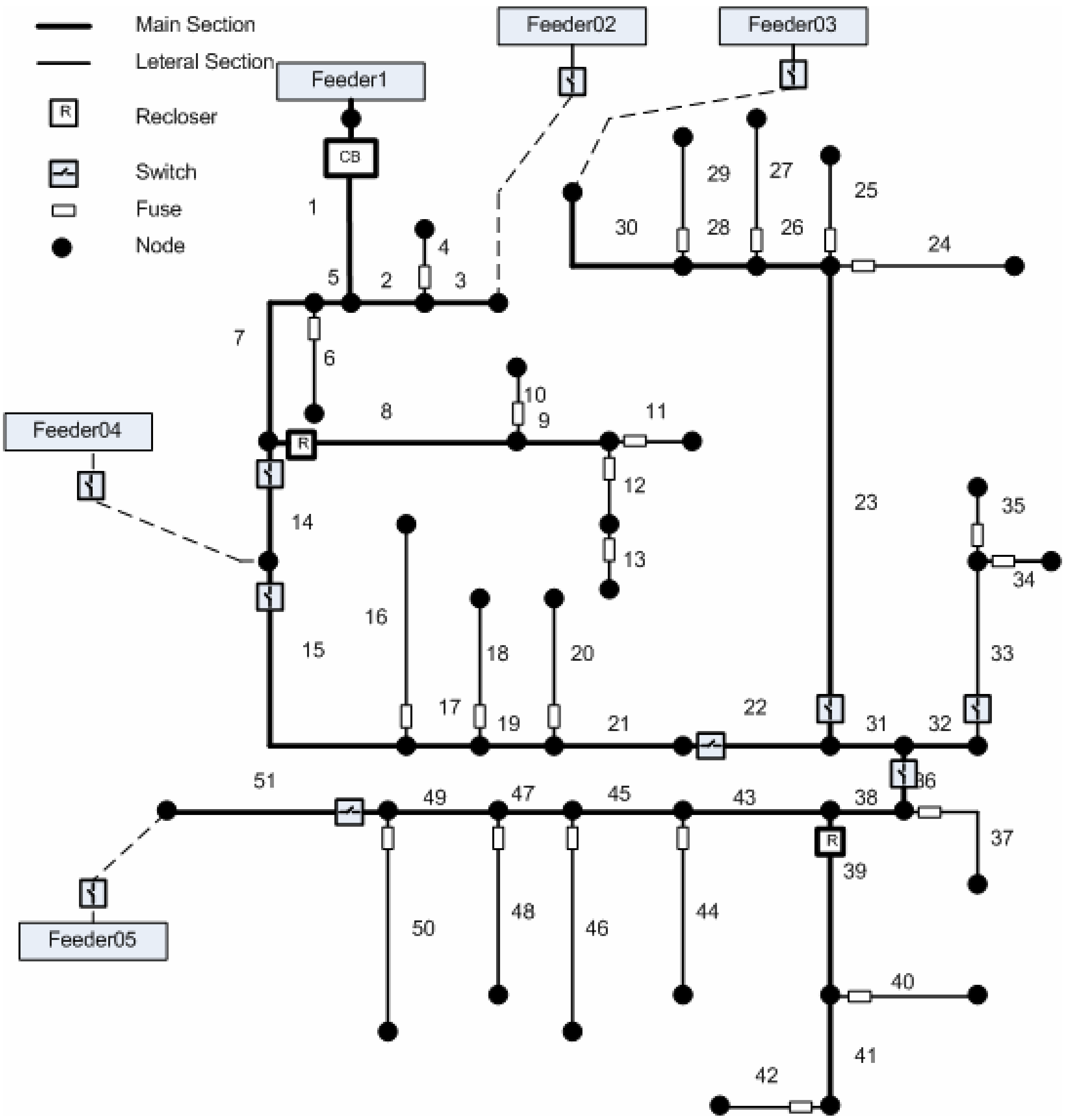

Figure 28 One-line diagram of the studied feeder for PEA system.

Table 30 Length, the average load (L_i) and the number of customers (N_i) of each section of the feeder in Figure 28.

section	Length (km)	L_i (kVA)	N_i (customers)
1	3.4	0	0
2	0.5	0	0
3	0.1	0	0
4	0.4	150	55
5	0.5	0	0
6	1.0	220	89
7	1.0	0	0
8	3.0	1250	145
9	0.5	90	85
10	0.3	90	1
11	1.2	445	200
12	1.0	720	2
13	1.0	30	55
14	0.3	0	0
15	2.9	150	55
16	3.0	50	57
17	1.7	60	105
18	1.3	310	243
19	2.0	340	147
20	1.4	30	47
21	1.0	2130	107
22	0.4	250	30
23	2.3	780	117
24	4.0	610	135
25	0.7	80	95
26	1.5	60	50
27	0.9	110	80
28	4.2	590	120
29	0.7	90	93
30	2.3	170	145
31	2.8	480	65
32	1.5	2400	80
33	1.3	210	102
34	0.6	50	20
35	0.5	100	30
36	0.1	0	0
37	2.5	100	65
38	3.2	480	50
39	0.8	500	1
40	3.0	450	220
41	2.7	150	95
42	3.0	110	125
43	9.3	60	167
44	3.5	150	141
45	1.2	50	21
46	2.0	140	93
47	0.9	36	106
48	1.3	60	90
49	1.3	30	17
50	5.0	160	145
51	2.0	1350	67

Permanent and temporary failure rates used in this test system are λ = 0.17 and γ = 0.25 failure per kilometer per year respectively. Average repair time is 2 h, and the average duration to perform the necessary fault isolation, switching, and load transfer activities from neighboring feeders is 0.5 h. The percentage of load types of this feeder is 85% for residence and 15% for small industry. Using the residential and industrial customer damage functions (CDF) in the paper written by Sohn et al. (2006), the composite customer damage function (CCDF) at the load points is shown in Table 31. The fixed cost of the devices and the parameter values of the MACS algorithm are the same as given in Table 6, and Table 7 respectively. In the test system, there are forty-five possible locations for the placement of isolators, twenty-four for the placement of fuses, and eight for placement of reclosers, with no limitation of load transfer capacity of the neighboring feeders.

Table 31 Load point composite customer damage function (CCDF).

Duration	CCDF ($US/kW)
temporary	0.245
30 min	0.937
1.5 hr	2.802

Table 32 The original locations of devices of the feeder in Figure 28.

Type	Location of devices
Fuse	4,6,10,12,16,18,20,24,27,29,34,37,40,42,44,46,48,50
Switch	14,15,22,23,33,36,51
Recloser	8,39

The single objective ACS is applied to separately minimize SAIFI, SAIDI, and total cost. Table 33, 34 and 35 summarize types and locations of devices obtained by minimizing each of the single objectives. Table 42 shows the total cost (TC), in $US, the SAIFI in interruptions per customer per year, and the SAIDI in hours per customer per year. In case of the double objective functions, the results show non-dominated sets in two dimensions. Figure 29 presents the set of results of minimizing SAIFI and total cost, and Figure 30 presents the set of results of minimizing SAIDI and total cost. The final result of types and locations of devices are shown in Table 36 and 38. The values of reliability indices and total cost are shown in Table 37 and 39. Figure 31 shows the non-dominated set in three dimensions resulted from minimizing the triple objective function. Table 40 shows types of devices and locations of them, and Table 41 shows the values of reliability indices and total cost of this triple objective problem.

Table 33 The best locations of devices in case of minimizing cost for PEA system.

Type	Location of devices
Fuse	16,20,37
Switch	12,21,26,38,45,51
Recloser	8,15,23,32,39,43

Table 34 The best locations of devices in case of minimizing SAIFI for PEA system.

Type	Location of devices
Fuse	4,6,10,11,12,13,16,18,20,24,25,27,29,34,35,37,40,42,44,46,48,50
Switch	9,41,49
Recloser	8,15,23,26,32,39,43,47

Table 35 The best locations of devices in case of minimizing SAIDI for PEA system.

Type	Location of devices
fuse	4,10,12,16,20,37,46
switch	5,6,9,11,13,17,18,19,21,22,24,25,27,28,29, 30,31,34,35,38,40,41,42,44,45,48,49,50,51
recloser	8,15,23,26,32,39,43,47

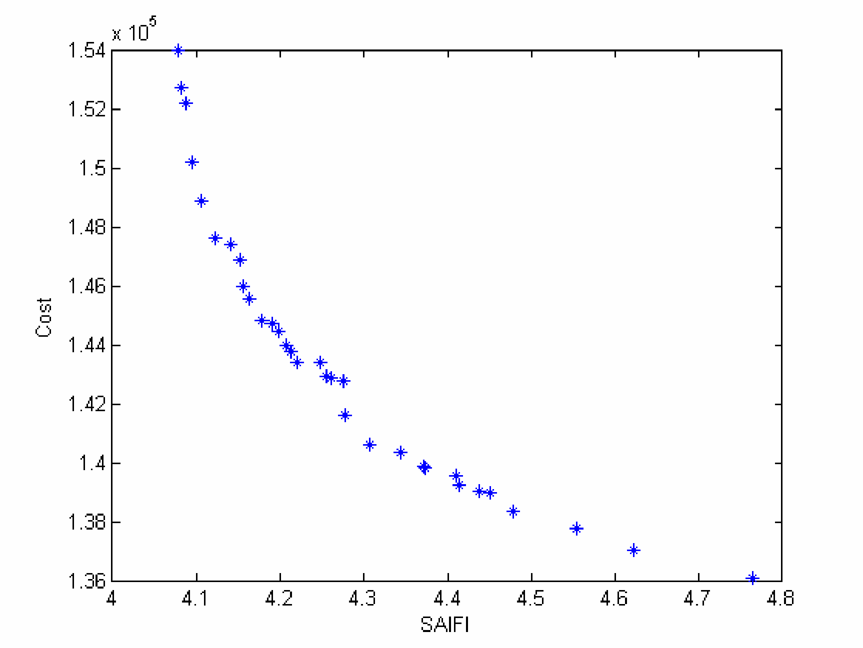

Figure 29 The non-dominated solution set from a case of minimizing SAIFI and cost for PEA system.

Table 36 The best locations of devices in case of minimizing SAIFI and cost for PEA system.

Type	Location of devices
fuse	50,24,6,4,46,20,37,16,44,40,42,12,18
switch	22,51
recloser	8,15,23,26,32,39,43

Table 37 The best reliability indices and cost in case of minimizing SAIFI and cost for PEA system.

Total cost ($US)	SAIFI index	SAIDI index
141,590	4.2777	7.1886

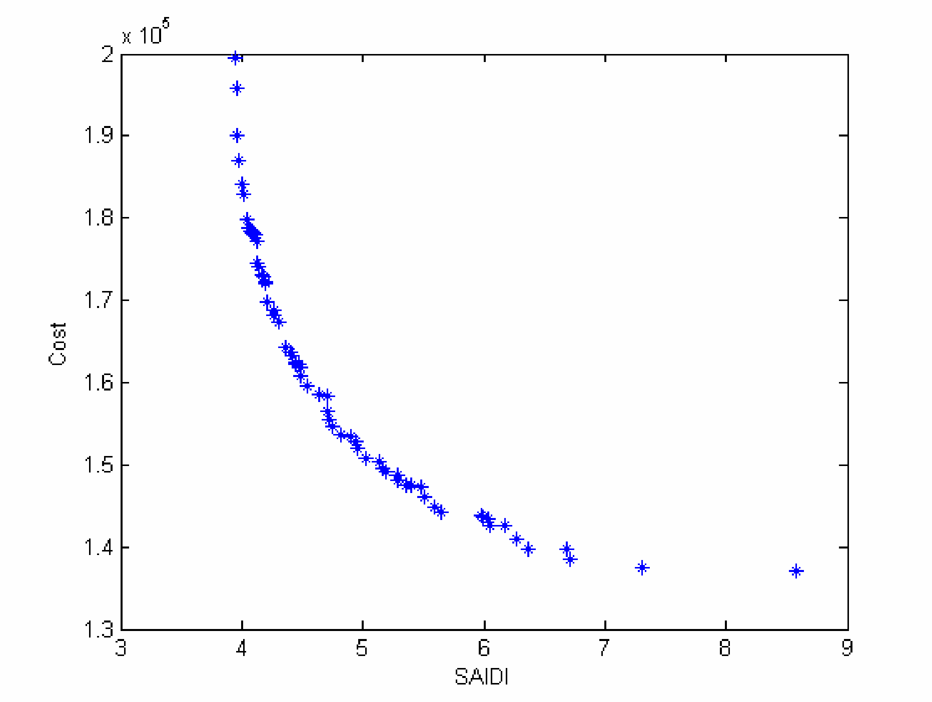

Figure 30 The non-dominated solution set from a case of minimizing SAIDI and cost for PEA system.

Table 38 The best locations of devices in case of minimizing SAIDI and cost for PEA system.

Type	Location of devices
fuse	6,11,12,16,18,20,24,25,37,50
switch	9,17,19,30,31,41,44,45,49
recloser	8,15,23,26,32,39,43

Table 39 The best reliability indices and cost in case of minimizing SAIDI and cost for PEA system.

Total cost ($US)	SAIFI index	SAIDI index
150,690	4.5477	5.0257

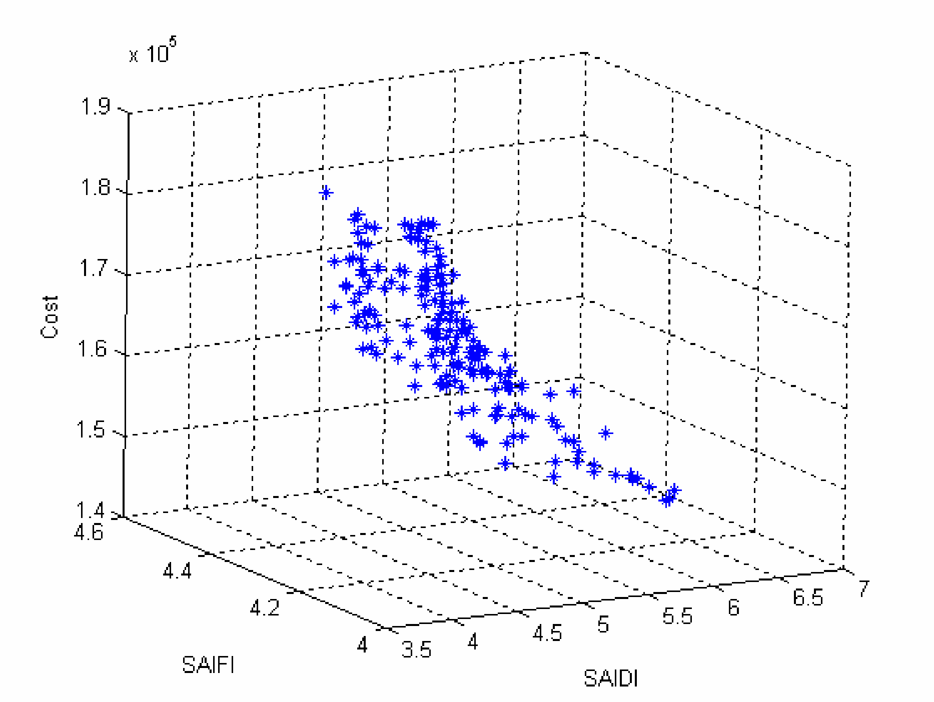

Figure 31 The non-dominated solution set from a case of minimizing SAIFI, SAIDI and cost for PEA system.

Table 40 The best locations of devices in case of minimizing SAIFI, SAIDI and cost for PEA system.

Type	Location of devices
fuse	4,6,12,16,18,20,24,37,40,42,44,46,48,50
switch	9,17,19,21,30,31,45,49
recloser	8,15,23,26,32,39,43,47

Table 41 The best reliability indices and cost in case of minimizing SAIFI, SAIDI and cost for PEA system.

Total cost ($US)	SAIFI index	SAIDI index
159,900	4.1593	4.8454

Table 42 Summary of the results for PEA system.

Method	Reliability indices		
	Total cost ($US)	SAIFI index	SAIDI index
Existing system	210,990	8.6712	10.2540
Minimizing cost	138,470	5.3743	7.4986
Minimizing SAIFI	163,190	4.0784	6.7213
Minimizing SAIDI	200,600	4.8658	4.0255
Minimizing SAIFI&cost	141,590	4.2777	7.1886
Minimizing SAIDI&cost	150,690	4.5477	5.0257
Three objective functions	159,900	4.1593	4.8454

Discussion

From the results of performance evaluation, the graphical representation of non-dominated sets in case of the double objectives and triple objectives show that the values resulted from the MACS is lower than that of the NSGA. Similarly, the values of C metrics show that the NSGA-II is covered by the MACS and the MACS is not covered by the NSGA-II. Therefore, it can be concluded that the MACS has a positive outcome in the cases of bi-criteria and tri-criteria TSP. Considering the box plots of SP metrics, the results of bi-criteria instances show that the MACS is above the NSGA-II, but the results of the tri-criteria instance show that the MACS is lower than the NSGA-II. The interpretation of this metric is that the smaller the value, the better the distribution in the set. These results show a difference between the bi-criteria and tri-criteria functions. This difference may be caused by the number of obtained solutions correlated with values of the metric.

According to the results of the applications in the three cases of electrical distribution systems, they show that the ACO can be used for optimal placement or replacement of switches and protective devices in single, double and triple objective functions. The single objectives give only one result. However, the multi-objective functions give the set of results or non-dominated set. The engineer or planer can select the final non-dominated solution, by considering the most satisfactory values of the objectives and according to his/her experience and professional point of view. However, the selection for the best result can be achieved by the min-max method.

The results of single objective functions show that the optimal placement of switches and protective devices for each scenario results in a substantial reduction in the SAIFI, SAIDI and cost as shown in Table 17, 29 and 42. For example, in case of the PEA system, the decreases in cost, SAIFI and SAIDI indices, as compared with the existing system, are about 34.37 %, 52.96% and 60.74% respectively. In the double objective MACS, the results show the balance of minimizing two objective functions. For example, in Table 42, the result of simultaneously minimizing SAIFI and cost is better than the single objective optimization, which gives the low value only for the interested function, while the values of neglected functions are still high. Similarly, the case of minimizing SAIDI and cost gives the good result balancing SAIDI and cost. In a superior way, the triple MACS demonstrates the better balance among three objective functions, that causes the lowest cost and the best reliability simultaneously.

CONCLUSION AND RECOMMENDATION

Conclusion

This research presents a multi-objective optimization technique for placement of switches and protective devices in electric power distribution systems. The reliability indices and total cost are considered as the objective functions. They are simultaneously minimized in order to identify the number and location of switches, reclosers and fuses to be installed in a selected distribution system.

An algorithm based on the multiple ant colony system (MACS) is developed to find the optimal placement of switches and protective devices. However, to the demonstrate effectiveness of the MACS algorithm, this thesis presents performance evaluation by comparing the proposed method and the NSGA-II. The standard benchmark problem, bi-criteria and tri-criteria TSP, are used for testing performance, and the results show that the MACS has a positive outcome with the multi-criteria TSP.

In this thesis, the models of distribution feeders consisting of main and lateral sections are represented by a tree graph. The set theory is used to describe the feeder topology including locations of load points and protective devices. As a result, the values of SAIFI, SAIDI and total cost used as the objectives in this research can be conveniently determined. The Pareto optimal principle is used to obtain the set of non-dominated multi-objective solutions. It enables the planning engineer to select the most satisfactory non-dominated solution according to his or her experience.

To illustrate the performance of the proposed algorithm, the RTBS (bus 2 and bus 4) and the actual distribution feeder of the Provincial Electricity Authority of Thailand (PEA) are selected as the test systems. The number, type and location of protective devices are identified to simultaneously minimize the SAIFI, SAIDI and total cost. From the test results, the proposed technique presents much better cost and reliability indices in comparison with that of the existing system. Additionally, this algorithm shows the advantage of the multi-objective optimization above the single-objective ones in terms of providing a superior balance between cost and reliability indices.

Recommendation

From the results, the triple MACS can be effectively applied to the problems associated with optimal placement of switches and protective devices. Then future research can be extended by adding more objective functions in the proposed procedure such as minimizing Momentary Average Interruption Frequency Index (MAIFI) and/or minimizing loss of the feeder. Additionally, the multi objective optimization can be applied to other areas, for example, optimal load flow or economic dispatch problems.

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APPENDIX

The benchmark instances of symmetric traveling salesman problems

Appendix Table 1 The data of KroA 100-city problem.

NODE	COORD SECTION		NODE	COORD SECTION	
	x	y		x	y
1	1380	939	28	1795	962
2	2848	96	29	3384	1498
3	3510	1671	30	3520	1079
4	457	334	31	1256	61
5	3888	666	32	1424	1728
6	984	965	33	3913	192
7	2721	1482	34	3085	1528
8	1286	525	35	2573	1969
9	2716	1432	36	463	1670
10	738	1325	37	3875	598
11	1251	1832	38	298	1513
12	2728	1698	39	3479	821
13	3815	169	40	2542	236
14	3683	1533	41	3955	1743
15	1247	1945	42	1323	280
16	123	862	43	3447	1830
17	1234	1946	44	2936	337
18	252	1240	45	1621	1830
19	611	673	46	3373	1646
20	2576	1676	47	1393	1368
21	928	1700	48	3874	1318
22	53	857	49	938	955
23	1807	1711	50	3022	474
24	274	1420	51	2482	1183
25	2574	946	52	3854	923
26	178	24	53	376	825
27	2678	1825	54	2519	135

Appendix Table 1 (Continued)

NODE	COORD SECTION		NODE	COORD SECTION	
	x	y		x	y
55	2945	1622	78	3822	899
56	953	268	79	378	1048
57	2628	1479	80	1178	100
58	2097	981	81	2599	901
59	890	1846	82	3416	143
60	2139	1806	83	2961	1605
61	2421	1007	84	611	1384
62	2290	1810	85	3113	885
63	1115	1052	86	2597	1830
64	2588	302	87	2586	1286
65	327	265	88	161	906
66	241	341	89	1429	134
67	1917	687	90	742	1025
68	2991	792	91	1625	1651
69	2573	599	92	1187	706
70	19	674	93	1787	1009
71	3911	1673	94	22	987
72	872	1559	95	3640	43
73	2863	558	96	3756	882
74	929	1766	97	776	392
75	839	620	98	1724	1642
76	3893	102	99	198	1810
77	2178	1619	100	3950	1558

Appendix Table 2 The data of KroB 100-city problem.

NODE	COORD SECTION		NODE	COORD SECTION	
	x	y		x	y
1	3140	1401	28	3834	1827
2	556	1056	29	3417	1808
3	3675	1522	30	2938	543
4	1182	1853	31	71	1323
5	3595	111	32	3245	1828
6	962	1895	33	731	1741
7	2030	1186	34	2312	1270
8	3507	1851	35	2426	1851
9	2642	1269	36	380	478
10	3438	901	37	2310	635
11	3858	1472	38	2830	775
12	2937	1568	39	3829	513
13	376	1018	40	3684	445
14	839	1355	41	171	514
15	706	1925	42	627	1261
16	749	920	43	1490	1123
17	298	615	44	61	81
18	694	552	45	422	542
19	387	190	46	2698	1221
20	2801	695	47	2372	127
21	3133	1143	48	177	1390
22	1517	266	49	3084	748
23	1538	224	50	1213	910
24	844	520	51	3	1817
25	2639	1239	52	1782	995
26	3123	217	53	3896	742
27	2489	1520	54	1829	812

Appendix Table 2 (Continued)

NODE	COORD SECTION		NODE	COORD SECTION	
	x	y		x	y
55	1286	550	78	399	850
56	3017	108	79	2614	195
57	2132	1432	80	2800	653
58	2000	1110	81	2630	20
59	3317	1966	82	563	1513
60	1729	1498	83	1090	1652
61	2408	1747	84	2009	1163
62	3292	152	85	3876	1165
63	193	1210	86	3084	774
64	782	1462	87	1526	1612
65	2503	352	88	1612	328
66	1697	1924	89	1423	1322
67	3821	147	90	3058	1276
68	3370	791	91	3782	1865
69	3162	367	92	347	252
70	3938	516	93	3904	1444
71	2741	1583	94	2191	1579
72	2330	741	95	3220	1454
73	3918	1088	96	468	319
74	1794	1589	97	3611	1968
75	2929	485	98	3114	1629
76	3453	1998	99	3515	1892
77	896	705	100	3060	155

Appendix Table 3 The data of KroC 100-city problem.

NODE	COORD SECTION		NODE	COORD SECTION	
	x	y		x	y
1	1357	1905	28	3729	1188
2	2650	802	29	693	1383
3	1774	107	30	2361	640
4	1307	964	31	2433	1538
5	3806	746	32	554	1825
6	2687	1353	33	913	317
7	43	1957	34	3586	1909
8	3092	1668	35	2636	727
9	185	1542	36	1000	457
10	834	629	37	482	1337
11	40	462	38	3704	1082
12	1183	1391	39	3635	1174
13	2048	1628	40	1362	1526
14	1097	643	41	2049	417
15	1838	1732	42	2552	1909
16	234	1118	43	3939	640
17	3314	1881	44	219	898
18	737	1285	45	812	351
19	779	777	46	901	1552
20	2312	1949	47	2513	1572
21	2576	189	48	242	584
22	3078	1541	49	826	1226
23	2781	478	50	3278	799
24	705	1812	51	86	1065
25	3409	1917	52	14	454
26	323	1714	53	1327	1893
27	1660	1556	54	2773	1286

Appendix Table 3 (Continued)

NODE	COORD SECTION		NODE	COORD SECTION	
	x	**y**		**x**	**y**
55	2469	1838	78	138	1610
56	3835	963	79	2082	1753
57	1031	428	80	2302	1127
58	3853	1712	81	805	272
59	1868	197	82	22	1617
60	1544	863	83	3213	1085
61	457	1607	84	99	536
62	3174	1064	85	1533	1780
63	192	1004	86	3564	676
64	2318	1925	87	29	6
65	2232	1374	88	3808	1375
66	396	828	89	2221	291
67	2365	1649	90	3499	1885
68	2499	658	91	3124	408
69	1410	307	92	781	671
70	2990	214	93	1027	1041
71	3646	1018	94	3249	378
72	3394	1028	95	3297	491
73	1779	90	96	213	220
74	1058	372	97	721	186
75	2933	1459	98	3736	1542
76	3099	173	99	868	731
77	2178	978	100	960	303

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