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配電管理系統自動區段開關之多目標最佳配置研究

Multi-objective Optimal Placement of Automatic Line Switches in Power Distribution Networks

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Abstract

In modern power distribution utilities, there is a growing demand for an improved system response in case of outages. In order to address that demand, automatic line switches can be installed in distribution networks to reduce the number and durations of power interruptions. However, automatic switching devices involve an increased investment cost. For distribution utilities, obtaining a high level of reliability at a relatively low cost becomes a multi-objective optimization problem. To solve the problem, a computational procedure based on Elitist Nondominated Sorting Genetic Algorithm (NSGA-II) is developed in the present study. Following the proposed methodology, we are able to obtain a set of optimal trade-off solutions identifying the number and placement of automatic switches in a distribution network for which we can obtain the most reliability benefit out of the utility investment. To determine the effectiveness of the procedure, two case studies were carried out. For comparison purposes, one of the cases corresponds to a previous study of an actual distribution system belonging to Taipower Company. The result of both tests indicates the improvement in system reliability indices due to the addition of a certain degree of automation investment in the distribution network, and demonstrates the present methodology is able to satisfy the system requirements in a better way than the mentioned previous study.

Keywords: Power distribution systems, automatic line switches, multi-objective optimization, NSGA-II, optimal placement, case study simulation.

中文摘要

現代輸配電業界對停電改進回饋系統的要求日益增加，為滿足這樣的需求，安裝在電力配給網路上的自動區段開關可有效減少電力干擾的次數與時間。然而，自動區段開關裝置的使用也意味著更高的投資成本。對電力公司而言，如何使用相對低廉的成本支出來達到電力配給的高可靠度成為一個多目標最佳化問題。為解決這樣的問題，本論文發展一種基於精英策略非支配排序遺傳演算法的演算模式。根據論文所提的方法，我們可得到一組經過權衡後的解決方案，決定一特定配電網路自動區段開關裝置的數量與安裝配置，作為電力公司在一定成本下的最高可靠度參考。本研究以兩個案分析檢驗演算法的有效與否，為達到兩相對照的效果，其中一個案分析是對應於先前台灣電力公司真實配電網路的類似研究。個案分析的結果顯示，對於配電網路的一些自動化投資確可有效提升可靠度指標，間接驗證論文所提演算法相較於先前研究，更能有效滿足系統需求。

關鍵詞：電力配給系統、自動區段開關、多目標最佳化、非優勢排列遺傳演算法、最佳化配置、個案分析模擬

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$NSGA-II$	Elitist Nondominated Sorting Genetic Algorithm
$SAIFI$	System Average Interruption Frequency Index
$SAIDI$	System Average Interruption Duration Index
$TCOST$	Total Investment Cost
λ_{is}	Permanent failure rate of load point *i* due to failure in section *s*
r_{is}	Average time per interruption of load point *i* due to outages in section s
λ_s	Permanent failure rate of section *s*
r_{rs}	Average repair time of the fault
r_{sw}	Average switching time of the devices
N_i	Number of customers at load point *i*
n	Number of load points
m	Number of sections
S_s	Set of all sections connecting the power source and section *s*
L_i	Set of the section path that links power source and load point *i*
D	Set of available automatic sectionalizing switches
TP	Set that contains the available automatic tie-point switches
$Num_D \times C_D$	Total cost due to the investment on Num_D auto sectionalizing sw
$Num_{TP} \times C_{TP}$	Total cost due to the investment on Num_{TP} auto tie-point sw

Chapter 1: Introduction

1.1. Background and Motivation

The distribution system is a vital component of any electric power system. It constitutes the final linkage between bulk power source and end customers. However, distribution is also one of the most susceptible to failures within the power system (Brown, 2008a). Therefore, power quality and continuity have become among the most important objectives that distribution utilities have concentrated significant efforts on in order to satisfy system load and energy requirements as economically as possible.

Distribution system reliability can be improved by reducing the frequency of occurrence of faults and by reducing the repair time by means of maintenance strategies (Zheng et al., 2011).

The addition of switches along the distribution network contributes to reduce the number and duration of interruptions; however, this involves investment costs. The two aspects of obtaining high level of reliability at a relatively low cost are often in direct conflict due to the fact that providing a higher reliability will cost utilities more capital.

The above statement drives a motivation to emphasize on the multi-objective optimization of utility investment costs and reliability benefits, the result of which will be a set of trade-off solutions that optimize both objectives so that the decision-maker can choose from.

Two types of line switches are normally installed along the distribution feeders: sectionalizing switch (normally closed switch) and tie-point switch (normally open switch). The former is a device that isolates a faulted section from the system so that the healthy sections upstream can still be electrically supplied. The latter is a device that restores power to the disconnected loads downstream the failure by transferring them to a neighbor distribution feeder without violating operational and engineering constraints.

Whenever a fault has been identified at any point of a network, acting as soon as possible may result in a minimum affected area. The process of restoring a feeder from a fault, (Bernardon et al., 2011), can be stated in the following steps:

- Identify the exact fault position,
- Isolate the faulted section by opening normally closed switches,
- Restore power supply to customers upstream and downstream of the isolated block,
- Correct the problem,
- Re-operate the switches to get back to normal network status.

Automation of distribution systems significantly contributes to reduce the time to perform the service restoration procedure and utterly minimize the impact of power interruptions. With the installation of automatic or remote-controlled line switches in the network, we can experience a faster response to isolate the fault without maintenance personnel even having to physically be at the location. New regulation policies have allowed automatic sectionalizing switches to operate faster, more efficient and reliable than traditional manual switches (Romero, Wesz da Silva, & Mantovani, 2011). Automatic switches have also shown to be an economically viable solution due to the emergence of a large number of automation equipment suppliers and new communication technologies.

A frequent topic currently discussed is how the electric power distribution systems of the future will be. In this sense the term “smart grid” has arisen to describe how the new distribution systems will behave, this is in a “smart” or “intelligent” manner. A deeper analysis about Smart Grid will be presented in Chapter 2, but as an introduction we can mention that among the features of the Smart Grid are the ability to carry out maneuvers in automatic mode (self-reconfiguration) and high reliability, all with low operation and maintenance costs.

The selection of an efficient methodology to determine the optimum location and number of automatic line switches is essential for utilities, since that procedure is closely related to the restoration time and consequently associated to the system reliability indices. The optimization methodology constitutes not an easy task because it is a combinatorial[1] constrained problem described by a nonlinear and nondifferentiable objective function and its solution can be challenging to solve (Tippachon & Rerkpreedapong, 2009).

Different approaches have proposed solutions for the problem of switch placement in distribution networks. Some studies develop optimization methodologies for a single objective function (mono-objective) such as minimizing economic cost or reliability indices (Chen et al., 2006), (Bernardon, et al., 2011). Other researches are focused on covering the impact of automatic switches, without considering its optimal allocation (Zheng, et al., 2011). Finally, some important studies about multi-objective allocation in distribution networks do not consider automatic switches after all (Tippachon & Rerkpreedapong, 2009), (Ferreira, Bretas, & Cardoso, 2010). The multi-criteria methodology for optimal placement of automatic line switches has not been included.

The multi-objective optimal placement of switches in distribution networks allows better operation and improvement on the reliability of the system (Ferreira, et al., 2010). Moreover, the

[1] Combinatorial optimization consists, in a sentence, on finding the optimal solution among a finite set of solutions (Schrijver, 2003).

reliability indices most commonly used to quantify the quality of the utilities services are related to sustained interruptions (interruptions longer than 5 minutes): System Average Interruption Frequency Index (SAIFI), and System Average Interruption Duration Index (SAIDI). These two indices highly depend on network topology and location of automatic switching devices.

Therefore, our optimization task will be driven to design a methodology for optimal placement of automatic line switches in distribution networks that simultaneously minimizes cost expenditures and maximizes system reliability (by minimizing SAIFI and SAIDI).

As more study on this new trend of power distribution technologies has extended around the world, Taiwan is also taking steps to become a major force in Smart Grid. According to MOEA's Bureau of Energy, the Taiwanese government plans to invest an additional US$4.6 billion in smart power grid infrastructure starting from first quarter 2012 (Wu, 2011). This amount includes NT$123.7 billion for improvement of power grid efficiency, NT$10.1 billion for the promotion of smart grid industry and NT$ 6.1 billion for technological research and development. It is expected that this project will create an output value of NT$1 trillion (Wu, 2011) in smart grid industry by 2030, making Taiwan an output country for global smart grid industry and equipment manufacturing.

Taiwan has a long-term experience in the ICT (Information and Communications Technology) industry which represents a solid foundation for developing the smart grid industry. However, the expertise with individual components will have to lead to research on abilities for system integration. That constitutes another of the motivations for developing the present research topic, giving the need of research in terms of network automation that will allow self-regulation, including automatic reconfiguration in the event of failures, threats, or disturbances.

1.2. Research Purpose

This study aims to the development of a computational algorithm to address the automatic line switch allocation problem on the basis of a Nondominated Sorting Genetic Algorithm (NSGA-II), in order to improve the reliability of the distribution systems and minimize costs expenditures. This method has proven to be effective in solving multi-objective optimization problems and promoting satisfactory solutions belonging to the Pareto-optimal front. The algorithm can be configured according to the needs of the utilities and help the network designer in the decision making process. Therefore, the proposed methodology will indicate where the utility should invest resources for switching automation in order to improve the reliability of the system, which constitutes an important decision support tool for planning and operating the distribution networks.

The proposed approach was tested in actual distribution feeders belonging to Taipower Company and its effectiveness, on the specified portion of the real system, was seen in the sense of the improvement in the reliability indices (SAIFI and SAIDI) and the different trade-off possibilities for reliability that we can expect depending on the degree of automation investment, letting one conclude the relevant economic benefits obtained by providing a set of optimal solutions to the decision-maker so that he/she can decide the most appropriate alternative based on his/her own professional experience.

Consequently, the main contributions of this study are highlighted as follows:

1) A new algorithm to assess the impact on reliability due to the installation of automatic line switches in distribution networks.

2) A new multi-objective optimization methodology for solving the automatic switch allocation problem using a modified integer version of NSGA-II.

1.3. Research Procedure

In this study we propose a methodology that specifies the optimal number and location of automatic line switches in distribution networks by following the steps below:

1) Understanding the function of line switches in distribution networks and how their number and allocation can impact system reliability.
2) Propose a mathematical model that represents the behavior of distribution networks due to the installation of automatic line switches.
3) Development of a computational algorithm based on integer-coding NSGA-II in order to search for the best combinations of line switch number and locations that optimizes the objective functions.
4) Simulation of the prosed algorithm for two case studies. One of them, an actual distribution system of Taipower Company. Additionally, results discussion for every case study.
5) Research study conclusions.

1.4. Chapter Outline

The remainder of this thesis dissertation is organized as follows:

In Chapter 2 we introduce some basic definitions of distribution systems and the problem formulation for the placement of line switches in distribution networks.

In Chapter 3, the algorithm foundations are presented concerning to multi-objective optimization theory, genetic algorithms and the concepts behind Elitist Nondominated Sorting Genetic Algorithm (NSGA-II).

Chapter 4 is dedicated to explain the proposed algorithm and its working mechanism.

In Chapter 5 we perform the simulation of the implemented algorithm in case studies and present the results discussion.

Finally, we outline the conclusions of this study in Chapter 6.

Chapter 2: Literature Review and Problem Formulation

2.1. Power Distribution Systems

Since distribution systems account for up to 90% of all customer supply interruptions and reliability problems (Brown, 2008a), improving distribution reliability is key in order to improve customer reliability. For succeeding in this task, a basic outline of power distribution systems will be stated. The following sections present fundamental concepts and terminology that will provide foundation for further reliability analysis.

2.1.1. Generation, Transmission, Distribution

Generation plants consist of one or more generating units that convert mechanical energy into electricity by turning a turbine coupled to an electric generator. Most turbines are driven by steam produced in a boiler fired by coal, oil, natural gas, or nuclear fuel. Others may be driven by non-thermal sources such as hydroelectric dams and wind farms. Typically, generators produce line– to–line voltages between 11 kV and 30 kV, but since this is not a sufficiently high voltage to transport electricity long distances, generation substations step up voltages to transmission levels (typically between 115 kV and 1100 kV).

Transmission systems transport electricity over long distances from bulk power generation facilities to substations that serve sub-transmission or distribution systems. Most transmission lines are overhead but there is a growing trend towards the use of underground transmission cable.

To increase flexibility and improve reliability, transmission lines are interconnected at transmission switching stations and transmission substations. This improves overall performance, but makes the system vulnerable to cascading failures[2].

Distribution systems deliver power from bulk power systems to retail customers. To do this, distribution substations receive power from sub-transmission lines and step down voltages with power transformers to utilization levels. Distribution systems consists on distribution transformers (which supply distribution feeders and contain a main 3ϕ trunk, 2ϕ and 1ϕ laterals), feeder interconnections, and distribution feeder.

In order to illustrate the above definitions, Figure 2-1 presents an overview of Taipower System – based on (F. Lin, 2011) – where we can distinguish the three stages that take place before power is delivered to the final customers. After being generated at a power station, the power is firstly steeped up to 345KV in order to be transported long distances. In transmission substations, the power is steeped down to 161KV. For the case of Taipower, there is a series of distribution transformers that converts 161 KV to 69 KV and 11.4 KV since there is specific customers that need those power levels. Finally, distribution power transformers lower down 11.4 KV to utilization levels (220-110V).

[2] Cascading failure is a type of failure in a system of interconnected parts in which a failure of one part can trigger the failure of successive parts.

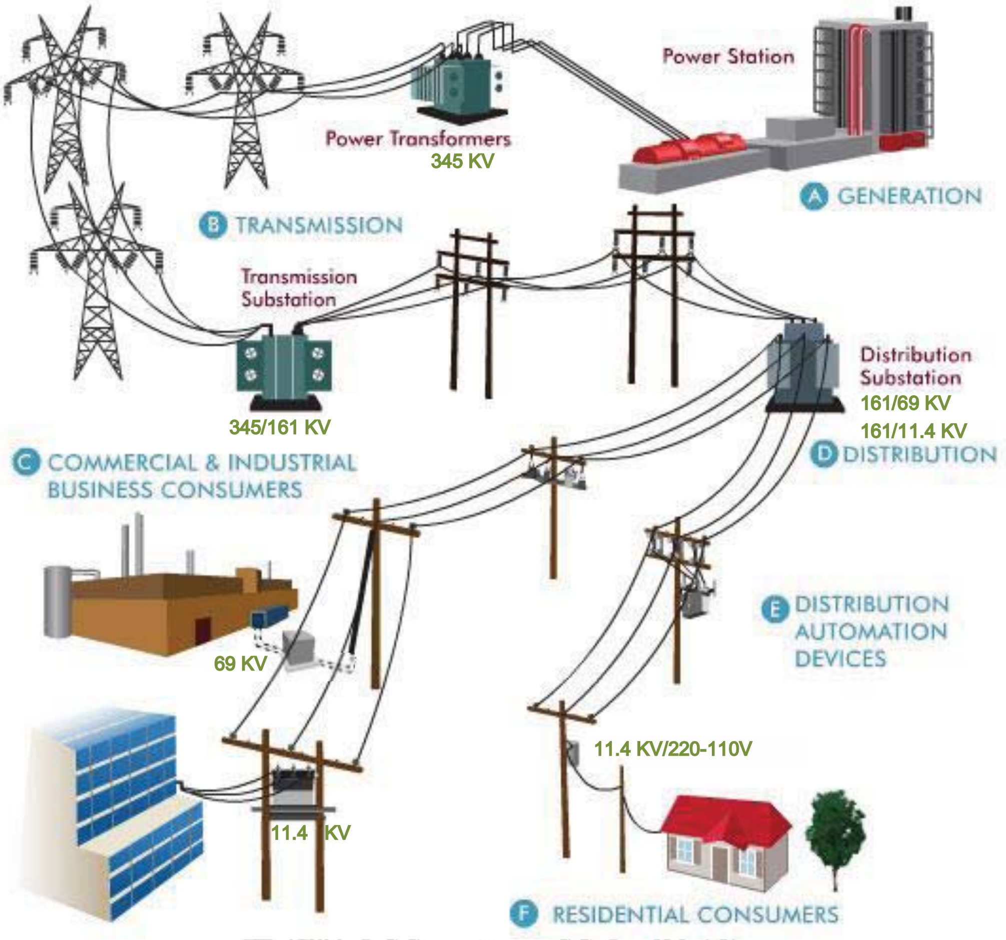


Figure 2-1 Overview of Taipower System

It is important to note that the key elements and principles of operation for interconnected power systems were established before the 1960s (Massoud Amin & Wollenberg, 2005), which means before the emergence of extensive computer systems and communication networks. Nowadays, computation is heavily applied throughout all levels of power network planning and optimization as well as local control of the equipment and data processing.

The incorporation of Smart Grid technologies allows us to have a two-way communication interaction to get access to a better real time network control and data acquisition which permits an easier task fulfillment. However, the new technologies require improvements in the approaches for solving existing problems in automation applications and research on new ones (Farhangi, 2010).

We present next a more formal definition to what Smart Grid involves and the philosophies and technologies within.

2.1.2. Concepts in Smart Grid

Our current electric grid was conceived around a century ago when electricity needs were simpler. Power generation was localized and built around the communities; in addition, most homes only had small energy demands. The grid was designed for utilities to deliver electricity to consumer homes and then bill them for the service every month. However, this limited one-way interaction makes it difficult for the grid to respond to the always changing and rising energy demands of the 21th century. The Smart Grid introduces a two-way communication where electricity and information can be exchanged between the utility and its customers. According to (Litos, 2008) Smart Grid is a developing network of communications, controls, automation and new technologies and tools working together to make the grid more efficient, more reliable, more secure and greener.

Some of the benefits associated with the Smart Grid include:

- More efficient transmission of electricity
- Self-reconfiguration and quicker restoration of electricity after power disturbances
- Reduced operations and management costs for utilities, and ultimately lower power costs for consumers
- Enabling active participation by consumers in demand response

- Reduced peak demand, which will also help lower electricity rates
- Increased integration of renewable energy systems
- Improved security

Today, an electricity disruption such as a blackout can have a domino effect—a series of failures that can affect banking, communications, traffic, and security. A smarter grid will add resiliency to the electric power system and make it better prepared to address emergencies such as severe natural disasters. Because of its two-way interactive capacity, the Smart Grid will allow automatic rerouting when equipment fails or outages occur. This will minimize outages and minimize the effects when they do happen.

Distribution automation (DA) is one the most research-active areas in the field of Smart Grid (Brown, 2008b). It refers to monitoring, control, and communication functions located out on the feeder. From a design perspective, the most important aspects of distribution automation are in the areas of protection and switching (Brown, 2008b).

Automatic switches allow detection of a fault event and containment of it before it becomes a large-scale interruption. This technology also help ensure that electricity resumes quickly and strategically after an interruption occurs: automatically routing electricity to sections downstream the isolated faulty area, for instance.

Consequently, the optimal placement of automatic switches in Smart Grid networks plays a significant role that will contribute to future networks to have better operation and improved reliability and also permits new technology to be incorporated on the network system.

2.1.3. Power Distribution Networks

The function of power distribution networks is to deliver electricity to each end-customer, transforming it to a suitable voltage when necessary. However, it has been estimated (Falaghi, Haghifam, & Singh, 2009) that most of the supply interruptions to customers are because of failures in the distribution networks.

The frequency of interruptions can be reduced by improving the network failure rates, while the duration can be reduced by decreasing the restoration time. An effective way to reduce the frequency of interruption and restoration time is the installation of automatic line switches in the feeders of distribution systems (Chao-Shun Chen et al., 2006).

Sectionalizing and tie-point switches work together to identify faults, automatically isolate problem areas and reconfigure the controlled feeders in order to restore power to un-faulted customer as soon as possible from the main or alternative sources. This reduces the number and length of electric system outages, and minimizes the impact to customers.

The effectiveness of this process strongly depends on the number and location of sectionalizing and tie-point switches. Therefore, an algorithm that addresses the automatic switch optimal allocation problem has significant importance since it allows Smart Grids to embrace advanced controls, monitoring and innovative metering systems.

2.2. Distribution Feeder Model

An illustration of a radial feeder of a distribution system is presented in Figure 2-2. It consists of one main and several lateral sections. The main feeder CB-1 is interconnected to an adjacent feeder (CB-2) by the existence of normally open (N.O.) tie-point switch, through which power can be supplied to the main feeder when needed.

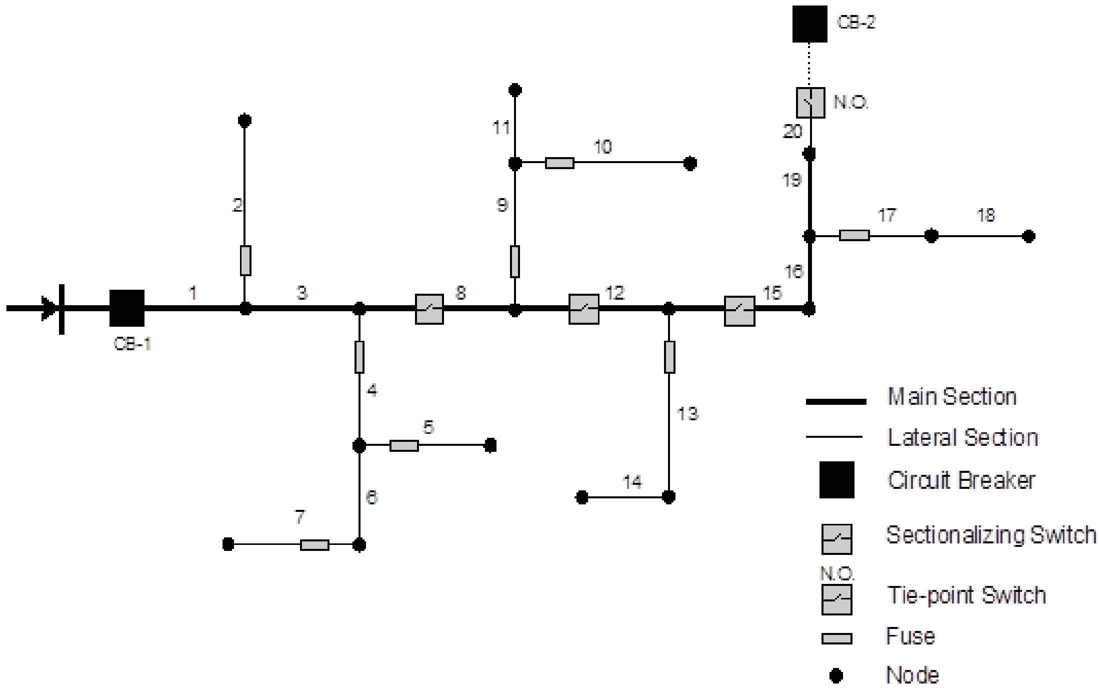


Figure 2-2 Radial Distribution Feeder and its Line Switches

Each portion of feeder in the above figure has a unique end node. The end node of section j also constitutes the physical connection point for customers to the distribution feeder. Any device allocated in section j of the distribution system is also identified by j.

Let $s(i)$ be the immediate predecessor of section i. We define s_i as the section path which contains all sections belonging to the path that connects the power source to section i. For example, for Figure 2-2, let us suppose a failure has occurred in section 17. The section path to the failure event corresponds to the expression: $s_{17} = \{1,3,8,12,15,16,17\}$.

Similarly, the load point path L_i is the pathway containing all sections that connects the power source to the load point i. For the same illustration, the load point path for customer 7 is: $L_7 = \{1,3,4,6,7\}$.

Switches and protective devices shown in Figure 2-2 play a vital role for reliability improvement of the distribution system (Tippachon & Rerkpreedapong, 2009). Each type of devices has unique functionalities. Following we give more details about them:

Circuit Breakers have switching and protective properties, which are used to handle permanent and temporary faults. Circuit breakers are located in transmission substations and they protect a distribution feeder from damage caused by overload or short circuit. Its basic function is to detect a fault condition and, by interrupting continuity, immediately disconnect electrical flow to the entire distribution network. A circuit breaker can be reset (trip-reclose function), either manually or automatically, to resume normal operation.

Fuses have only protective function, which means no switching capability. It separates a fault by melting its fuse-link. A fuse can only perform open-circuit function, and is not able to clear the momentary fault by itself. Fuses are not allowed to be installed on the main feeder.

Switches can be of two types: sectionalizing or tie-point switches. Both types, they cooperate to isolate faulted sections of the network and restore power to customers in healthy areas through the main or neighbor feeders. This reduces the number of customers affected by the interruption and the duration of it, which is beneficial to the overall reliability of the system.

Sectionalizing switches and tie-point switches installed in the distribution feeder are grouped into sets D and TP, respectively. In other words, for Figure 2-2, the sets of switching devices can be expressed: $D = \{8,12,15\}, TP = \{20\}$.

2.3. Line Switches in Distribution Networks

After a fault is cleared by the circuit breaker, the system needs to be reconfigured to isolate the fault and restore power for the remaining customers. This reconfiguration is performed by sectionalizing and tie-point devices, most of which are manually operated. Thus, the customers have to wait for a crew to drive to the location and manually switch these devices on or off to execute the reconfiguration. In order to enhance reliability and improve customer satisfaction, electric utilities have begun to install automatic switching systems in their distribution systems.

Automatic switching systems are usually composed of several automatic switches with the capability to isolate the faulted circuits, and these switches “talk” with one another through communication equipment to determine the status of the portion they cover. The selection of the location of an automatic switch should guarantee that the adjacent feeders, to which the load will be transferred, have sufficient capacity to pick up the customers affected by the fault on their main feeder.

2.3.1. Automatic Sectionalizing Switches and Tie-point Switches

The installation of automatic sectionalizing switches benefits distribution network reliability, above all, by reducing the outage duration time when a fault occurs, given that the fault is isolated in a period of time equal to the switching time of the device –in automatic switches, less than five minutes. With reduction of outage duration time, the unsupplied amount of energy to the customers is also decreased.

An automatic sectionalizing switch typically employed by utilities in distribution systems is the SF6 Gas Insulated Automatic Sectionalizing Switch for overhead lines operating at a voltage up to 25.8kV. The full specification datasheet for the mentioned device is presented in Appendix1.

Automatic tie-point switches in distribution networks contribute to the improvement of interruption frequency on the system. Tie-switches are able to restore electrical service to sections of feeder within the order of minutes avoiding that sustained interruption events are accounted for those sections and hence affect network reliability.

2.4. Problem Formulation for Placement of Automatic Line Switches

As discussed previously, distribution automation in terms of installation of automatic or remote-controlled switches provides major benefits to distribution utilities. However, its implementation requires economic justification, and the contribution to the performance should be also quantified. Benefits of automated sectionalizing and tie-point switches can be calculated in terms of reduced duration of outage and reduced number of customers affected during permanent faults by fast restoration of power to un-faulted customers.

The main purpose of this study is to find the optimal number and location of automatic switches in order to minimize System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), in conjunction with line switch capital investment costs (TCOST).

We present Figure 2-3 in order to investigate the benefits of implementing automatic line switches in a typical distribution feeder. In this figure we have a main radial feeder connected to a neighbor network through an automatic tie-point. Additionally, two automatic sectionalizing switches will be allocated in each feeder, in sections 2 and 5. This analysis will allow us to differentiate the benefits of the installation of automatic switches.

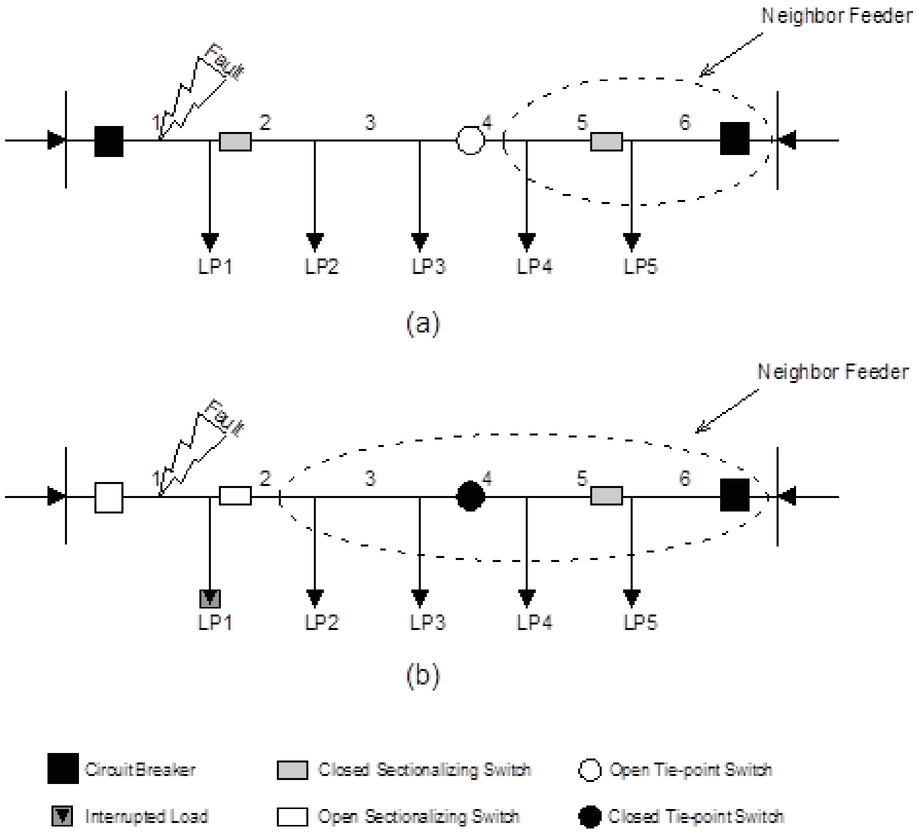


Figure 2-3 Operation of Automatic Sectionalizing and Tie-point switches in Distribution Networks

Let us consider a case where a fault[3] occurs on the main feeder in section 1 of Figure 2-3 (a). Firstly, the circuit breaker operates and de-energizes all the downstream load points. Following, the automatic sectionalizing switch located in section 2 will open and "tell" the automatic tie-point in section 4 that there is a fault in section 1. Then, after the tie-point switch receives the information and makes sure that the automatic switch in section 1 has isolated the fault, it will close and transfer the load downstream the open sectionalizing switch to the neighbor feeder. At this point, the loads in the main feeder located between the two automatic switches will experience an interruption equal to the switching time of the devices (less than five minutes). Therefore, as seen in Figure 2-3 (b), customers in load points LP2 and LP3 will suffer no impact

[3] In this study, fault is defined as the occurrence of a permanent disturbance on a feeder section or transformer or occurrence of a sustained interruption due to the failure of any component of the system.

on SAIFI given they did not experience any sustained interruption, and a considerably reduction in SAIDI because of the automatic switching time of the devices. However, customers in load point LP1 will experience outage duration equal to the repair time of feeder section 1, which is much longer than the switching time.

Mathematically, the benefits of automatic line switches in improving the reliability of distribution network can be determined by considering all possible switch placement combinations and evaluating all possible contingencies utilizing the objective functions for SAIFI and SAIDI. On the other hand, the impact on investment cost for utilities due to the installation of line switches in distribution networks can be quantified by the objective function TCOST.

2.4.1. Assumptions

Before we state to the formulation of the objective functions it is worth mentioning the assumptions under which they will be estimated:

- The network under study is radially operated;
- A fault is repaired before a subsequent fault occurs;
- The power substation is assumed to be fully reliable. So that we can calculate our reliability indexes independently from another subsystems.

2.4.2. Objective Functions

This study deals with a multi-objective optimization algorithm to obtain the best possible distribution system reliability while simultaneously minimizing investment costs as a result of acquisition of automatic switches.

There exist several reliability indices that are used to assess the performance of distribution systems (Billinton & Jonnavithula, 1996). The most common indices used by distribution utilities are System Average Interruption Frequency Index (SAIFI), and the System Average Interruption Duration Index (SAIDI) (Tippachon & Rerkpreedapong, 2009). They are used to calculate the impact on reliability of power outages in terms on number of interruptions and interruption duration, respectively.

We select three objectives to be minimized: SAIFI, SAIDI and TCOST. The last corresponds to the total investment cost that the distribution utility has to incur due to switch automation purchase and installation.

Based on the study performed by (Tippachon & Rerkpreedapong, 2009), we present a modification to that original work in order to obtain the mathematical models that fit our described problem allowing us to achieve the three mentioned objectives; the ones that are defined as follows:

1) *SAIFI*, $f_1(\boldsymbol{x})$: system average interruption frequency index. It represents the average frequency of sustained interruptions per customer. This index can be calculated using the following equation:

$$SAIFI = \frac{\sum_{i=1}^{n}(\sum_{s=1}^{m}\lambda_{is})N_i}{\sum_{i=1}^{n}N_i} \qquad \frac{total\ number\ of\ customer\ interruptions}{total\ number\ of\ customers\ served} \quad (int./cust.-year) \qquad eq.(1)$$

where N_i is the number of customers at load point *i*, *n* identifies the number of load points and m the number of sections. λ_{is} is the permanent failure rate of load point *i* due to failure in section *s*. It depends on the topology of the system and location of the switching devices. From the characteristics of automatic line switches and the model of the distribution networks in sections 2.3.1 and 2.2, respectively, λ_{is} can be estimated as follows:

$$\lambda_{is} = \begin{cases} \lambda_s & if \quad S_s \cap (D \cup TP) - L_i \cap (D \cup TP) = \emptyset \\ & and \;\; S'_s \cap (D \cup TP) - L'_i \cap (D \cup TP) = \emptyset \\ 0 & otherwise \end{cases}$$

$$eq. (2)$$

where λ_s is the permanent failure rate of section *s*. S_s is the set of all sections connecting the power source and section *s*. Analogically, L_i is the set of the path that links power source and load point i. S'_s and L'_i are the complement of S_s and L_i, and are defined as the pathway that connects, either *s* or *i*, to the neighbor feeder power source.

The purpose of the above set operations is to identify if there is any switching device between the faulted section and the load point and also verify if there is an alternative way to restore power through a tie-point. Based on those parameters we are able to decide λ_{is} accordingly.

2) *SAIDI*, $f_2(\boldsymbol{x})$: system average interruption duration index. It is referred to as the average time that a customer is interrupted per year. The following equation is employed to calculate this index:

$$SAIDI = \frac{\sum_{i=1}^{n}(\sum_{s=1}^{m}\lambda_{is}r_{is})N_i}{\sum_{i=1}^{n}N_i} \quad \frac{\sum interrupted\ customers\ \times interruption\ duration}{total\ number\ of\ customers\ served}\ (min./cust.-yr.)$$

$$eq. (3)$$

where r_{is} is the average time per interruption of load point i due to outages in section s. It also depends on the topology of the system and location of the switching devices. Using the same concepts as mentioned before, r_{is} can be calculated with the following expression:

$$r_{is} = \begin{cases} 0 & if \quad S_s \cap TP - L_i \cap TP \neq \emptyset \\ & or \quad S'_s \cap TP - L'_i \cap TP \neq \emptyset \\ r_{rs} & if \quad S_s \cap D - L_i \cap D = \emptyset \\ & and \;\; S'_s \cap D - L'_i \cap D = \emptyset \\ r_{sw} & otherwise \end{cases}$$

$eq. (4)$

r_{rs} is the average repair time of the fault. On the other hand, r_{sw} represents the switching times of the devices.

3) TCOST, $f_3(\boldsymbol{x})$: total cost. It is the objective function that accounts for the summation of the total expenses associated to the investment on automatic line switches. It can be computed by the equation:

$$TCOST = Num_D \times C_D + Num_{TP} \times C_{TP} \; (US\$ - year)$$

$eq. (5)$

where Num_D accounts for the number of sectionalizing switches and Num_{TP} for the number of tie-point switches to be installed. C_D and C_{TP} are the total costs including purchase and installation of sectionalizing and tie-points, respectively.

The possible switch placement locations will be grouped together into a set of possible combinations and they will be considered as feasible solutions for the optimization problem. For this task, a decision variable will be associated to every section and its value (0, 1 or 2) represents the cases in which: 0 – no device is assigned to that section, 1 – a sectionalizing switch is assigned, or 2 – a tie-point switch is assigned. By doing so, we are able to the generate feasible combinations for placement of switches in the distribution network; the ones that a search algorithm will compare looking for closeness to the minimal objective functions in order to obtain the set of optimal solutions.

2.4.3. Constraints

To guarantee that the proposed methodology does not violate technical restrictions, the following operation constraints are considered in this study:

- Only one automatic tie-point switch can connect two neighbor feeders. In other words, only one section for every feasible combination is allowed to be given a value of 2 as its decision variable;
- When performing the load transfer for service restoration, no overloading should be introduced to the power transformers. In Taipower distribution system, the rated levels for transformers are 450A.

In conclusion, SAIFI, SAIDI and TCOST represent the three objective functions for the multi-objective optimization problem to be addressed by the search algorithm that will be presented in Chapter 4. Meanwhile, in the following Chapter 3 we will provide the algorithm background we need before formulating the proposed algorithm approach.

Chapter 3: Algorithm Background

This chapter is imperative for our analysis since it will present the three most important concepts we need in order to implement the proposed methodology for the switch allocation problem. They are termed as follows: Multi-Objective Optimization, Genetic Algorithm, and Elitist Nondominated Sorting Genetic Algorithm (NSGA-II).

In order to better understand each concept, a review concerning their basic approaches will also be presented in the way of subsections.

3.1. Multi-objective Optimization

Optimization is a procedure of finding and comparing feasible solutions until no better solution can be found (K. Deb, 2001). Solutions are considered good or bad in terms of an *objective function*, which is often the cost of fabrication, product reliability, efficiency of a process, or other factors. A significant amount of research efforts in the optimization field are carried in terms of a *single objective*, although most real-world problems involve more than one objective (Engelbrecht, 2005).

Real-world optimization problems habitually involve simultaneous optimization of multiple and often conflicting objectives (such as simultaneously minimizing cost of fabrication and maximizing product reliability). In a multi-objective optimization problem, it is not always possible to find a solution that is the best with respect to all objectives. A solution may be optimal regarding to one objective, but at the same time be inferior regarding to another objective. Typically, the goal is to find a set of optimal trade-off solutions known as *Pareto-optimal set*.

Solutions belonging to the Pareto set are optimal in a broader sense given that no other solutions in the search space are better than them when all objectives are considered. Additionally, since no any solution in the Pareto-optimal set can be said to be absolutely better than any other solution in the same set with respect to all objectives, all solutions belonging to the set are recognized as acceptable solutions for the optimization problem. The decision-maker is able to select one solution over the others based on his/her previous knowledge about the problem and professional experience.

3.1.1. Multi-objective Optimization Problem

The purpose of the multi-objective problem is to minimize or maximize a number of objective functions. Those objective functions are subject to constraints which any feasible solution, including the optimal solution set, must satisfy. Based on (K. Deb, 2001), the multi-objective optimization problem (MOOP), in its general form, can be expressed using the following structure:

$$\begin{aligned} Minimize/Maximize \;\; & f_m(\boldsymbol{x}), && m = 1,2,\dots,M; \\ subject\ to \;\; & g_j(\boldsymbol{x}) \geq 0, && j = 1,2,\dots,J; \\ & h_k(\boldsymbol{x}) = 0, && k = 1,2,\dots,K; \\ x_i^{Lower} \leq \; & x_i \leq x_i^{Upper}, && i = 1,2,\dots,n. \end{aligned}$$

A *solution* $\boldsymbol{x}$ is a vector of n *decision variables* $\boldsymbol{x} = (x_1, x_2, \dots, x_n)^T$. The terms $g_j(\boldsymbol{x})$, $h_k(\boldsymbol{x})$ are the *inequality and equality constraints*, respectively. Additionally, $x_i^{Lower} \leq x_i \leq x_i^{Upper}$ is also a constraint called *variable bounds*. These bounds establish a *decision variable space D* or *decision variable*, simply, and they are the ones that restrict each decision variable x_i to take a value within x_i^{Lower} and x_i^{Upper}.

A solution $\boldsymbol{x}$ that satisfies all the $(J + K)$ constraints and is allocated within the $2N$ variable bounds is known as *feasible solution*. Moreover, the set of all feasible solutions is called *feasible region S* or *search space*.

We have M objective functions $f(\boldsymbol{x}) = (f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \ldots, f_M(\boldsymbol{x}))^T$and each one of them can be either minimized or maximized. However, for our case only minimization of objective functions is allowed in the search algorithm.

In multi-objective optimization the objective functions constitute a multi-dimensional space called *objective space Z.* For each solution $\boldsymbol{x}$ in the decision space there exist a point in the objective space and the mapping takes place between a n-dimensional solution vector and a M-dimensional objective vector.

Figure 3-1 shows us the feasible decision space in the left and the feasible objective space in the right. Every feasible solution in the decision space can be mapped to a solution in the feasible objective space. This correspondence shows us the different trade-off solutions between the two objectives.

3.1.2. Pareto-optimality

In this section we are going to provide a number of definitions that are needed when talking about multi-objective optimization. Those definitions include dominance, Pareto-optimal set, Pareto-optimal front and others.

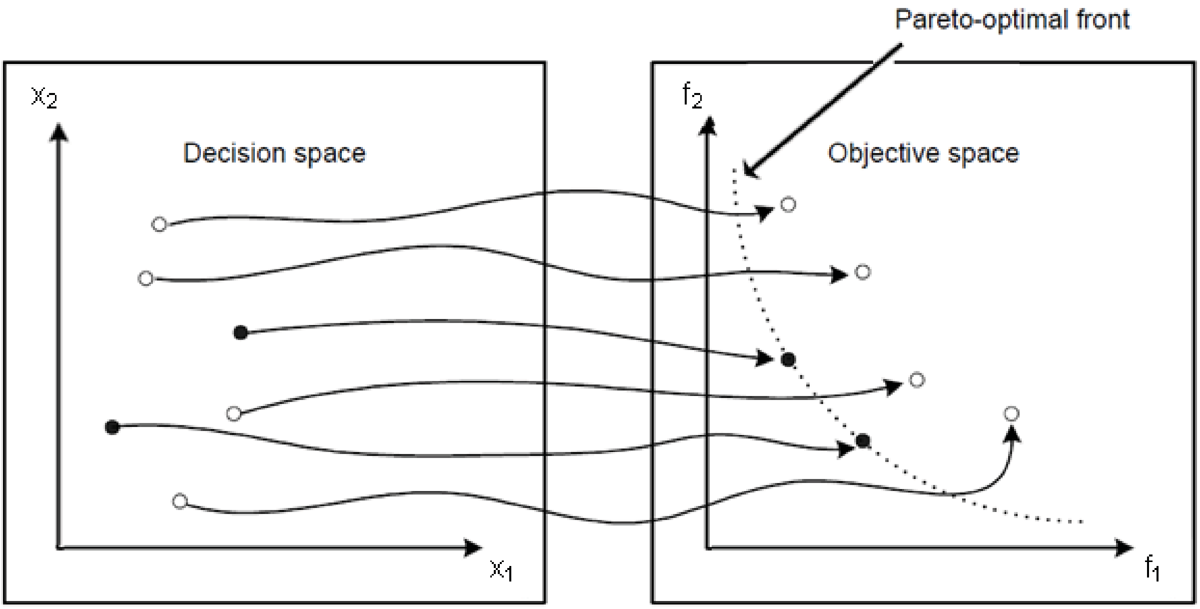


Figure 3-1 Illustration of a general multi-objective optimization problem (Tran, 2006)

We can observe in Figure 3-1 that in some cases if we pick and compare some pair of solutions from the feasible objective space, one of the solutions is better than the other in both objectives. For another pair of solutions, one is better than the other in one of the objective but worse in the second objective. In order to determine which solutions are optimal with respect to both objectives we are going to introduce the concept of *dominance*.

In Figure 3-2 we illustrate a number a solutions coming from the feasible objective space. Solution 1 provides the lowest value for objective 1 but the highest value for objective 2, while solution 4 offers the minimum value for objective 2 but under the highest sacrifice of objective 1. None of these two solutions can be said to be better than the other when considering both objectives. The same reassembles when considering solutions 2 and 3, no superiority of any of the solutions can be established if the two objectives are equally important. When this happens we can call them *non-dominated solutions*.

All non-dominated solutions are jointed together using a curve. The solutions lying on that curve are special in terms of multi-objective optimization and are called *Pareto-optimal solutions.* The curve that contains these solutions is called *Pareto-optimal front.* We can distinguish the mentioned curve in Figure 3-2. It is interesting to note that for optimization problems in which the minimization of the two objective functions is required, this curve is located in the bottom-left corner.

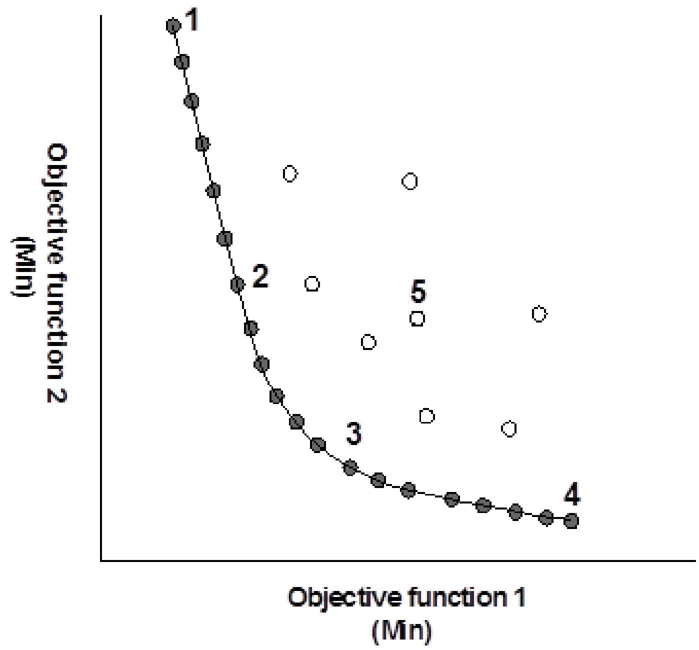


Figure 3-2 Pareto-optimal front including Pareto-optimal solutions and a non-optimal solution

We can deduce that the feasible objective space is constituted by Pareto-optimal solutions and by solutions that are non-optimal, in fact, the total feasible objective space can be divided into Pareto-optimal set, or non-dominated set, and non-optimal set. If we consider solutions 3 and 5 in Figure 3.2, for instance, we can realize that solution 3 is better than solution 5 in both objectives. Thus, we can say that solution 3 *dominates* solution 5. There always exists at least one solution in the Pareto-optimal set which is better than any member of the non-optimal solution set. A formal definition for dominance will be stated below assuming minimization problems.

3.1.3. Domination

Definition 3.1: Domination (K. Deb, 2001): A solution $\boldsymbol{x_1}$ is said *to dominate* the other solution $\boldsymbol{x_2}$ (*denoted by* $\boldsymbol{x_1} \prec \boldsymbol{x_2}$), if and only if:

- $\boldsymbol{x_1}$ *is not worse than* $\boldsymbol{x_2}$ in all objectives, i.e. $f_k(\boldsymbol{x_1}) \leq f_k(\boldsymbol{x_2}), \forall k = 1, \dots, M$, and
- $\boldsymbol{x_1}$ *is strictly better than* $\boldsymbol{x_2}$ in at least one objective, i.e. $\exists k = 1, \dots, M$: $f_k(\boldsymbol{x_1}) < f_k(\boldsymbol{x_2})$.

If any of the above conditions is not satisfied, the solution $\boldsymbol{x_1}$ does not dominate solution $\boldsymbol{x_2}$.

We can perform all possible pair-comparisons for a finite set of solutions, and find which solutions dominate which and the solutions that are non-dominated with respect to each other. In the end, we will obtain a set of non-dominated solutions which any of its elements will dominate any solution outside of this set.

Definition 3.2: Non-dominated set (K. Deb, 2001): Among a set of solutions P, the non-dominated set of solutions P' are those that are not dominated by any member of the set P.

If the set P is the entire search space, then P=S, and the obtained non-dominated set P' is called the *Pareto-optimal set*.

From the above discussion we can conclude that the Pareto-optimal set is the non-dominated set. But there may be some Pareto-optimal sets containing some Pareto-optimal solutions and some non-Pareto optimal solutions. The task of finding the true Pareto-optimal solutions is usually computational prohibitive (Engelbrecht, 2005). Therefore, it is important to realize that the nondominated solutions found by an optimization algorithm need not to represent the true Pareto-optimal set but rather an approximation such that:

1. The set of solutions represent as close as possible the true Pareto-optimal front.
2. The set of non-dominated solutions, Pareto-optimal set, is as diverse as possible.

The first goal represents the desirable near-optimality property the Pareto-optimal set must have. The second goal let us know that being converged close to the true Pareto-optimal front is not enough, only a diverse set of solutions can guarantee adequate Pareto-front coverage.

Therefore, the population-based search algorithm must adequately emphasize the non-dominated set of a given population to ensure the two goals mentioned above are satisfied. We are now interested in a computational efficient procedure to identify the non-dominated set from a population of feasible solutions.

In this study we propose a computational algorithm based on Nondominated Sorting Genetic Algorithm (NSGA-II). The tests we perform on the mentioned algorithm have showed that this methodology ensures a very good approximation to the true Pareto-front and diversity of the solutions is also guaranteed, all of this while being computationally efficient when performing the procedure of finding the non-dominated set from a population of feasible solutions.

Before get into more detail with such algorithm, we first need to know how genetic algorithms perform their search technique, since that constitute the basis for the former algorithm.

3.2. Genetic Algorithms

Genetic Algorithms (GAs) are one of the main types of Evolutionary Algorithms (EA). In general, EA indicate any population-based stochastic search algorithm that uses mechanisms inspired by biological evolution and genetic operators such as reproduction, mutation, crossover, natural selection and survival of the fittest.

GAs for computer simulation were mainly developed by Holland in the 1960s and published in his book (Holland, 1975). Over the years, Holland's original GA has evolved into many forms Multi-objective GA (MOGA), Nondominated Sorting GA (NSGA), Niched-Pareto GA (NPGA), Elitist Nondominated Sorting GA (NSGA-II), and others. However, the general framework remains the same as in the basic GA.

A simple GA attempts to find a good solution to some problem (finding the minimum of a function, for instance) by generating a random population of candidate solutions and then manipulating those solutions using genetic operators of *reproduction*, *crossover* and *mutation*.

Once the initial population of solutions has been generated, the GA begins to evaluate and rank each candidate solution based on the on its fitness to the objective function. Solutions with higher fitness value will have better chances of survival and reproduction according to the evolutionary process. Hence, the best fitted solutions will be selected to produce the next generation of candidate solutions using genetic operators. Finally, when a terminating condition has been satisfied, usually number of generations, the most excellent solution, which is the most evolved one, constitutes the optimal to the optimization problem.

3.2.1. Solution Representation

In GAs, each feasible solution can be denoted by a *chromosome*, which is a coding representation. In order to perform this task, first we need to code the decision variables of the optimization problem using finite-length character strings, from *phenotype* (decimal representation) to *genotype* (binary or real representation). There are two main ways for coding a variable:

1) *Binary-valued representation* (binary coding) consisting of 0 and 1. One character (0 or 1) in the binary strings is called a *gene*.
2) *Real-valued representation*. In this case the variable is coded using real numbers instead.

The set of chromosomes is called *population*, and each member evolves in every generation toward better solutions. The number of chromosomes in a population is called the *population size*.

In our proposed algorithm for the optimal placement of line switches in distribution networks, we will apply integer-representation for the coding of the decision variables, which is an special case of real coding. This way we are able to reduce computational complexity, because variables are used directly without any string coding, and also due to the fact that this type of representation is ideally suited for solving combinatorial problems (K. Deb, 2001) and when solutions are composed of many variables.

3.2.2. Fitness Assignment

Fitness is an indicator for measuring a solution quality for survival. All solutions are evaluated and ranked based on their fitness values at each generation. The fitness is similar to the objective function in conventional optimization problems. Thus, solutions having higher fitness are good ones. During the evolution process, therefore, relatively good solutions reproduce, and relatively bad solutions with lower fitness die in each generation. Finally, the solution having maximum fitness is obtained as an optimal solution.

One of the reasons why we decided on a GA-based methodology in this study is due to the fact that GAs can deal with a wide range of objective functions (nonlinear, non-differentiable, constrained, or discontinuous) without the need of additional requirements for the fitness evaluation.

3.2.3. Genetic Operators

There are mainly three types of genetic operators in GAs: reproduction and selection, crossover, and mutation. The population of solutions is modified by genetic operators and a new (hopefully better) population is created.

3.2.3.1. Reproduction and Selection

The main purpose of the reproduction operator is to make duplicates of good solutions and eliminate bad ones from the population, while keeping the population size constant.

There exist several alternatives to achieve this task, one of the most common methods is *tournament selection,* and since it is the one we are going to apply in our proposed algorithm, we will provide more details about it next.

In *binary-tournament selection*, tournaments are played between two solutions in terms of ranked fitness. The better solution is chosen and placed in a *mating pool*. Two other solutions are picked and another slot of the mating pool is filled with the better one. If this methodology is performed accordingly, each solution will participate in exactly two tournaments. The best solution in the population will win both rounds; therefore, two copies of it will be present in the new population. On the other hand, the worst solution will lose both tournaments and will be eliminated from the population. Thus, each solution will have zero, one or two copies of it in the new population.

In Figure 3-3, we find six different solutions ranked according to their fitness with the objective function. Tournaments are played among these solutions and each one gets to participate in two rounds. The two solutions for each tournament are chosen at random, and for the first tournament we have the solution with a hypothetical fitness of 12 being better and hence a copy of it is placed in the mating pool. The same process is followed for the rest of tournaments, and the mating pool is formed. It is interesting to note better solutions (with minimum values) have handled to have multiple copies in the mating pool and worse solutions have gotten discarded.

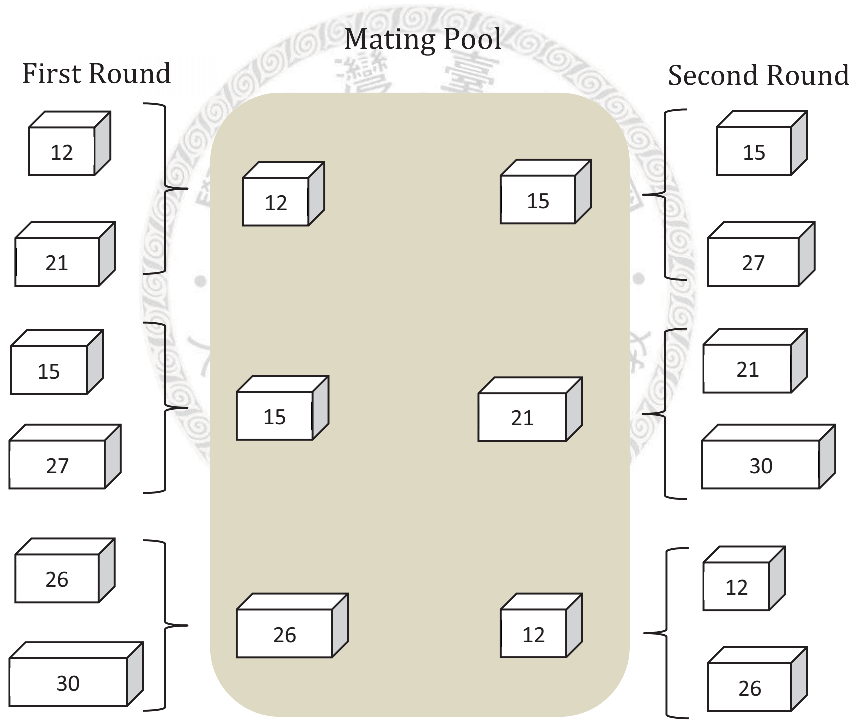


Figure 3-3 Creation of Mating Pool from six hypothetical solution fitness using Tournament Selection

3.2.3.2. Crossover

It is clear that the reproduction operator does not create any new solutions in the population, it just make copies of good solutions and deletes not so good ones. By proliferating good solutions in the mating pool we ensure better chances of crossover and mutation for them than those with lower fitness values, this is how we stimulate the creation of more excellent solutions in each generation.

The crossover operator combines the features of two different solutions (parents) into two new solutions (offspring). It operates by picking two random solutions belonging to the mating pool and exchanging some portion of their coded strings in order to create two new strings. Like reproduction operator, there are many ways to perform the crossover task: single-point crossover, multi-points crossover, uniform, intermediate crossovers and so on, but almost all operators have the same above notion.

The crossover rate, p_c, is used to determine that $100p_c$% of strings will experience crossover and the rest 100(1-p_c)% of the population is simply copied to the new population. Crossover rate ranged from 0.6 to 0.8 is usually used in order to allow new offspring to be created sufficiently. The higher the crossover rate, the more excellent created individuals will be. If the crossover rate is too low, the searching process may deteriorate due to lack of new strings with better performance.

3.2.3.3. Mutation

Mutation randomly alters one or more genes of a solution string to generate a new mutated solution. The mutation operation increases the variability of the population and helps to prevent premature convergence to local optima in the evolution process.

The number for mutation events depends on the mutation rate, p_m. The mutation rate in natural evolution is usually very small. Therefore, the mutation rate is traditionally given by low values at the range of 0.01 – 0.1. In each generation, $100p_m$% solutions undergo mutation. The lack of mutation induces poorer performances in evolution. Therefore, if mutation rate is too low, the possibility to fall into local optima increases. Relatively high mutation rates up to 0.4 or 0.6 have been found beneficial (Morimoto, 2006). It is to be noted, however, that a significantly high mutation rate leads to an essentially random search.

The three genetic operators (reproduction, crossover, mutation) are straightforward. The reproduction operator selects good strings and makes copies of them, crossover operator recombines good string sections from two solutions in order to obtain a hopefully better string, and mutation operator alters a string locally to hopefully create a better solution.

Since none of these operations are performed deterministically, these claims are not guaranteed, nor explicitly tested, during the GA generation (K. Deb, 2001). Nevertheless, parents that undergo crossover and mutation are not any two arbitrary random strings. These strings have survived tournaments played with others solutions during the reproduction operator. Therefore, it is expected that if bad solutions are created, then the reproduction operator will eliminate them in the next generations and when good solutions are created, they will be emphasized to ensure next generation will contain better solutions.

In conclusion, GAs are powerful search techniques that have proven to be successful in many optimization applications (Morimoto, 2006). Their capacity to handle virtually any objective function with no requirement of derivatives or other knowledge, and their ability to reach global (or at least near global ones) optimal solutions makes GA-base algorithms a major tool when considering complex optimization problems.

3.3. Elitist Nondominated Sorting GA (NSGA-II)

The original NSGA (Srinivas & Deb, 1994) was one of the first EA to emphasize on approximation to the true Pareto-optimal front while maintaining a diverse set of solutions (Deb, Pratap, Agarwal, & Meyarivan, 2002). However, over the years there have been many criticisms about to the NSGA approach, such as: high computational complexity, lack of elitism, and need for specifying a diversity parameter (Deb, et al., 2002).

Deb and his students (2002) suggested an enhanced methodology they called: a fast and elitist multi-objective genetic algorithm: NSGA-II, in order to address all the above drawbacks of the original approach. The major features of NSGA-II include:

3.3.1. Crowded-Comparison Operator

NSGA-II uses the same genetic operator as the simple GA, but introduces a new definition about the way selection is performed. In order to obtain solutions uniformly spread along the Pareto-front, a crowded-operator was proposed. This operator does not need to be set by the user, rather performs a density estimation of solutions. The way this is made is mentioned below:

Density Estimation: Estimates the number of solutions surrounding a particular solution. In order to achieve this, the average distance between two points on either side of a certain point is defined as *crowding distance* $i_{distance}$.

Crowded-Comparison Operator ($\prec_n$): Guides the selection process to reach uniformly spread solutions. Two attributes are taken in consideration for selection of solution *i*:

1) nondomination rank (i_{rank})
2) crowding distance ($i_{distance}$)

In the selection process between two solutions with different nondomination ranks, we prefer the solution with the lower (better rank). Otherwise, if both solutions belong to the same rank (front), we prefer the one in the lesser crowded region. (Deb, et al., 2002)

3.3.2. NSGA-II Main Loop

Step 1) Randomly create a parent population P_0 with size N.

Step 2) Use typical binary tournament selection, crossover and mutation operator to generate an offspring population Q_0 with size N.

Step 3) Combine parent and offspring populations: $R_t = P_t \cup Q_t$ of size $2N$.

Step 4) Population R_t is sorted based on nondomination and every solution is assigned a fitness (or rank) equal to its nondomination level (1 being the best level, 2 the next one, and so on). Minimization of the objective function is assumed. Additionally, since all previous and current generations are included in R_t elitism is ensured.

Step 5) Solutions with rank 1 belonging to the best nondominated set F_1 are copied into the new population P_{t+1}, the remaining members of P_{t+1} are chosen subsequently: solutions in set F_2, F_3 and so on; until no more sets can be accommodated in N spots of the new population. If F_l is that last set to be accommodated in P_{t+1}, and the number of solutions from $F_1$to F_l is larger than N; F_l is sorted using the crowded-comparison operator $\prec_n$ and choose the best solutions to complete N members in the new population P_{t+1}. In order to illustrate this procedure we present Figure 3-4.

Step 6) If Number of Generations has been reached, then stop and present results. Else, $t = t + 1$, $P_t = P_{t+1}$, $Q_t = Q_{t+1}$, and go to Step 3.

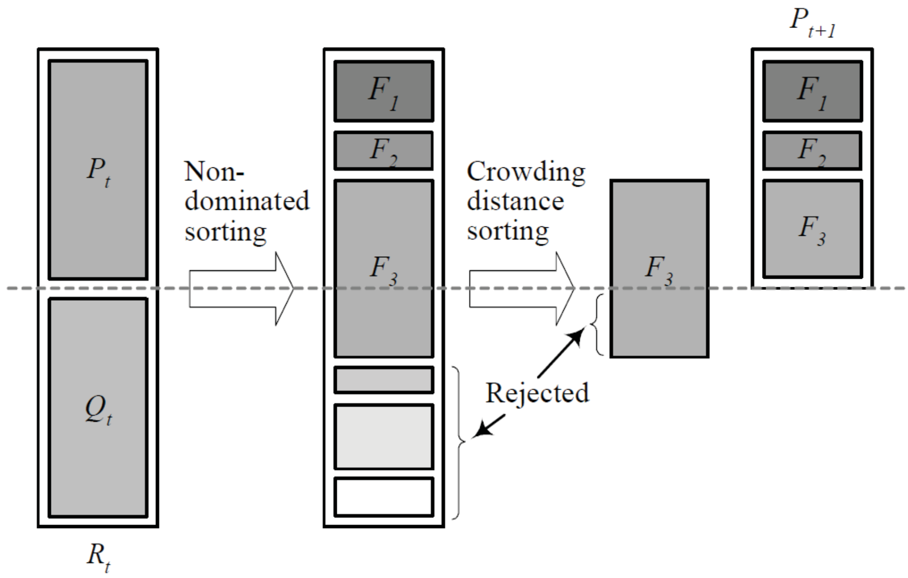


Figure 3-4 Elitist Selection Mechanism of NSGA-II (Tran, 2006)

Due to its clever mechanisms, NSGA-II is much more efficient (computationally speaking) than its predecessor, and with an outstanding performance that has become very popular in the last few years, allowing significant number of applications and becoming some sort of landmark for multi-objective EA.

Chapter 4: Proposed Algorithm for the Optimal Placement of Automatic Line Switches

When considering the increasing demand from power distribution utilities of an enhanced system response in case of outages, the contribution that automatic line switches provide in terms of fast power restoration to customers constitutes a step forward in distribution industry. Therefore, it is imperative the introduction of some methodology that determines the number and placement of those devices in order to obtain the most reliability benefit out of the utility capital investment.

The main purpose of this study is to develop a computational algorithm that allows the identification of the best locations and combinations of automatic line switches in distribution networks with regard to system reliability maximization and investment cost minimization.

In this study, objective functions were defined in order to represent the distribution network reliability indexes (SAIFI, SAIDI) and utility investment costs (TCOST). The mathematical representation for each was presented in Section 2.4 by equations (1), (3) and (5), respectively. The possible switch combinations and technical feasibility for load transfer were assumed as constraints.

We illustrate our previously formulated optimization problem for the line switch placement as follows:

- Objective Functions:

$$
Minimize \begin{cases} SAIFI = \dfrac{\sum_{i=1}^{n}(\sum_{s=1}^{m}\lambda_{is})N_i}{\sum_{i=1}^{n}N_i} \\ SAIDI = \dfrac{\sum_{i=1}^{n}(\sum_{s=1}^{m}\lambda_{is}r_{is})N_i}{\sum_{i=1}^{n}N_i} \\ TCOST = Num_D \times C_D + Num_{TP} \times C_{TP} \end{cases}
$$

- Constraints
  1) Only one automatic tie-point switch can connect two neighbor feeders.
  2) Each decision variable can only take integer values 0, 1 or 2.
  3) No overloading should be introduced to the power transformers when performing the load transfer for service restoration.

The nonlinear, combinatorial, and nondifferentiable nature of the objective functions presented above, makes it difficult the application of traditional linear or nonlinear programming to solve this optimization problem. Additionally, since all of the objectives are equally important and should be optimized at the same time, classical techniques of objectives aggregation for solving multi-objective problems, such as objective weighting, are difficult to apply in this case, besides the fact that they alone suffer from some drawbacks in their methodology (Ferreira, et al., 2010).

Genetic Algorithms (GAs) handle a population of solutions that is modified over the course of a number of generations using genetic operators in order to obtain a close approximation to the true Pareto-optimal front. They are able to work with a wide range of types and number of objective functions making them suitable for our multi-objective optimization problem. Among them, the Elitist Nondominated Sorting Genetic Algorithm (NSGA-II) represents one of the most important studies in the field of multi-objective optimization due to its efficient procedure and outstanding performance which have allowed it to become intensively applied with satisfactory results on a number of test studies.

We now analyze the main features of our proposed version of NSGA-II used to solve the optimal placement of line switches in distribution networks in the following sections.

4.1. Proposed Integer Version of NSGA-II

The optimal placement of automatic line switches in distribution networks can be considered as an integer optimization problem (integer phenotype). NSGA-II is capable of working with integer-coded solutions (integer genotype) or binary-coded solutions (binary genotype).

Binary-coding representation for the decision variable would involve the presence of one binary value which does not represent any of the values we assumed (0, 1, or 2). Therefore, integer-coding seems to be the best option for our study given that the number of possible values for the decision variable is not multiple of two (Conti, Nicolosi, & Rizzo, 2011).

4.1.1. Solution Representation

All possible combinations of switch placement in a distribution feeder constitute feasible solutions for the optimization problem. In order to replicate this feature, a decision variable has been associated to every section of the distribution feeder where a switch can be allocated. This decision variable can take integer values: 0, 1, or 2; each one representing a specific case:

$$0 \rightarrow no\ switch\ in\ this\ section$$

$$1 \rightarrow an\ auto\ sectionalizing\ switch\ is\ located\ in\ this\ section$$

$$2 \rightarrow an\ auto\ tie-point\ switch\ is\ located\ in\ this\ section$$

Let us assume a distribution feeder which contains *m* sections, meaning *m-2* feasible places for switch allocation. The decision variable in each section represents a gene in a chromosome whose length is *m-2*. Hence, considering that every decision variable can assume one of the three values (0, 1, or 2), the problem size is 3^{m-2} possible switch combinations. An illustration of the chromosomal representation for this feeder is shown in Figure 4-1.

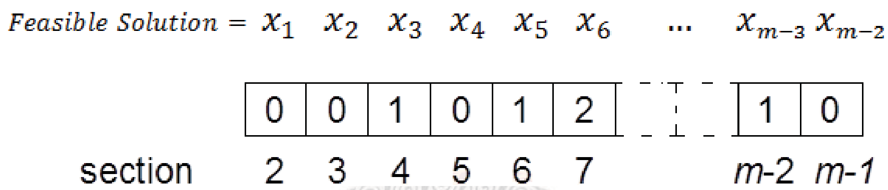


Figure 4-1 Chromosomal Representation for a Feasible Solution

Using the above representation we are able to generate the feasible solutions for placement of line switches in the distribution network. At the same time, the set of all feasible solutions constitutes the decision space that the NSGA-II has to sort looking for the optimal solutions.

The optimal solution searching process performed by the proposed NSGA-II follows the procedures shown in the Figure 4-2, each of which will be explained next.

4.1.2. Generate Initial Population

In the first step of NSGA-II, a random initial solution population P_0 of size *N* will be generated, from which an initial offspring population Q_0 will be created using genetic operators. Recursively, an offspring population Q_t of size *N* will be created by applying binary tournament selection, crossover and mutation operators to a parent population P_t in order to obtain new (hopefully better) solutions. Later, those two populations are combined together (size *2N*) and sorted for nondomination (ranking and crowding distance) to obtain a new parent population

P_{t+1} for the next generation which will have the best characteristics of both parents and offspring found so far. This procedure will be repeated until a stopping criterion (number of generations) is reached.

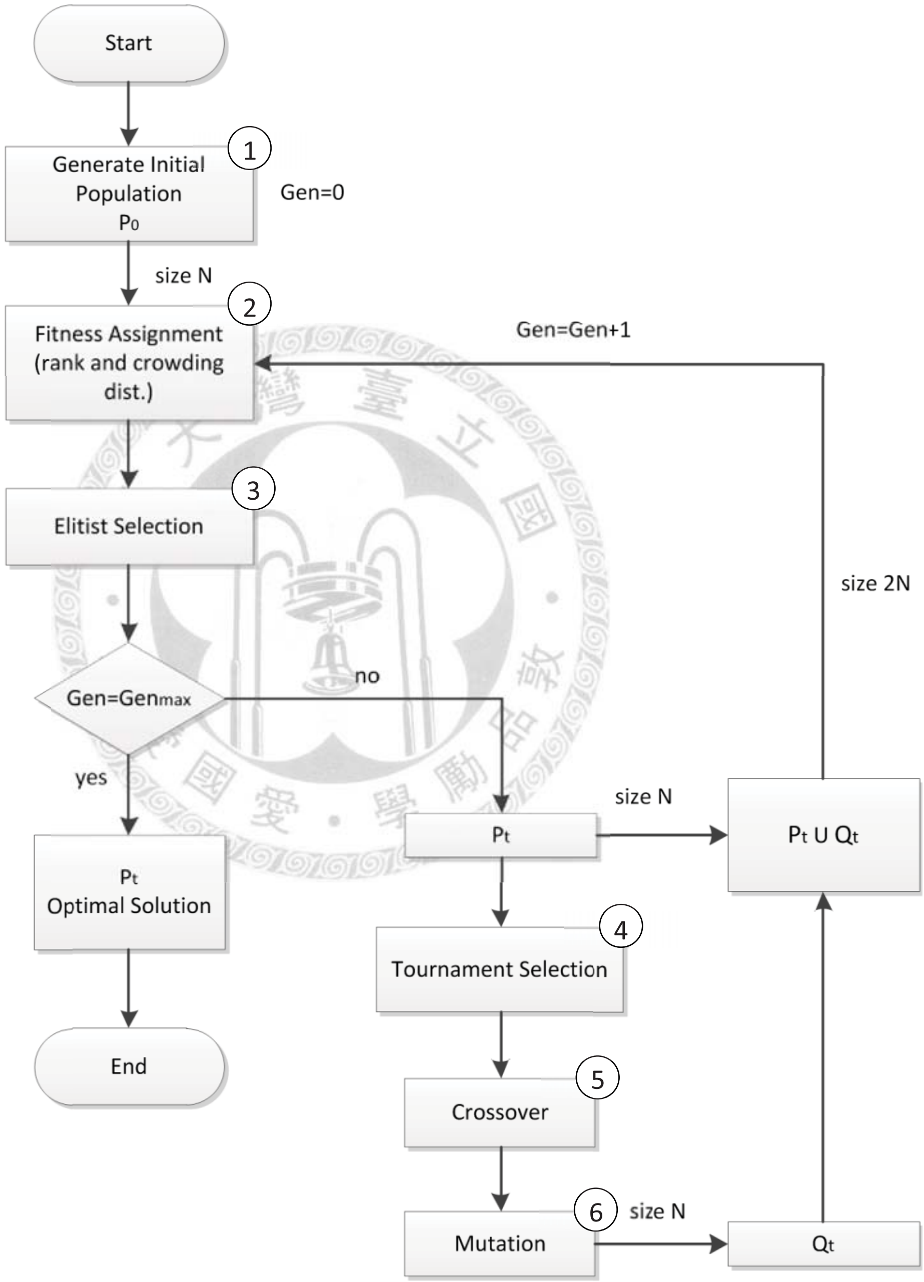


Figure 4-2 Procedures performed in the proposed NSGA-II

In order to illustrate the creation of the initial population, and the other procedures yet to be explained, we present in Figure 4-3 an example of a distribution network containing 12 sections, with 11 load points served, and 10 possible line switches locations.

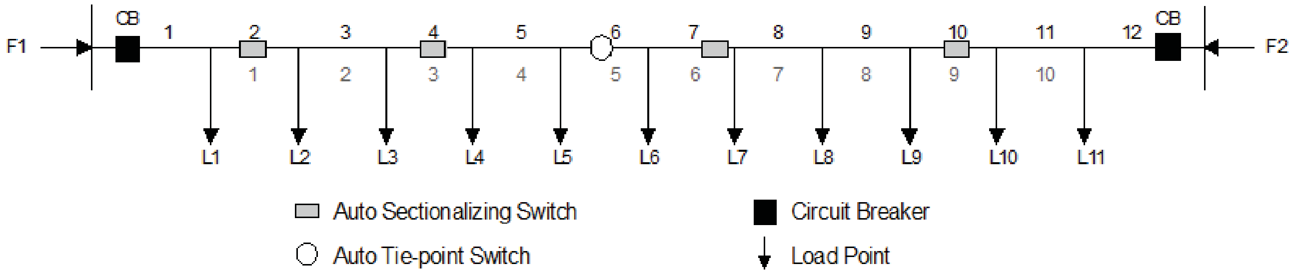


Figure 4-3 Distribution Network having 2 neighbor feeders, 11 load points and 10 possible switch locations. In this model: $\boldsymbol{D} = \{\mathbf{1}, \mathbf{3}, \mathbf{6}, \mathbf{9}\}$ and $\boldsymbol{TP} = \{\mathbf{5}\}$.

The result of the generation of a random initial population of 6 feasible switch locations is presented in the table below:

Solution	**Chromosomal Representation** x_1 x_2 x_3 x_4 x_5 x_6 x_7 x_8 x_9 x_{10}	**D - Sectionalizing Sw.**	**TP - Tie-point Sw.**
1	0 0 1 0 1 1 2 0 1 0	4, 6 , 7, 10	8
2	0 1 0 0 2 1 1 0 0 1	3, 7, 8, 11	6
3	1 1 1 0 2 1 1 1 1 1	2, 3, 4, 7, 8, 9, 10, 11	6
4	0 0 1 2 1 0 0 0 0 1	4, 6, 11	5
5	0 0 2 1 1 0 1 0 0 1	5, 6, 8, 11	4
6	1 1 1 2 1 0 1 1 1 1	2, 3, 4, 6, 8, 9, 10, 11	5

Table 4-1 Random Generation of 6 Feasible Solutions

4.1.3. Fitness Assignment

The algorithm will now attach a nondomination rank and a crowding-distance assignment to every solution as mentioned in Section 3.3.2.

Concerning to the crowding-distance assignment, the same procedure as the original is kept in this study. However, the ranking process depends on the fitness evaluation of each solution with respect to the objective functions. Therefore, every solution arriving to this stage will be analyzed and used to build a computational model of the distribution feeder to determine values of SAIFI, SAIDI, and TCOST for the specific switch combination.

First, for each solution x belonging to population P we sort its coding representation looking for auto sectionalizing switches and tie-point switch. Next, we built a matrix λ_{is} containing the permanent failure rates for each load point i due to failure in section s. Analogically, we obtain a matrix r_{is} which contains the interruption duration that customers at load point i experience due to outages in section s. Using λ_{is} and r_{is} we calculate the value of SAIFI and SAIDI, accordingly. Finally, TCOST can be obtained by the addition of each type of device number and capital cost.

For a detailed illustration of the mechanism used to perform this stage, the pseudo code of this procedure is presented below:

Pseudo Code for the Fitness Evaluation in our Proposed Algorithm	
for each $x \epsilon P$	
for each $x(i)$	Each gene in the chromosome
if $x(i) = 1$ then	
$D = \{x(i)\}$	Set of auto sectionalizing switches
else if $x(i) = 2$ then	
$TP = \{x(i)\}$	Set of auto tie-point switch

for each s — Each possible faulted section in the feeder

for each i — Each load point connected to the feeder

$\lambda_{is} = \emptyset$

$r_{is} = \emptyset$

if $S_s \cap (D \cup TP) - L_i \cap (D \cup TP) = \emptyset$ and

$S'_s \cap (D \cup TP) - L'_i \cap (D \cup TP) = \emptyset$ then

$\lambda_{is} = \lambda_s$ — Permanent failure rate

else

$\lambda_{is} = 0$ — No permanent interruption

$InterruptedCustomers = InterruptedCustomers + \lambda_{is} \times NumberofCustomers_i$

if $S_s \cap TP - L_i \cap TP = \emptyset$ or

$S'_s \cap TP - L'_i \cap TP = \emptyset$ then — No effect to current feeder due to failure in the neighbor feeder

$r_{is} = 0$

else if $S_s \cap D - L_i \cap D = \emptyset$ or

$S'_s \cap D - L'_i \cap D = \emptyset$ then

$r_{is} = r_{rs}$ — Interruption Duration equal to repair time

else

$r_{is} = r_{sw}$ — Duration equal to devices switching time

$InterruptionDuration = InterruptionDuration + \lambda_{is} \times r_{is} \times NumberofCustomers_i$

$SAIFI = InterruptedCustomers/TotalNumberofCustomers$

$SAIDI = InterruptionDuration/TotalNumberofCustomers$

$TCOST = Num_D \times C_D + Num_{TP} \times C_{TP}$

Fitness evaluation for the distribution in Figure 4-3 can be calculated by assuming practical values for permanent failure rate, distance of sections and number of customers connected to each load point, and cost of devices; and we present the results for the 6 solutions generated in Table 4-1 next.

Solution	**SAIFI** $(int./cust.yr)$	**SAIDI** $(min./cust.yr)$	**TCOST** $(\$-yr.)$
1	0.1307	31.3718	45355
2	0.1073	25.7631	45355
3	0.0252	6.0402	81639
4	0.1816	43.5754	36284
5	0.1307	31.3718	45355
6	0.0262	6.2867	81639

Table 4-2: Fitness Evaluation

We can see in Table 4-2 that solution 2 is better than solution 1 in SAIFI and SAIDI at the same TCOST, the same resembles between solutions 3 and 6. Hence, there are some solutions in the population better than some other solutions. Elitist selection is introduced to sort the best solutions of the population.

For a better illustration on how the fitness calculation was performed please refer to Appendix 2.

4.1.4. Elitist Selection

At this point we have a combined population of size *2N* (parents + offspring). Yet, only *N* positions are available to accommodate the next generation of solutions. In our version of NSGA-II the Elitist Selection is performed in the same way as in the original approach and referred to in Section 3.3.5, Step 5.

The selection of the best solutions is performed according to their rank. The solutions copied into the next generation population start with the ones with rank 1 (best solutions) and continue with higher ranks (no so good solutions) until *N* spots are filled. When solutions belonging to the same rank are to be accommodated in the next generation but their number surpasses *N*, then those solutions are sorted based in crowding-distance. We prefer solutions in the less crowded area and fill the spots left to complete the size *N*.

4.1.5. Binary Tournament Selection

The new population P_{t+1} is used for selection, crossover and mutation to create a new offspring population Q_{t+1} of size *N*. For the case of the selection operator, the traditional binary tournament selection has been applied in the present algorithm, but the selection criterion is now based in ranking and crowding-distance. Tournament rounds will be played between two solutions (chosen at random) and the best solution (better rank or crowding-distance) will be copied in the mating pool. Every solution in the population will participate in exactly two rounds. So, it is intuitive to say that the best solutions will have more copies in the mating pool and that the worst solutions will get discarded.

4.1.6. Crossover Operator

In our integer NSGA-II, crossover will operate in the same way that it is conceived for the real-coded solutions in the original GAs. Specifically, it has been used *Intermediate Crossover* for performing the recombination of the parent solutions.

Intermediate Crossover creates two offspring solutions by a weighted average of two parent solutions picked by random from the mating pool according to the following rule (S. Lin, 2011):

$$child\ 1 = parent\ 1 + rand \times ratio \times (parent\ 1 - parent\ 2) \qquad eq.(6)$$

$$child\ 2 = parent\ 2 - rand \times ratio \times (parent\ 2 - parent\ 1)$$

$eq.(7)$

where $rand$ is a uniform random number. The parameter $ratio$ is the specific weight of the parents to children. If $ratio \in [0,1]$ the children produced will be between the parents. Otherwise, the children might lie outside the parents.

It is important to mention some characteristics of the crossover operator in the case of our optimization problem:

- All feasible solutions will be processed by the crossover operator.
- For every solution, a variable called *crossoverFraction* will determine the number of decision variables that will participate in the crossover operation.
- If the new gene (decision variable) created is < lb (lower bound=0), then gene=0. On the other hand, if the new gene is > ub (upper bound=2), then gene=2.

Now, we are going to illustrate the crossover operator over two solutions from the distribution in Figure 4-3. These solutions are randomly selected from the mating pool, let suppose we choose Solution 1 and Solution 3 from Table 4-1. To get to know the calculation step by step, please refer to Appendix 3. Next we present the offspring obtained:

Solution type	**Chromosomal Representation**	**SAIFI** ($int./cust.yr$)	**SAIDI** ($min./cust.yr$)	**TCOST** ($)
Parent 1 (Solution 1)	0 0 1 0 1 1 2 0 1 0	0.1307	31.3718	45355
Parent 2 (Solution 3)	1 1 1 0 2 1 1 1 1 1	0.0252	6.0402	81639
Child 1 (new solution)	0 0 1 0 0 1 2 0 1 0	0.1482	35.5630	36284
Child 2 (new solution)	1 0 1 0 1 1 2 1 1 0	0.0645	15.4702	63497

Table 4-3: Crossover operation

From the table above be can see that the new solutions created by the crossover operation present new characteristics concerning fitness alternatives. In this case, Child 1 has slightly worse reliability fitness than solution 1, for instance. However, the biggest impact of Child 1 is on TCOST, where a significant improvement in cost minimization has been reached. The same comparison can be done with Child 2 and solution 2. Even though the difference in SAIDI is considerable between two of them, the same can be said for TCOST in the case of Child 2,

4.1.7. Mutation Operator

Gaussian Mutation, also known as normal mutation, has been used as basis for the mutation procedure in this algorithm. This option of mutation operator adds a random number, taken from a normal distribution with mean zero, to a determined number of genes of the parent coding. The new mutated child is created using the following expression (S. Lin, 2011):

$$child = parent + S \times randn \times (ub - lb) \qquad eq. (8)$$

$$S = scale \times (1 - shrink \times currGen/maxGen) \qquad eq. (9)$$

The scalar parameter $scale$ determines the standard deviation of the normal distribution at the first generation. The $shrink$ parameter is also a scalar ϵ [0,1] and it controls how the standard deviation decreases as the optimization progress go forward. $shrink$ ϵ [0.5,1] is commonly used for local search. $shrink$=0 is used if a large mutation range is needed to get out of local Pareto-optimal fronts.

Similarly to the crossover operator, in the case of the mutation operator we present analogous characteristics:

- All feasible solutions will undergo mutation.
- Only *mutationFraction* of the decision variables will be included in the mutation procedure.
- If the new gene (decision variable) created is < lb (lower bound=0), then gene=0. In the other hand, if the new gene is > ub (upper bound=2), then gene=2.

We are now going to perform the mutation operator over the same example in Figure 4-3, Solution 4 (choose by random from the mating pool) in Table 4-1, specifically. More reference about this calculation is presented in Appendix 3. We obtain the following mutated child:

Solution type	**Chromosomal Representation**	**SAIFI** $(int./cust.yr)$	**SAIDI** $(min./cust.yr)$	**TCOST** ($)
Parent (Solution 4)	0 0 1 2 1 0 0 0 0 1	0.1816	43.5754	36284
Child (new solution)	0 1 1 2 1 0 1 0 0 1	0.0801	19.2299	54426

Table 4-4: Mutation Operation

The new mutated solution presents important improvements in the system reliability indexes, more than 50% reduction in SAIFI and SAIDI by including two additional auto sectionalizing switches in the network. This is an illustration of how mutation operator is able to create new feasible solutions for the search algorithm to consider for the next generation population.

4.2. Constraint Handling

As mentioned previously, solutions have to satisfy a number of constraints in order to become feasible for the optimization problem. We present the constraints that model our variable decision space one more time in order to introduce their implementation procedure in our proposed algorithm:

1) Each decision variable can only take integer values 0, 1 or 2.

$$0 \le x_i \le 2, \qquad i = 1,2,\dots,m-2$$

where x_i is an integer value and m is the total number of sections in the distribution feeder.

2) Only one automatic tie-point switch can connect two neighbor feeders.

$$number\ of\ elements(TP) = 1$$

where *TP* is the set of auto tie-point switches.

3) No overloading should be introduced to the power transformers when performing the load transfer for service restoration.

$$\sum_{i=1}^{n} I_i \le I_{trafo_{max}}$$

where I_i is the current needed by load point i and $I_{trafo_{max}}$ is the maximum current accepted by the power transformer.

Constraints 1 and 3 are fairly straightforward; we just need to configure lower and upper bounds for each decision variable accordingly while programming its settings.

The case of constraint 2 is a little more complex giving the difficulty to implement by a decision variable set-up. The handling of constraint 2 in our optimization problem will be carried out as follows: Every time a solution does not satisfy constraint 2, a penalty fitness (highest values of SAIFI, SAIDI and TCOST) will be assigned to that solution; simply because the possibility of having two tie-point switches in the same distribution feeder is not feasible. Therefore, that solution can be eliminated by the elitist selection in the next generation.

4.3. Performance Improvement

The proposed algorithm, as well as many evolutionary search techniques, is very time consuming while searching for the optimal solutions to the optimization problem. In order to contribute to reduce computational time, two improvements for performance are introduced:

1) *Limit the number of sections where auto tie-point switches can be allocated.* While it is true that, according to constraints 1 and 2, tie-point switches can be located in any section of the distribution feeder, in practice tie-point switches have certain feasible locations. For instance, it is not convenient to allocate tie-point switches in the sections at the beginning of the network. Permanent failure rate depends on distance, if we create a longer neighbor feeder, there are more chances of failure on the neighbor feeder and also more customers affected. This concept helps us reduce the problem size complexity.
2) *Parallel Computation.* (S. Lin, 2011). Parallel computation is very useful when the evaluation of the objective functions is time consuming and when a multicore processor computer in available. The Parallel Computation Toolbox in Matlab is been used (S. Lin,

2011) in order to start multiple process workers and use them to evaluate the objective functions for a number of solutions in parallel.

4.4. Decision Making Algorithm

NSGA-II will provide us with the set of nondominated solutions for the optimal placement of automatic line switches. Those solutions constitute the Pareto-optimal set and they represent the best solutions that can simultaneously satisfy the three objective functions. The decision-maker can select one of the nondominated solutions based on his/her own professional point of view. However, there exist some methods that can be used to obtain a final solution from the Pareto-optimal set.

In this study, a Max-Min approach has been used to select a final solution for the multi-objective problem. Each solution in the nondominated set has associated to it a vector of objective functions $(SAIFI_i, SAIDI_i, TCOST_i)$ that is first normalized using equation (10), (Tippachon & Rerkpreedapong, 2009) :

$$\left(\frac{SAIFI_{max} - SAIFI_i}{SAIFI_{max} - SAIFI_{min}}, \frac{SAIDI_{max} - SAIDI_i}{SAIDI_{max} - SAIDI_{min}}, \frac{TCOST_{max} - TCOST_i}{TCOST_{max} - TCOST_{min}}\right)$$

$eq. (10)$

where $SAIFI_{max}$, $SAIDI_{max}$, and $TCOST_{max}$ are the maximum values obtained for the three objective functions. On the other hand, $SAIFI_{min}$, $SAIDI_{min}$, and $TCOST_{min}$ are the minimum values.

Finally the selection of the final solution for the multi-objective optimization of automatic line switches in distribution networks using max-min approach can be expressed by the equation below (Tippachon & Rerkpreedapong, 2009).

$$max\left[min\left(\frac{SAIFI_{max}-SAIFI_i}{SAIFI_{max}-SAIFI_{min}},\frac{SAIDI_{max}-SAIDI_i}{SAIDI_{max}-SAIDI_{min}},\frac{TCOST_{max}-TCOST_i}{TCOST_{max}-TCOST_{min}}\right)\right]$$

$eq. (11)$

Chapter 5: Algorithm Simulation and Results Discussion

The proposed integer version of NSGA-II is implemented using Matlab on a dual-core personal computer with 4 GB of ram. In this study, in order to illustrate the application of the optimization algorithm and evaluate its performance, two case studies are used for simulation purposes. One corresponds to a one-line distribution feeder, and the second belongs to an actual distribution system from Taipower Company. These two case studies were taken from (Chen, et al., 2006) with the intention to drive comparisons in the different methodologies.

Based on the parameter-sensitivity analysis of the simulation results, the NSGA-II settings for both case studies are determined as follows:

	Parameter	Value
Crossover:	crossoverFraction	0.9
	ratio	0.1
Mutation:	mutationFraction	0.4
	scale	0.5
	shrink	0

Table 5-1: NSGA-II Parameter Settings

The permanent failure rate, repair time, and switching time required to restore power to customers have been retrieved from (Chen, et al., 2006) in the next table:

Parameter		Rate/Duration time
Average permanent failure rate, λ_s		0.132 failures/year-km
Average repair time, r_{rs}		240 min.
Switching time, r_{sw}	upstream the failure	5 min
(automatic switches)	downstream the failure	0.33 min

Table 5-2: Distribution Feeder Parameters

Finally, the investment cost for overhead automatic line switches is US$9071 with a life cycle of 15 years (Chen, et al., 2006). The costs of communication equipment have been also added.

5.1. Case 1: One-line Distribution Feeder

The diagram for the one-line distribution feeder to be simulated is presented in Figure 5.1. It contains 20sections, 19 load points and 18 possible switch locations. A tie-point switch will be connecting the neighboring feeders in other to facilitate load transfer.

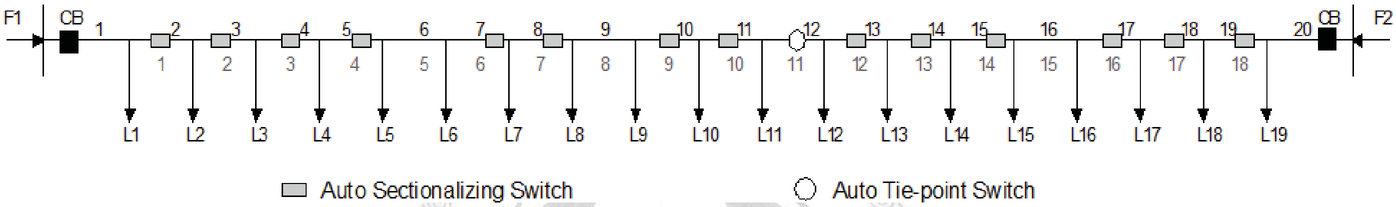


Figure 5-1 Optimal Solution (using Max-Min) in One-line Diagram for Case 1

For the present simulation, we assume the power transformers are able to receive any load from the neighbor feeder during the customer transfer. The later assumption is justified given the relatively low load and the sufficient power capacity that typical distribution power transformers can provide (Chen, et al., 2006). For the number of customers and load in each load point please refer to Appendix 4.

Using the simulation settings mentioned before, we run the proposed NSGA-II for this case study using a population size and number of generations of 50 and 100, respectively. The results of such simulation are presented in Figure 5-2.

Additionally, in Appendix 5 we present the set of Pareto-optimal solutions with their respective auto line switch combinations.

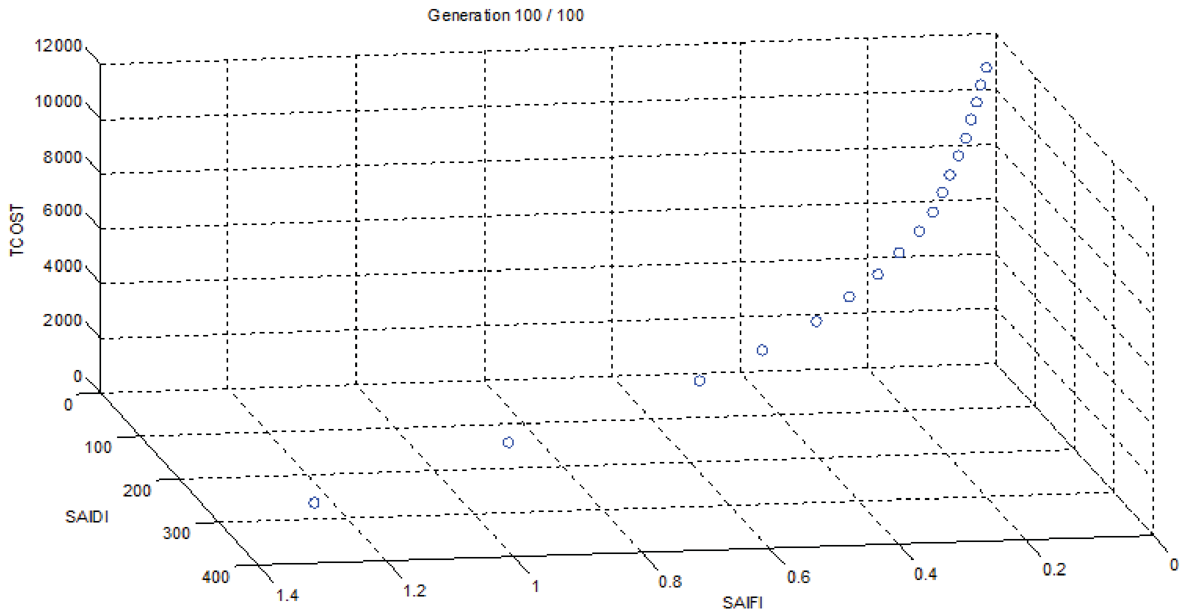


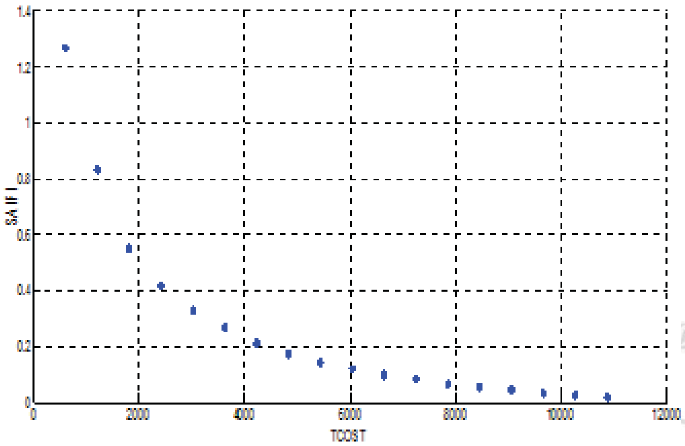
Figure 5-2 Scatter of the Pareto-optimal set obtained by the integer NSGA-II

In the above figure we can verify the predicted fact that the best solutions for system reliability (lower values of SAIFI and SAIDI), come with the highest investment costs. For instance, at the highest point of the curve, as we can expect, automatic switches have been located in every section of the distribution feeder, with the tie-point being placed in section 11. This most expensive switch combination can provide the lowest values possible for SAIFI and SAIDI, 0.018 int./cust.-yr. and 4.29 min/cust.-yr., respectively.

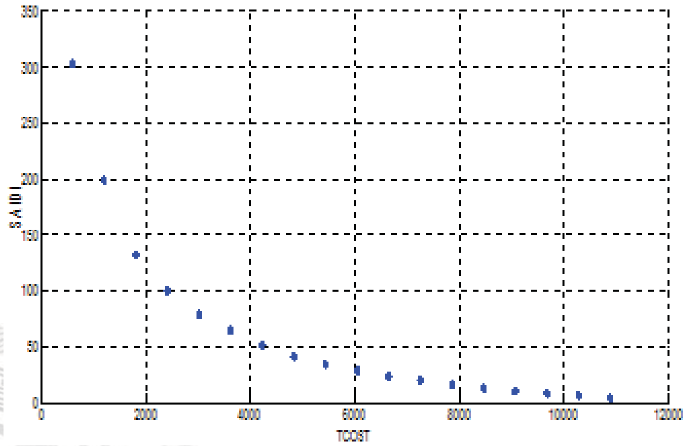
On the other hand, at the lowest point of the curve, the cheapest solution only includes the installation of one tie-point switch (which is a necessary condition) in section 11; no additional auto sectionalizing switches have been added. This is the cheapest, though the most inconvenient alternative from system reliability perspective.

Those are the two extreme solutions for the optimization problem in this case study. However, a number of solutions are allocated between the extremes and they propose different trade-offs between system reliability and investment costs.

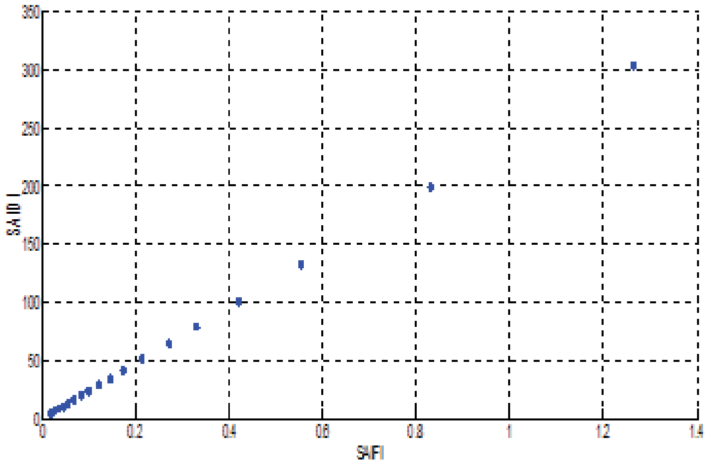
For a better illustration about the impact of automatic line switches in distribution system reliability, we present Figure 5-3, which shows us the influence on reliability indices due to different levels of switching automation investment.



(a)



(b)



(c)

Figure 5-3 (a) SAIFI vs TCOST (b) SAIDI vs TCOST (c) SAIFI vs SAIDI

If we pay close attention to Figure 5-3 (a) and (b), we will distinguish that both SAIFI and SAIDI decay at a certain rate depending the amount of automatic switches investment following the pattern of an exponentially decreasing function.

The following table presents the seven most expensive solutions for the above optimization problem in ascending order, from cheaper to more expensive. In addition, we will include the percentage of improvement on reliability indices due to a certain incremental degree in TCOST from one alternative to another.

No. of Auto Sect. Sw.	SAIFI (int./cust. −yr.)	SAIDI (min./cust. −yr.)	TCOST (US$ − yr.)	Reliability Improvement		Inv. Cost
				SAIFI [%]	SAIDI[%]	TCOST[%]
11	0.082	19.770	7256.760			
12	0.067	16.124	7861.490	18.443	18.442	7.692
13	0.054	13.045	8466.220	19.096	19.096	7.143
14	0.044	10.614	9070.950	18.633	18.634	6.667
15	0.034	8.183	9675.680	22.901	22.901	6.250
16	0.026	6.239	10280.400	23.762	23.762	5.882
17	0.018	4.294	10885.100	30.756	31.172	5.555

Table 5-3: Impact of Automatic Line Switches in Distribution Networks

In the above table we can see that that the solution alternatives in each incremental step represent the inclusion of one sectionalizer switch to the string combination, which is perceived in the diminution of SAIFI and SAIDI, both at about the same rate. We can also realize that this diminution of the reliability indices is greater than the required increment for TCOST.

It is important to mention two significant aspects from the above analysis:

1) The addition of automatic sectionalizing switches in the distribution feeder produces the same degree of beneficial impact for SAIFI and SAIDI. This is justified by Figure 5-3 (c), where we can distinguish the linear relationship between the two reliability indices.
2) Traditionally it has been considered that switching devices have no impact whatsoever on SAIFI. Nevertheless, that is only true when the sectionalizing switch is operated manually. According to the results obtained from Figure 5-3 (a) and Table 5-3, we can

say that automatic sectionalizing switches do have a beneficial effect on distribution system reliability (SAIFI and SAIDI) due to the fact that they contribute to have less customers affected by sustained interruptions.

If we go back to Figure 5-2, specifically to the lowest point (cheapest solutions) of the curve, there is an important characteristic of the gaps between the three cheapest solutions worth mentioning. From cheapest to more expensive, those solutions include 0, 1 and 2 automatic sectionalizing switches in their configuration. The gaps between the solutions represent the reliability improvement that each solution can provide to the system. Therefore, we can conclude that the first sectionalizing switches installed in a distribution feeder provide the biggest cost-benefit ratio. However, we can also mention that those alternatives may not meet the specifications required by a distribution utility.

For modern distribution utilities, decisions are not only driven from the economical perspective. There is a growing interest in the power distribution field to have a preference for reaching the best possible power service to customers rather than satisfy cost constraints. In the case of Taipower Company, for instance, a SAIDI of 21 min/cust.-yr. has been set for their current distribution system.

Therefore, with the purpose of satisfying this requirement, a new constraint has been added to the propose algorithm, where $SAIDI \leq 21$, and we run the simulation again to provide a solution according to Taipower Company standards. This time we include the proposed Max-Min approach for the decision making of a final solution as shown in Figure 5-4. The switch combination for the Max-Min solution is represented graphically in Figure 5-1.

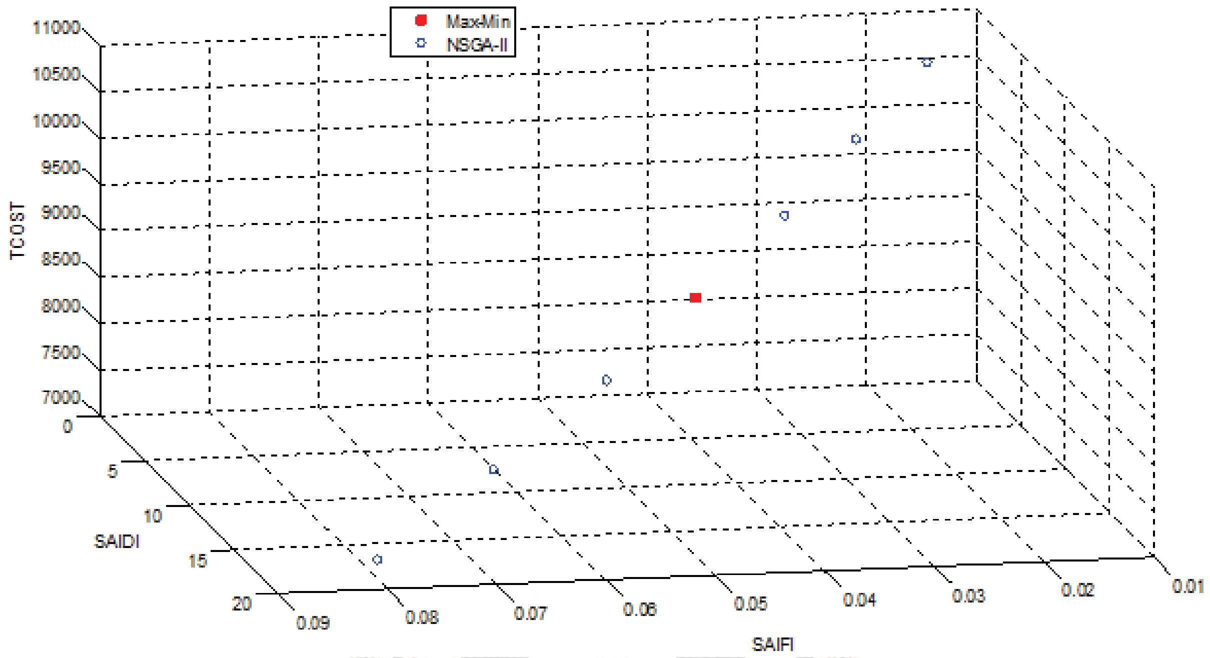


Figure 5-4 Scatter of the Constrained Pareto-optimal Solutions with Max-Min

In Figure 5-4 it is found that the Max-Min approach provides the following values for the reliability indexes: $\mathrm{SAIFI} = 0.044\ \mathrm{int./cust.-yr.}$, $\mathrm{SAIDI} = 10.614\ \mathrm{min./cust.-yr.}$, and $\mathrm{TCOST} = \mathrm{US\$9070.95 - yr.}$; which represents equal minimization benefits for the three objectives. This proposed solution satisfies by far the required minimum value for SAIDI, with a reduction of about 50% from the original constraint.

However, if the decision-maker is to choose a solution that optimizes TCOST, a more conservative solution is the one allocated at the bottom of the curve, whose reliability indices values are: $\mathrm{SAIFI} = 0.08\ \mathrm{int./cust.-yr.}$, and $\mathrm{SAIDI} = 19.283\ \mathrm{min./cust.-yr.}$; which is also optimal given that belongs to the Pareto set and also satisfies the problem requirements, while being 20% cheaper than the former proposed solution.

5.2. Case 2: Actual Distribution System of Taipower Company

In order to demonstrate the effectiveness of the proposed methodology to solve the optimal placement of line switches, an actual distribution system has been considered for simulation. The system is part of Taipower Company and it is located in the Fengshan area.

There are 11 feeders, 92 sections, 90 load points and a total of 85 possible switch locations for the proposed case study. The original system has 34 sectionalizing switches and 6 tie-point switches, all of which are manually operated. We present its original line diagram in Appendix 6.

Due to the difficulty of gathering real data for the characteristics of the system, in this analysis we assume some of the information based on adequate values that are typical in the Taiwanese distribution system. The mentioned data has to do with the number of customers in each load point, section lengths, and capacity of power transformers.

For this case study the settings for the proposed NSGA-II remain the same, but we modify the population size and number of generations to 100 and 500, respectively, which results in a total of 50,000 computational evaluations.

After solving the optimal switch placement using the proposed version of NSGA-II to obtain the optimal solutions that minimize the reliability indices of the distribution system, we present in Figure 5-5 the scatter of the non-dominated solutions for the switch placement optimization problem along with the final solution obtained by the Max-Min algorithm. For reader reference, we also attach the computational algorithm implemented for the Max-Min approach in Appendix 7.

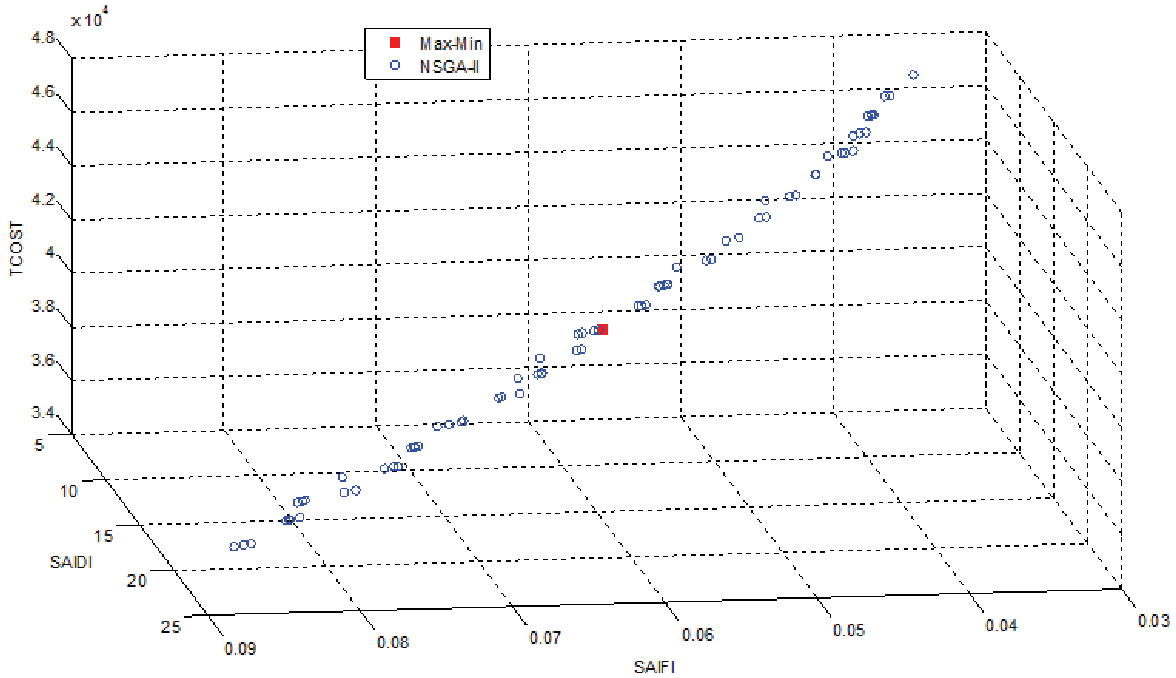


Figure 5-5 Pareto-optimal Solutions & Max-Min solution for Case 2

In Figure 5-5, we can see how the proposed NSGA-II is able to find optimal solutions uniformly distributed along the Pareto-front. The decision-maker can choose a specific combination of switch number and locations using his/her previous knowledge about the problem or a given economical investment a utility is willing to use in the automation project.

It has been found that 67 automatic lines switches were included in the new configuration resulting from the NSGA-II + Max-Min approach. From the total number of line switches, 61 are automatic sectionalizer switches and 6 are automatic tie-point switches. The Taipower distribution system diagram as proposed by the final solution obtained by the Max-Min algorithm is presented in Figure 5-6.

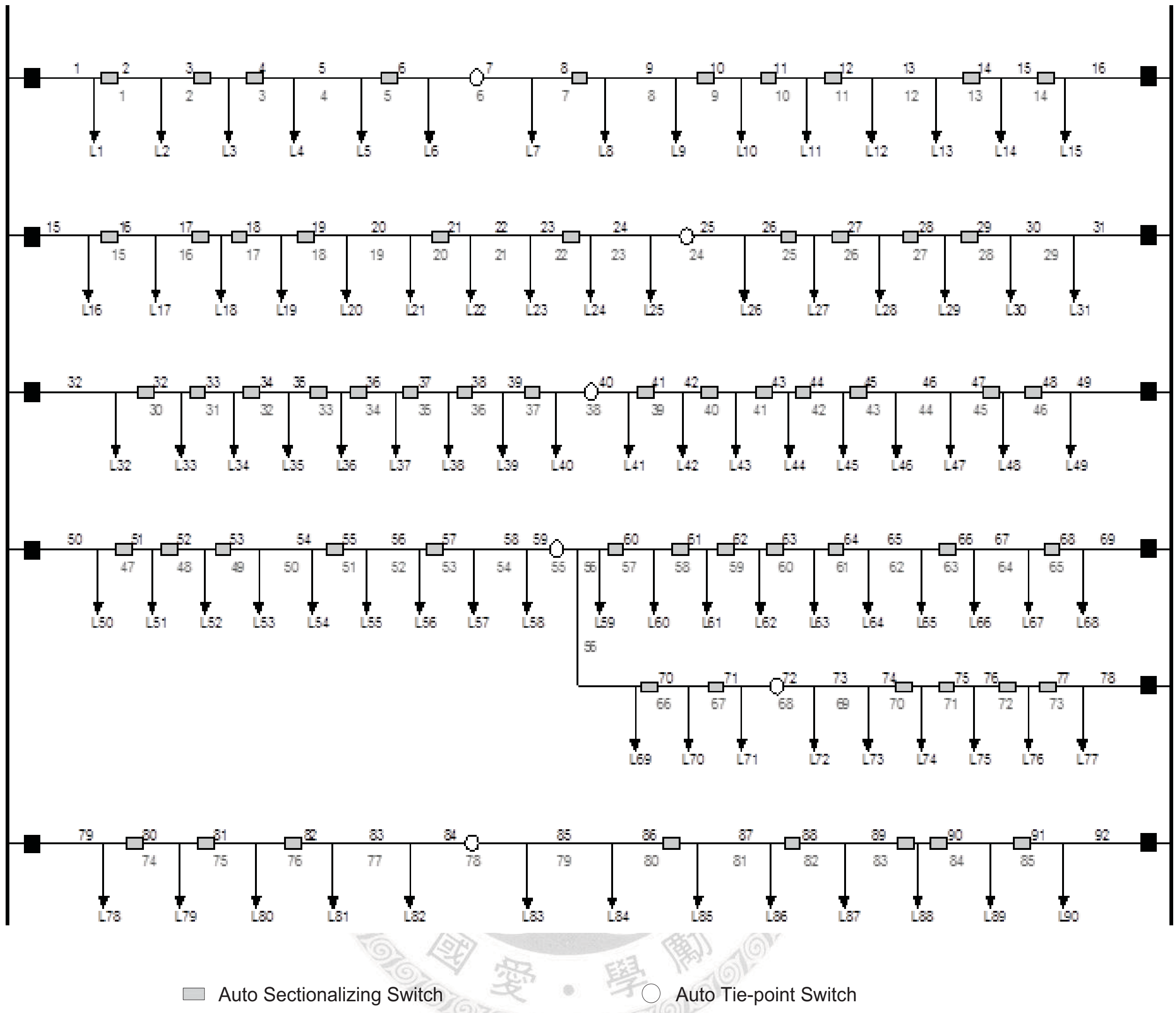


Figure 5-6 Optimal Placement of Line Switches using Max-Min approach

For comparison purposes we consider the study performed by (Chen, et al., 2006), which works in the same distribution system, however, it only contemplates partial automation of the networks by inclusion of some automatic switches, while reallocating already existing manual switches.

In this study, a Max-Min approach has been used to propose a final solution, for which the three objective functions experience equal minimization benefit at the same time. The obtained solution represents an improvement of 62% in SAIFI and 32% in SAIDI, when compared to the previous study. Consequently, SAIFI has been reduced from 0.157 to 0.059 $\mathrm{int./cust.-yr.}$, and SAIDI from 20.872 to 14.212 $\mathrm{min./cust.-yr.}$ Nevertheless, as one may expect, with the significant improvements that have been reached through the application of the present methodology, it comes higher economical costs. An investment 2.8 times higher than the later study is required for gaining the above mentioned reliability benefit.

In Table 5-4 we present a comparison of the reliability indexes in the original system, after the partial automation study and finally our proposed study for the optimal placement of automatic line switches.

	Original System manual switching	**Previous Study partial automation**	**Our proposed solution fully automated**
SAIFI $(\mathbf{int./cust.-yr.})$	0.231	0.157	0.059
SAIDI $(\mathbf{min./cust.-yr.})$	32.233	20.872	14.212
TCOST $(\mathbf{US\$ - yr.})$	---	14326	40516.9

Table 5-4 Results of the Proposed Study

Despite the higher TCOST, the economic justification for the proposed solution can be quantified by the benefits that automatic line switches contribute to the performance of the distribution system in terms of reduced outage duration and reduced number of customers affected by permanent faults.

We could also consider cheaper solutions located closer to the bottom of the Pareto-optimal front in Figure 5-5. However, the difference in TCOST between cheaper optimal solutions and the one obtained by Max-Min algorithm does not excuse the poorer improvement in reliability indices obtained by the former ones. For instance, for the cheapest solution: $\text{SAIFI} = 0.086\ \text{int.}/\text{cust.} - \text{yr.}$, $\text{SAIDI} = 20.724\ \text{min.}/\text{cust.} - \text{yr.}$, while only being 13% cheaper than the Max-Min solution.

The above reasons drive our criteria to support the Max-Min solution given it not only excels in providing a remarkable reduction in the current reliability indices, furthermore, the reliability values obtained by its possible implementation can be still useful in the future since Taipower Company has now set a new goal of $15.5\ \text{min.}/\text{cust.} - \text{yr.}$ for SAIDI by the year 2030 (Runte, 2012).

5.3. Results Discussion

The results obtained by the simulation of the two case studies have shown the effectiveness of the proposed integer version of NSGA-II to solve the multi-objective optimal placement of automatic line switches in distribution networks.

Each feasible solution for the optimization problem represents different combination of number and locations of automatic switches. Hence, the proposed methodology provides a set of Pareto-optimal solutions, which constitute the best trade-offs between system reliability and utility investment.

The decision-maker can select a final solution from the Pareto-set by considering the different objective function trade-offs according to his/her professional experience. However, a selection approach has also been presented in this study in order to choose the final solution based on Max-Min method.

The first simulation procedure was conducted in a one-line distribution network. The results obtained contributed to illustrate the beneficial impact of automatic line switches in distribution networks.

In Case 2, an actual distribution system was considered for simulation with notable results. A significant improvement of SAIFI and SAIDI was reached, a reduction of 62% and 32%, respectively, when considering a previous study. Nevertheless, the reliability benefit was reflected in a higher investment cost for the utility due to the fact that a larger number of line switches were required for installation in the distribution system. But, since the reliability values obtained by the proposed solution were able to satisfy future utility standards, it can indicate where the resources should be invested by the utility with concern to switching automation.

Chapter 6: Conclusions

This research study provides a methodology to solve the multi-objective optimal placement of automatic line switches in distribution networks. SAIFI, SAIDI, and TCOST represent the three objective functions to be minimized simultaneously. Furthermore, each feasible solution for the optimization problem is represented by a different combination of number and locations of automatic switches.

In this study, the distribution network is modeled using set operation theory in order to determine the presence of any switching device between the faulted section and the customers upstream or downstream. This technique helps us calculate easily the reliability indices SAIFI and SAIDI for a certain combination of switch locations.

We proposed an integer version of NSGA-II to solve the multi-objective optimization problem by sorting a population of feasible solutions in order to identify the set of Pareto-optimal solutions, which constitute the best trade-offs between system reliability and utility investment.

The person in charge of the network design-planning can select a final solution from the Pareto-set by considering the different objective function trade-offs according to his/her professional experience. However, a selection approach has also been presented in this study in order to choose the final solution based on Max-Min method.

The proposed version of NSGA-II was tested using two case studies, and the results have showed that this methodology guarantees a very good approximation to the true Pareto-front and diversity of the solutions is also ensured.

In Case 1, the beneficial impact of automatic line switches in distribution networks was illustrated through simulation in a one-line distribution network.

Case 2 considered the simulation of an actual distribution system with notable results for reliability indexes. Although, as expected, they involved higher investment cost for the utility.

In conclusion, the present methodology will indicate where the utility should invest resources for switching automation in order to improve the reliability of the system, proving this way its application as an important decision tool for distribution utilities.

This study is strongly related to sustained interruptions. It is suggested that a future research study includes an additional objective function that accounts for the effects of momentary interruptions in distribution networks. Another interesting objective function worth being evaluated is CIC (Customer Interruption Costs) given that it accounts for the economic losses of customers due to power outages.

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Appendix

Appendix 1: SF6 Gas Insulated Automatic Sectionalizing Switch for distribution systems Specifications datasheet

SF_6 Gas Insulated Automatic Sectionalizing Switch

This is installed in the branch point of below load capacity 8,000kVA of multiple earth neutral system 22.9kV-Y distribution system or in the service entrance of consumer. When over load or fault is occurred, minimizes the damage and prevent the fault expansion by breaking or opening exactly the fault section with the cooperation of protection device (CB, Recloser). Easy operation status monitoring is possible by built-in load current indicator and live line status distinction function. ASS is used for frequent lighting place, industrial line and has the following functions.

ETMFC50
Sectionalizing Control Relay

Main Function and Characteristic

1. Over-current Trip Function

This switch detects over-current and separates the fault section from the system during protection device is opening the line. Besides, detects over-current under the rated blocking current and cooperates with the protection device. OCR Trip, OCGR Trip function are provided.

2. Over-current Lock function and charge TRIP function

This switch inhibits the OCR Trip and OCGR Trip function if fault current is over 800A. As charge Trip function is operated when becomes no-voltage by the cooperation with the protection device, current over rated blocking current is not blocked.

3. Cold Load Pickup

Restrain the over-current Trip function and charge Trip function to prevent the malfunction by inrush current produced during the switch closing or when becomes live line by protection device closing in dead line status.
After the switch is opened, if the switch is closed before exceeding the 'Outage Time' setting time this function is not operated, if the switch is closed before finishing the 'Outage Time' this functions operates normally. When the switch is closing it becomes dead line by CB & REC and if becomes live line by reclosing of CB & REC before passing the 'Outage Time', this function does not work.

4. Line current and Live line indication

Each phase current (A,B,C,N) are displayed in LCD of control box and also Lamp that indicates the line status of source side(phase A) and Load side(phase R) is provided.

5. Easy function setting

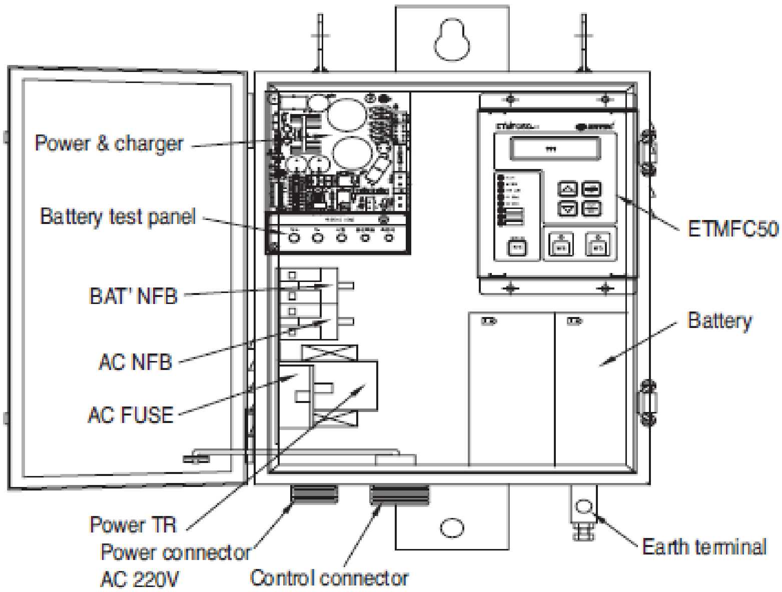
Min. pickup current, ovecurrent lock current and other all setting can be set in LCD menu of control box.

6. Battery discharge prevention

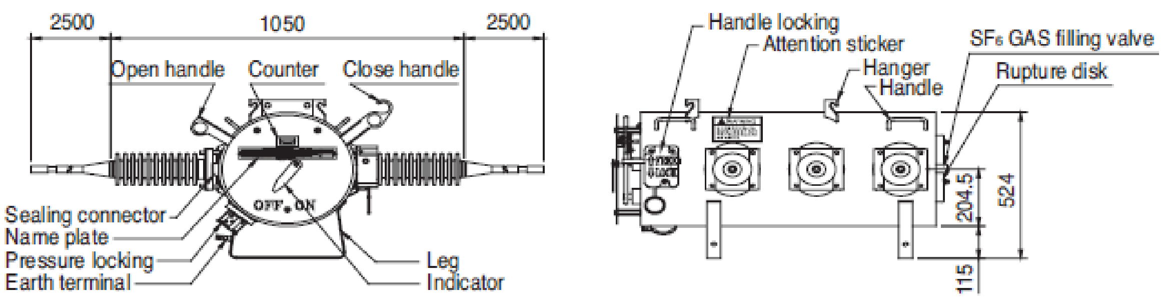
When AC power is lost, check the battery voltage. If the battery voltage is 20~21V, breaks automatically and prevents the damage by discharging. When AC power is applied returns to the normal operation.

Construction

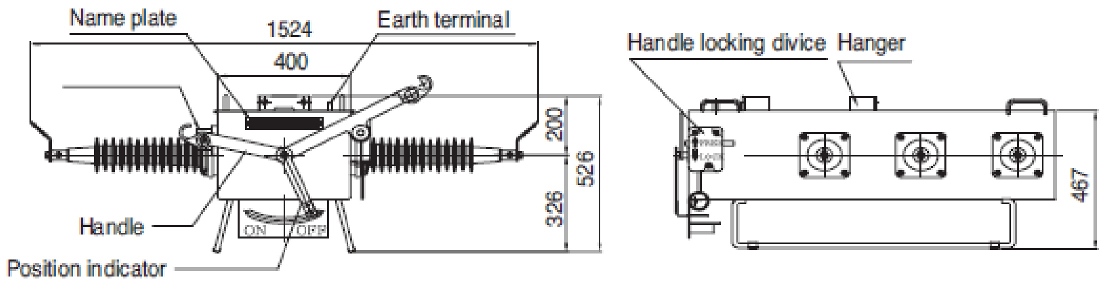
ETMFC50 Control Drawing



25.8kV SF6 Gas Automatic Sectionalizing Switch Drawing



36kV SF_6 Gas Automatic Sectionalizing Switch Drawing



Rating and Specification

ITEM		RATING	
Condition	Ambient Temperature	-25 °C ~ 40°C	
	Altitude	Up to 1,000M	
Rated voltage [kV]		25.8	36
Rated current [A]		400	630
Rated frequency [Hz]		50/60	
Rated short time current		12.5kA 1sec. / 10kA 1sec.	12.5kA 1sec
Rated making current (Asym)		32.5 kA(Peak) / 15kA(Peak)	32.5kA(Peak)
Rated breaking current		900 A	630A
Power frequency withstand voltage	dry	60 kV / 1min.	70 kV / 1min.
	wet	50 kV / 10 sec.	60 kV / 10 sec.
Impulse withstand voltage (1.2 × 50 ㎲)		150 kV	170kV
Over current LOCK current		800 A (±10%)	
Min. pickup current	Phase	OFF, 16 ~ 640 A(Block), 1A Step	
	Ground	OFF, 3.5 ~ 320 A(By Pass), 0.5A Step	
Cold Load Pickup		0.0 ~ 5.0 sec. (±10%), 0.1sec. Ste	
Load switching	900A	3 times	
	400A	200 times	
Insulation method		SF6 Gas	
Standard GAS pressure		0.17 MPa(gauge), 20°C	

Control power	Battery	DC 24 V (12V7.0AH*2EA) 50 times or 24 hours operation at the fully charged battery
	External Power	AC 220 V / 25 VA, Max.300 V
Control box internal ambient Test	Power frequency withstand voltage	2kV/1min
	Impulse withstand voltage	IEEE C62.45 Voltage Waveform:6kV,1.2/50㎲ Current Waveform:3kA,8/20㎲
	Surge withstand capability	ANSI/IEEE C37.90.1 EFT/BURST Test: 4 kV(2.5 Hz) Oscillatory SWC Test: 2.5 kV(1 MHz)
	Radiated electromagnetic interference withstand test	IEEE C37.90.2 35V/m

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Appendix 2: Fitness Evaluation for Solution 1 in Table 4-1

1. SAIFI

sections

$$\lambda_{is} = \begin{bmatrix} 0.0660 & 0.0660 & 0.0660 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.0660 & 0.0660 & 0.0660 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.0660 & 0.0660 & 0.0660 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.0660 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.0660 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0660 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0660 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0660 & 0.0660 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0660 & 0.0660 \end{bmatrix}$$

load points

$\lambda_s = 0.132 failure/years - km$

NumberofCustomers = [40 37 40 25 5 19 15 14 10 24 28]

InterruptedCustomers = 33.5940

TotalNumberofCustomers = 257

$$SAIFI = InterruptedCustomers/TotalNumberofCustomers$$

$$SAIFI = 0.13071\ int./cust.yr$$

2. SAIDI

$$\begin{array}{r}
\textit{sections} \\
\begin{bmatrix}
240 & 240 & 240 & 0.33 & 0.33 & 0.33 & 0.33 & 0 & 0 & 0 & 0 & 0 \\
240 & 240 & 240 & 0.33 & 0.33 & 0.33 & 0.33 & 0 & 0 & 0 & 0 & 0 \\
240 & 240 & 240 & 0.33 & 0.33 & 0.33 & 0.33 & 0 & 0 & 0 & 0 & 0 \\
5 & 5 & 5 & 5 & 240 & 0.33 & 0.33 & 0 & 0 & 0 & 0 & 0 \\
5 & 5 & 5 & 5 & 240 & 0.33 & 0.33 & 0 & 0 & 0 & 0 & 0 \\
5 & 5 & 5 & 5 & 5 & 5 & 0.33 & 0 & 0 & 0 & 0 & 0 \\
5 & 5 & 5 & 5 & 5 & 5 & 5 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 240 & 5 & 5 & 5 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 240 & 5 & 5 & 5 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.33 & 0.33 & 240 & 240 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.33 & 0.33 & 240 & 240
\end{bmatrix}
\end{array}$$

$\textit{load points}$

$r_{rs} = 240$ min

$r_{sw1} = 0.33$ min $upstream\ the\ failure$

$r_{sw2} = 5$ min $downstream\ the\ failure$

NumberofCustomers = [40 37 40 25 5 19 15 14 10 24 28]

InterruptionDuration = 8062.3

TotalNumberofCustomers = 257

$$SAIDI = InterrupionDuration/TotalNumberofCustomers$$

$$SAIFI = 31.371\ min/cust.yr$$

3. TCOST

$Num_D = 4$

$Num_{TP} = 1$

$C_D = C_{TP} = US\$9{,}071 - 15 years$

$$TCOST = Num_D \times C_D + Num_{TP} \times C_{TP}$$

$$TCOST = \text{US\$45355}$$

Appendix 3:

1. Crossover Operator Procedure

Parent 1:

0	0	1	0	1	1	2	0	1	0

Parent 2:

1	1	1	0	2	1	1	1	1	1

$crossoverFraction = 0.7$

$ratio = 1.5$

$$child\ 1 = parent\ 1 + rand \times ratio \times (parent\ 1 - parent\ 2)$$

$$child\ 2 = parent\ 2 - rand \times ratio \times (parent\ 2 - parent\ 1)$$

Child 1:

1	-0.0468	1	0	-0.2880	1	2.3763	1	1	-1.2423

Child 2:

1	0.1892	1	0	1.4979	1	2.0120	1	1	-0.2352

After rounding and setting lower and upper bounds:

Child 1:

0	0	1	0	0	1	2	0	1	0

Child 2:

1	0	1	0	1	1	2	1	1	0

2. Mutation Operator Procedure

Parent:

0	0	1	2	1	0	0	0	0	1

$mutationFraction = 0.4$

$scale = 0.5$

$shrink = 0$

$$child = parent + S \times randn \times (ub - lb)$$

Child:

0	1.3145	1	2	1.0872	0	0.9780	0	-0.5747	1

After rounding and setting lower and upper bounds:

Child:

0	1	1	2	1	0	1	0	0	1

Appendix 4: Load and Number of Customers of Load points for Case 1 (Chen, et al., 2006)

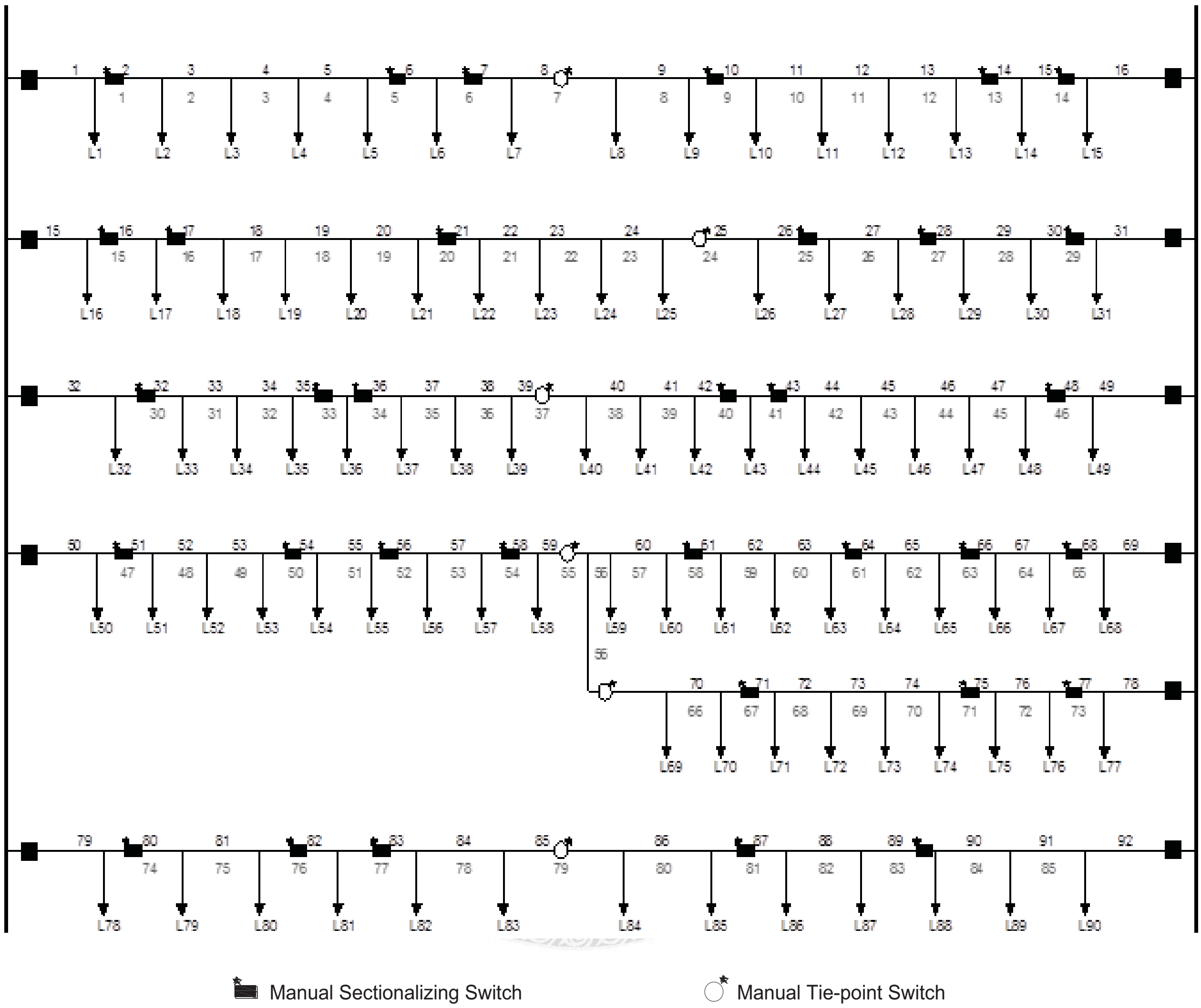
Load Points	Load (Kw)	Total Customers
L1	69	40
L2	233	37
L3	58	40
L4	113	25
L5	98	5
L6	269	19
L7	251	15
L8	331	14
L9	188	10
L10	1205	24
L11	210	28
L12	989	16
L13	43	22
L14	96	23
L15	129	19
L16	44	11
L17	76	20
L18	81	10
L19	112	13

Appendix 5: Pareto-optimal Solutions for Case 1

Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var8	Var9	Var10	Var11	Var12	Var13	Var14	Var15	Var16	Var17	Var18	Obj1	Obj2	Obj3
0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1.26531	303.674	604.73
1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	0.0178926	4.29422	10885.1
0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1.26531	303.674	604.73
1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	0.0178926	4.29422	10885.1
0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0.830824	199.398	1209.46
0	0	0	1	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0.551969	132.473	1814.19
0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0.830824	199.398	1209.46
0	1	0	0	0	1	0	0	0	2	0	0	0	1	0	0	0	0	0.419294	100.631	2418.92
0	0	0	1	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0.551969	132.473	1814.19
0	1	0	0	0	1	0	0	0	2	0	0	1	0	0	1	0	0	0.329831	79.1595	3023.65
0	1	0	0	0	1	0	0	0	2	0	0	0	1	0	0	0	0	0.419294	100.631	2418.92
0	1	0	1	0	1	0	0	0	2	0	0	1	0	0	1	0	0	0.269739	64.7374	3628.38
0	1	0	0	0	1	0	0	0	2	0	0	1	0	0	1	0	0	0.329831	79.1595	3023.65
0	1	0	1	0	1	0	0	0	2	0	0	1	0	0	1	0	0	0.269739	64.7374	3628.38
0	1	0	1	0	0	1	0	0	2	0	1	0	1	0	0	1	0	0.21201	50.8825	4233.11
0	1	0	1	0	0	1	0	0	2	0	1	0	1	0	0	1	0	0.21201	50.8825	4233.11
1	1	0	1	0	0	1	0	0	2	0	1	0	1	0	0	1	0	0.173524	41.6458	4837.84
1	1	0	1	0	1	0	1	0	2	0	1	0	1	0	0	1	0	0.144153	34.5968	5442.57
1	1	0	1	0	0	1	0	0	2	0	1	0	1	0	0	1	0	0.173524	41.6458	4837.84
1	1	0	1	0	1	0	1	0	2	0	1	0	1	0	1	0	1	0.119509	28.6821	6047.3
1	1	0	1	0	1	0	1	0	2	0	1	0	1	0	0	1	0	0.144153	34.5968	5442.57
1	1	0	1	0	1	0	1	0	2	0	1	0	1	0	1	0	1	0.119509	28.6821	6047.3
1	1	1	1	0	1	0	1	0	2	0	1	0	1	0	1	0	1	0.0975652	23.4157	6652.03
1	1	1	1	0	1	1	0	2	1	1	0	1	1	0	1	0	1	0.0671816	16.1236	7861.49
1	1	1	1	0	1	0	1	0	2	0	1	0	1	0	1	0	1	0.0975652	23.4157	6652.03
1	1	1	1	0	1	0	1	0	2	0	1	1	1	0	1	0	1	0.0823734	19.7696	7256.76
1	1	1	1	0	1	0	1	0	2	0	1	1	1	0	1	0	1	0.0823734	19.7696	7256.76
1	1	1	1	0	1	1	0	2	1	1	1	1	1	0	1	0	1	0.0543529	13.0447	8466.22

1	1	1	1	0	1	1	0	2	1	1	0	1	1	0	1	0	1	0.0671816	16.1236	7861.49
1	1	1	1	0	1	1	0	2	1	1	1	1	1	0	1	0	1	0.0543529	13.0447	8466.22
1	1	1	1	0	1	1	0	1	1	2	1	1	1	1	1	0	1	0.0442251	10.614	9070.95
1	1	1	1	0	1	1	0	1	1	2	1	1	1	1	1	1	1	0.0340972	8.18332	9675.68
1	1	1	1	0	1	1	0	1	1	2	1	1	1	1	1	0	1	0.0442251	10.614	9070.95
1	1	1	1	1	1	1	0	1	2	1	1	1	1	1	1	1	1	0.0259949	6.23877	10280.4
1	1	1	1	1	1	1	0	1	2	1	1	1	1	1	1	1	1	0.0259949	6.23877	10280.4
1	1	1	1	0	1	1	0	1	2	1	1	1	1	1	1	1	1	0.0340972	8.18332	9675.68
0	0	0	1	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0.551969	132.473	1814.19
0	1	0	0	0	1	0	0	0	2	0	0	1	0	0	1	0	0	0.329831	79.1595	3023.65
0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0.830824	199.398	1209.46
0	1	0	1	0	1	0	0	0	2	0	0	1	0	0	1	0	0	0.269739	64.7374	3628.38
0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0.830824	199.398	1209.46
1	1	0	1	0	1	0	1	0	2	0	1	0	1	0	1	0	1	0.119509	28.6821	6047.3
1	1	0	1	0	1	0	1	0	2	0	1	0	1	0	1	0	1	0.119509	28.6821	6047.3
0	0	0	1	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0.551969	132.473	1814.19
0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0.830824	199.398	1209.46
0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0.830824	199.398	1209.46
0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0.830824	199.398	1209.46
0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0.830824	199.398	1209.46
0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1.26531	303.674	604.73
1	1	0	1	0	1	0	1	0	2	0	1	0	1	0	1	0	1	0.119509	28.6821	6047.3

Appendix 5: Original Diagram for Taipower System in Case 2 (Chen, et al., 2006)



Appendix 5: Max-Min Algorithm – Matlab Implementation

```
function MaxMin = DecisionMaking (data)

%Function that returns the final solution from the set of non-dominated
%solutions

data1=unique(data,'rows');  %non-repeated values
[r c]=size (data1);
f1max = max(data1(:,1));
f2max = max(data1(:,2));
f3max = max(data1(:,3));
f1min = min (data1(:,1));
f2min = min (data1(:,2));
f3min = min (data1(:,3));
A=f1max-f1min;
B=f2max-f2min;
C=f3max-f3min;


normalz=zeros(r,3);   %Normalized-values matrix initialization

for i=1:c
    for j=1:r
        if i==1
            normalz(j,i)=(f1max-data1(j,i))/(A);
        elseif i==2
            normalz(j,i)=(f2max-data1(j,i))/(B);
        else
            normalz(j,i)=(f3max-data1(j,i))/(C);
        end
    end
end
Part1=zeros(r,1);
for i=1:r
    Part1(i,1)=min(normalz(i,:));

end
AUX=max(Part1(:,1));
for i=1:r
    if Part1(i,1)==AUX
        count=i;
    end
end

MaxMin=data1(count,:);
end
```