รายงานวิจัยฉบับสมบูรณ์

โครงการ การประยุกต์ใช้ดิฟฟีเรลเชียลอัลกอริทึมที่ได้รับการ
ปรับปรุงแล้วในการวางแผนการขยายสายส่งโดยพิจารณาข้อจำกัด
ด้านความปลอดภัยและการสูญเสียของระบบ

โดย ดร.ธนาธิป สุ่มอิ่ม

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สัญญาเลขที่5480091

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สนับสนุนโดยสำนักงานกองทุนสนับสนุนการวิจัย

(ความเห็นในรายงานนี้เป็นของผู้วิจัย
สกว. ไม่จำเป็นต้องเห็นด้วยเสมอไป)

Abstract (บทคัดย่อ)

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Project Title: An enhanced differential evolution algorithm application to transmission expansion planning with security constraint and system losses considerations

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ABSTRACT

In the present situation, modern electric power systems comprise large-scale and highly complex interconnected transmission networks, thus transmission expansion planning (TEP) is now an important power system optimization problem. Regarding the modern TEP problem is a complex and mixed integer nonlinear problem where a number of candidate solutions to be evaluated increases exponentially with system size. An accurate solution of the TEP problem is very significant in order to plan electric power systems in both an economic and efficient manner. Therefore, the applied optimization techniques should be sufficiently efficient when solving such problem. Over several past decades, a large number of computational techniques were presented for solving this efficiency issue. Such methods include algorithms inspired by observations of natural phenomena for solving complex combinatorial optimization problems. These algorithms are successfully applied to a wide variety of electrical power system optimization problems.

In recent years, a differential evolution algorithm (DEA) methodology has been attracting significant attention from many researchers as such the procedure has been found to be effective in solving power system optimization problems, for instance, economic power dispatch, unit commitment, optimal power flow, including TEP problem as presented in the author's Ph.D. thesis. Although a novel DEA method proposed in the author's Ph.D. thesis

was successfully applied many cases of the TEP problem, it was not yet sufficiently robust for practical use for industry. Such DEA method has the notable limitation of DEA control parameter tuning due to a complex interaction of parameters. Therefore, a further improvement of the conventional DEA method is essentially required before it can be generally adopted for practical use in industry.

The main goal of this research is to improve the conventional DEA method as proposed in the previous author's works. An enhanced DEA technique has been directly applied to a DC power flow based model in order to solve the TEP problem with *n*-1 security constraint and system losses considerations. The *n*-1 security criterion is an essential index in power system reliability study as it states that the system should be expanded in such a way that, if a single line or generator is withdrawn, the expanded system should still operate adequately. Moreover, the TEP with system losses consideration is a significant issue that should be included in the TEP problem for enhancing the solution accuracy in practical operation. Therefore, the proposed TEP problem has been investigated in both *n*-1 security criterion and system losses considerations in this research. The analyses of an enhanced DEA optimization procedure have been performed within a mathematical programming environment of MATLAB and detailed comparisons between the proposed method and other algorithms are also presented in this final report.

Keywords: Transmission Expansion Planning, Differential Evolution Algorithm, Security Constraint, Transmission Losses, Power System Optimization

บทคัดย่อ

ในสภาวะการณ์ปัจจุบัน ระบบไฟฟ้ากำลังสมัยใหม่มักจะประกอบไปด้วยโครงข่ายสายส่งไฟฟ้าที่มีขนาดใหญ่และมีความซับซ้อนมาก ดังนั้นในการวางแผนการขยายสายส่งไฟฟ้าจึงเป็นหัวข้อที่สำคัญมากในเรื่องปัญหาของการหาค่าความเหมาะสมที่สุดในระบบไฟฟ้ากำลัง เนื่องด้วยปัญหาการวางแผนการขยายสายส่งไฟฟ้ามีลักษณะของปัญหาที่ซับซ้อนและไม่เป็นเชิงเส้น ซึ่งจำนวนของคำตอบที่เป็นไปได้จะเพิ่มขึ้นทวีคูณเป็นเลขยกกำลังแบบเอ็กโพเนนเชียลตามขนาดของระบบไฟฟ้า และคำตอบที่เหมาะสมที่สุดสำหรับปัญหาการวางแผนการขยายสายส่งนี้จึงเป็นสิ่งที่สำคัญมากสำหรับการทำแผนงานของระบบไฟฟ้าทั้งในด้านของเศรษฐศาสตร์และเรื่องประสิทธิภาพในการทำงานของระบบ ดังนั้นเทคนิคการหาค่าเหมาะสมที่สุดควรมีความสามารถและประสิทธิภาพเพียงพอสำหรับการแก้ปัญหาดังกล่าว ในหลายทศวรรษที่ผ่านมาเทคนิคการคำนวณจำนวนมากได้ถูกนำเสนอเพื่อแก้ปัญหานี้ โดยที่เทคนิคต่างๆ เหล่านี้ได้รวมถึงอัลกอรึทึมที่ได้มาจากการสังเกตปรากฏการณ์ทางธรรมชาติสำหรับใช้แก้ปัญหาการหาค่าเหมาะสมที่สุดเชิงการจัดของเชิงซ้อน และจากการศึกษาพบว่าอัลกอรึทึมดังกล่าวประสบความสำเร็จในการประยุกต์เพื่อใช้แก้ปัญหาการหาค่าเหมาะสมที่สุดของระบบไฟฟ้ากำลังได้เป็นอย่างดี

ในช่วงระยะเวลาไม่กี่ปีที่ผ่านมานี้ ทฤษฎีดิฟฟีเรนเชียลอีโวลูชั่นอัลกอรึทึมได้รับความสนใจเพิ่มขึ้นจากนักวิจัยเป็นจำนวนมากอันเนื่องจากพบว่า กระบวนการทำงานของอัลกอรึทึมนั้นสามารถค้นหาคำตอบได้อย่างมีประสิทธิผลที่ดีมากสำหรับการแก้ปัญหาการหาค่าความเหมาะสมที่สุดในระบบไฟฟ้ากำลัง ตัวอย่างปัญหาเช่น การวางแผนจัดสรรสำหรับการจ่ายโหลดของโรงไฟฟ้าอย่างประหยัด การทำยูนิตคอมมิตเม้นของโรงไฟฟ้า การคำนวณการไหลของกำลังไฟฟ้าที่ให้ค่าเหมาะสมที่สุด รวมถึงการวางแผนการขยายสายส่งไฟฟ้าซึ่งได้ปรากฏอยู่ในวิทยานิพนธ์ระดับปริญญาเอกของผู้แต่ง ถึงแม้ว่าทฤษฎีดิฟฟีเรนเชียลอีโวลูชั่นอัลกอรึทึมแบบใหม่นี้จะประสบความสำเร็จในการแก้ปัญหาการวางแผนการขยายสายส่งไฟฟ้าสำหรับหลายๆ กรณีศึกษาแล้วนั้น แต่ด้วยคุณสมบัติของอัลกอรึทึมที่นำเสนอยังไม่แข็งแรงเพียงพอสำหรับการประยุกต์ใช้ในทางปฏิบัติกับอุตสาหกรรม เนื่องด้วยวิธีการดิฟฟีเรนเชียลอีโวลูชั่นอัลกอรึทึมยังมีข้อจำกัดในเรื่องการปรับค่าของตัวพารามิเตอร์ควบคุมซึ่งมีความสัมพันธ์กันที่ค่อนข้างซับซ้อนและยุ่งยาก ดังนั้นการปรับปรุงคุณสมบัติของอัลกอรึทึมจึงเป็นสิ่งที่มีความจำเป็นอย่างมากก่อนที่จะนำไปใช้งานจริงในภาคอุตสาหกรรม

เป้าหมายหลักของงานวิจัยชิ้นนี้คือ การปรับปรุงคุณสมบัติการทำงานของดิฟฟีเรนเชียลอีโวลูชั่นอัลกอรึทึมแบบดั้งเดิมดังแสดงในงานวิจัยของผู้แต่งก่อนหน้านี้ สำหรับเทคนิคดิฟฟีเรนเชียลอีโวลูชั่นอัลกอรึทึมที่ได้รับการปรับปรุงแล้วจะถูกนำไปประยุกต์ใช้ในการวางแผนการขยายสายส่งโดยพิจารณาข้อจำกัดด้านความปลอดภัยแบบ n-1 และการสูญเสียของระบบโดยใช้รูปแบบจำลองการไหลของกำลังไฟฟ้ากระแสตรง การพิจารณาความปลอดภัยแบบ n-1 นั้นเป็นดัชนีที่สำคัญในการศึกษาถึงความเชื่อถือได้ของระบบไฟฟ้ากำลังในกรณีที่สายส่งหรือเครื่องกำเนิดไฟฟ้าหายไปจากระบบจำนวน 1 หน่วยแล้วระบบไฟฟ้านั้นยังคงสามารถทำงานอยู่ได้ ทั้งนี้รวมถึงแผนการขยายสายส่งไฟฟ้าควรมีการพิจารณาถึงความปลอดภัยของระบบในหัวข้อนี้ด้วย ยิ่งไปกว่านั้นการพิจาณาการ

สูญเสียในสายส่งควรได้รับการพิจารณาและนำมาใช้ศึกษาสำหรับการวางแผนการขยายสายส่งอีกด้วยเพื่อให้คำตอบที่ได้รับมามีค่าที่ใกล้เคียงในทางปฏิบัติมากขึ้น ในโครงการวิจัยนี้การศึกษาและวิเคราะห์กระบวนการทำงานของวิธีดิฟฟีเรนเชียลอีโวลูชั่นอัลกอรึทึมที่ได้รับการปรับปรุงแล้ว จะดำเนินการโดยใช้โปรแกรม MATLAB และการเปรียบเทียบผลการทดสอบระหว่างทฤษฎีที่นำเสนอกับวิธีอัลกอรึทึมอื่นๆ จะถูกแสดงในรายงานวิจัยฉบับสมบูรณ์นี้

คำสำคัญ การวางแผนการขยายสายส่งไฟฟ้า ดิฟฟีเรนเชียลอีโวลูชั่นอัลกอรึทึม ข้อจำกัดด้านความปลอดภัย การสูญเสียในสายส่งไฟฟ้า การหาค่าเหมาะสมที่สุดในระบบไฟฟ้ากำลัง

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EXECUTIVE SUMMARY

1. Introduction

Transmission expansion planning (TEP) has always been a rather complicated task especially for large-scale real-world transmission systems. First of all, electricity demand changes across both area and time. The change in demand is met by the appropriate dispatching of generation resources. As an electric power system must obey physical laws, the effect of any change in one part of network (e.g. changing the load at a node, raising the output of a generator, switching on/off a transmission line or a transformer) will spread instantaneously to other parts of the interconnected network, hence altering the loading conditions on all transmission lines. The ensuing consequences may be more marked on some transmission lines than others, depending on electrical characteristics of the lines and interconnection.

The TEP problem involves determining the least investment cost of power system expansion and technical operating through the timely addition of electric transmission facilities in order to guarantee that the constraints of the transmission system are satisfied over the defined planning horizon. Transmission system planners are entrusted with ensuring the above-stated goals are best met whilst utilizing all available resources. Therefore, a purpose of transmission planning is to determine the timing and type of new transmission facilities. The facilities are required in order to provide adequate transmission capacity to cope with future additional generation and power flow requirements. Transmission plans may require introduction of higher voltage levels, installation of new transmission elements, and new substations. Transmission network planners tend to use many techniques to solve such problem. The planners utilize automatic expansion models to determine an optimum expansion network by minimizing the mathematical objective function subject to a number of constraints.

In recent years, a differential evolution algorithm (DEA) method has been attracting increasing attention for a wide variety of engineering applications including electrical power system engineering. There have been many researches that applied DEA for solving electrical power system problems such as power system transfer capability assessment [5], power system planning [6], economic power dispatch [7-9], distribution network reconfiguration problem [10], short-term hydrothermal scheduling problem [11], optimal reactive power flow [12-13], and optimal power flow [14]. Moreover, the conventional DEA method has been successfully solved static and dynamic transmission expansion planning problems by the author in [15] where the DEA method performed superior to conventional genetic algorithm (CGA) in terms of simple implementation with high quality of solution and good computation performance. Meanwhile, DEA requires less control parameters while being independent from initialization. In addition, its convergence is stable as DEA procedure uses rather greedy selection and less stochastic approach to solve optimization problems than other CGA. Unfortunately, there remains a drawback of DEA procedure that is a tedious task of the DEA control parameters tuning due to complex relationship among problem's parameters. The optimal parameter settings of the DEA method may not be found and the final results may be trapped in a local minimum.

It is important to note that few algorithms have been practically applied to solve the TEP problem at present [1]. Although the method proposed in [15] by the author was successfully solved many cases of TEP problem, it was not yet sufficiently robust for practical use for industry. The conventional DEA method proposed in [15] has the notable limitation of DEA control parameter tuning due to a complex interaction of parameters as above mentioned. Therefore, a further improvement of the novel DEA method is essentially required before it can be generally adopted for practical use in industry.

The TEP problem as studied in [15] is called a basic planning, in which the security criterion has not been considered. In other words, the optimal expansion plan is determined without considering the *n*-1 contingencies caused by a transmission line or generator outage. The *n*-1 security criterion is an important index in power system reliability study as it states that the system should be expanded in such a way that, if a single line or generator is withdrawn, the expanded system should still operate adequately. Moreover, the TEP with system loss consideration is a significant issue that should be included in the planning problem for enhancing the result accuracy. Therefore, the proposed TEP problem has been investigated in both *n*-1 security criterion and system losses considerations in this research project.

2. Objectives of Research Project

The ultimate goal of undertaken research is to take advantage of computational simulations more effectively in an overall planning study and consequently determine an appropriate transmission network expansion plan. The main objectives of this project are:

- To enhance a conventional DEA method for solving a wide variety of mathematical and real-world optimization problems;

- To apply the proposed technique, self-adaptive DEA method, for solving power system optimization problems especially the TEP problem with security constraint and system losses considerations;
- To use the obtained results of planning study in order to design future transmission network and test its performance;
- To employ the novel knowledge from this research for application to the author's teaching on a course of electric power system analysis and a course of electric power system operation & design.

3. Contributions of Research Work

The major contributions of this research are development of a conventional DEA method and investigation of the applicability of an enhanced DEA technique when applied to TEP problem with security constraint and system losses considerations. In addition, a detailed comparison of the enhanced DEA method and the conventional DEA procedure used for solving the TEP problem is presented. The most significant original contributions presented and investigated in this report are outlined as follows:

- Firstly, a novel methodology is proposed in this research where the conventional DEA procedure is further improved its performance by reducing a tedious task of control parameters tuning. In order to validate its searching capability and reliability, the proposed methodology has been tested with some selected mathematical benchmark test functions before applied to real-world optimization problems.
- Regarding the effectiveness of an enhanced DEA method as tested on several numerical benchmark test functions, the proposed technique is implemented to solve a real-world optimization problem, which is the TEP problem with losses consideration. For this planning study, two test networks, Garver's 6-bus system and IEEE 25-bus system, have been investigated and presented in this report.
- Finally, the research utilizes the proposed effective technique to deal with the TEP problem with *n*-1 security criterion consideration, which is more complex and difficult when compared to the basic TEP problem as shown in [15]. In this work, the TEP problem considering *n*-1 contingency constraint has been analyzed and it is an especially difficult task with regard to large-scale real-world transmission system. The enhanced DEA method as applied to solve the TEP problem with *n*-1 contingency criterion consideration is tested on three transmission systems that are the Garver's 6-bus system, IEEE 25-bus system, and Colombian 46-bus system.

4. Outputs of the Research Project

Arising from the research project, two conference papers were presented and published in conference proceedings. In addition, a journal paper has been submitted to a selected international journal. These proposed articles are listed as follows:

4.1 Refereed Journal Paper: Submitted

- T. Sum-Im and W. Ongsakul, "An enhanced differential evolution algorithm application to transmission network expansion planning with security constraint consideration," *IET Proc. Gener. Transm. Distrib.*, (Submitted 2013).

4.2 Refereed International Conference Paper: Published

- T. Sum-Im and W. Ongsakul, "A self-adaptive differential evolution algorithm for transmission network expansion planning with system losses consideration," *Proc. 2012 IEEE International Conference on Power and Energy* (*PECON 2012*), Kota Kinabalu, Malaysia, pp. 153-158, 2^{nd}-5^{th} Dec. 2012.

4.3 Refereed National Conference Paper: Published

- Thanathip Sum-Im, "An enhanced differential evolution algorithm for transmission expansion planning with system losses consideration," *Proc. 9^{th} Naresuan and Tao-Ngam Research Conferences*, Phitsanulok, Thailand, pp. 3, 28^{th}-29^{th} Jul. 2013.

5. An Enhanced Differential Evolution Algorithm Method

Regarding a difficult task of the DEA control parameters tuning due to complex relationship among problem's parameters has been a drawback of the conventional DEA method. Therefore, a further improvement of the conventional DEA method is essentially required before it can be generally adopted for practical use in industry. In this research, the conventional DEA method has been developed its optimization procedure. A self-adaptive DEA (SaDEA) technique is proposed and explained in this report. The design of SaDEA optimization procedure is to develop two DEA control parameters, mutation factor (F) and crossover probability (CR), which are self-tuning parameters using probability methodology. This enhanced method is called "Method 2jDE" as found in [34].

As such proposed method, user must define two constant values (T_1 and T_2) that are the indices of control parameters (F and CR) changing respectively. The user-defined values T_1 and T_2 are usually selected from within the range [0,1] and set as 0.1 in this research for avoiding local optimum trapping. The control parameters F and CR are updated in their setting bounds when the uniformly distributed random numbers within the range (0,1) are less than T_1 and T_2. The main concept of the self-adaptive DEA optimization process is illustrated in figure 1.

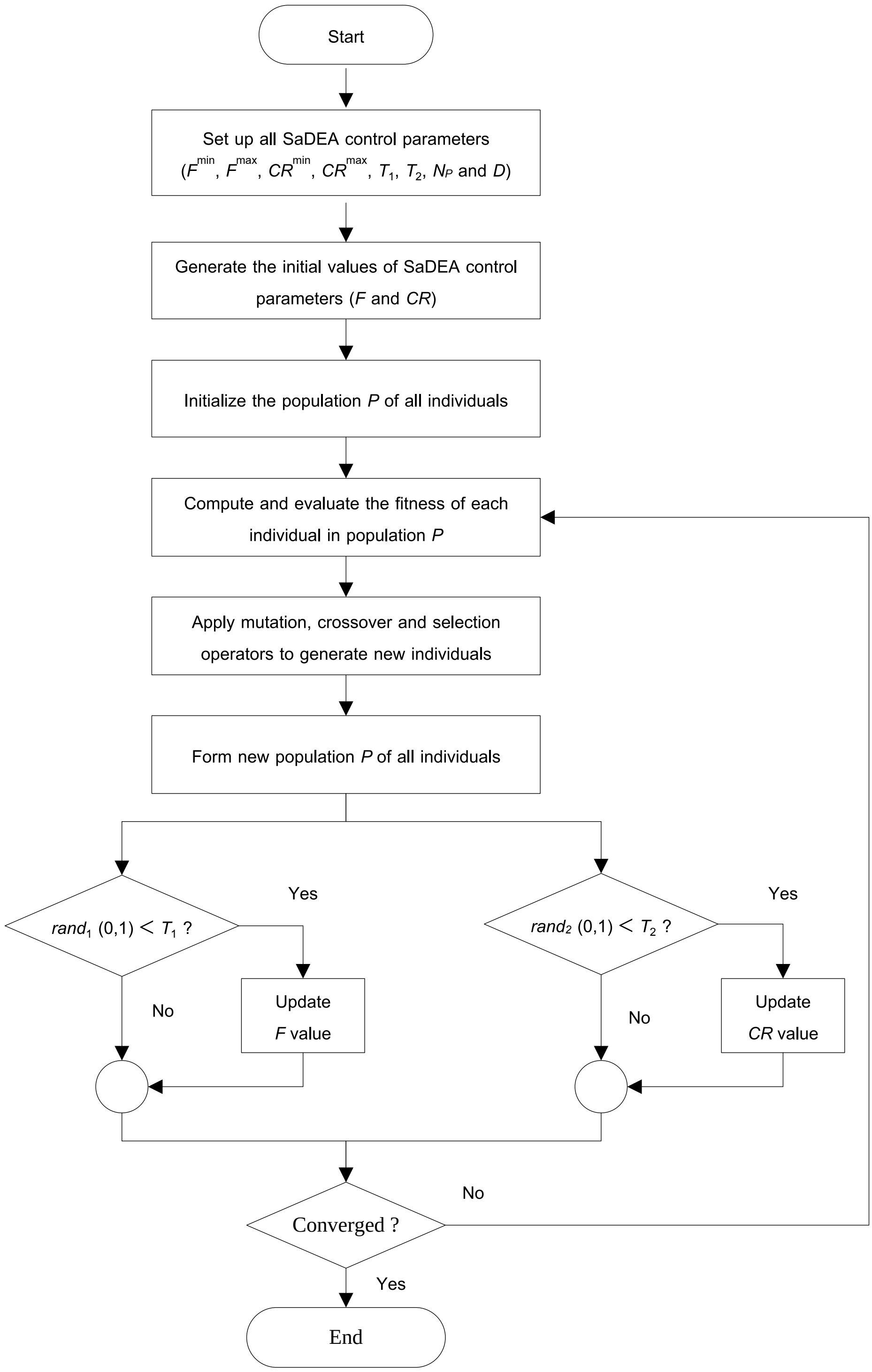

Figure 1 The main flowchart of a self-adaptive DEA optimization process

6. A Self-Adaptive DEA Method for the TEP Problem with System Losses Consideration

The SaDEA methodology is proposed to enhance the performance of conventional DEA method by reducing a tedious task of control parameters tuning. In addition, the SaDEA technique was successfully adopted to solve an economic dispatch problem in a previous author's work [35]. From the achieved successful results, the SaDEA method is proposed to solve the TEP problem with transmission system losses consideration in this work.

6.1 The SaDEA Optimization Procedure

An initial population is generated before applying optimization process. For the TEP problem formulation, each individual vector (X_i) contains many integer-valued parameters n, where $n_{j,i}$ represents the number of candidate lines in the possible branch j of the individual i. The problem decision parameter D is the number of possible branches for expansion.

$$X_i^{(G)} = [n_{1,i}^{(G)}, ..., n_{j,i}^{(G)}, ..., n_{D,i}^{(G)}], \quad i = 1, ..., N_p \tag{1}$$

After new individuals are initialized successfully, then the individuals of next iteration are created by applying mutation, crossover, and selection operators, respectively. The optimization process is repeated in search of the final solution until maximum number of generations ($G^{\max}$) is reached or other predetermined convergence criterion (ε) is satisfied.

6.2 Fitness Function of the TEP Problem Considering Line Losses

In this work, a fitness function $F(X)$ of the TEP problem is assigned according to (2) for each individual. The fitness function is a combination of an objective function and two penalty functions. The fitness function is adopted to find the optimal solution, measure the performance of candidate solutions, and check for violation of the TEP problem constraints. An individual is the best solution if its fitness value $F(X)$ is highest. The penalty functions are also included in the fitness function in order to represent violations of both equality and inequality constraints. For the TEP problem, an equality constraint penalty function (4) considers the DC power flow node balance constraint and then an inequality constraint penalty function (5) considers the constraints of power flow limit on each transmission line, power generation limit, bus voltage phase angle limit, and right-of-way, respectively. The general fitness function of the TEP problem can be formulated as follows:

$$F(X) = \frac{1}{O(X) + \omega_1 P_1(X) + \omega_2 P_2(X)} \tag{2}$$

$F(X)$ and $O(X)$ are fitness function and objective function of the TEP problem, respectively. $P_1(X)$ and $P_2(X)$ are the equality and inequality constraint penalty functions respectively. X denotes the individual vector of decision variables. ω_1 and ω_2 are penalty weighting factors that are set to 0.5 in this work. For the TEP problem, the objective function and penalty functions are formulated as follows:

$$O(X) = V(X) = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} + K \sum_{m=1}^{NL} I_m^2 R_m \tag{3}$$

$$P_1(X) = \sum_{k=1}^{nb} \left| d_k + B_k \theta_k - g_k \right| \tag{4}$$

$$P_2(X) = \begin{cases} C & \text{if an individual violates the TEP} \\ & \text{inequality constraints.} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where C is an inequality constraint constant that is used when an individual violates the inequality constraints. In this research, the constant C is set as 0.5 for all cases.

A computer program of the SaDEA method for application to TEP problem with system losses consideration is designed as illustrated in figure 2.

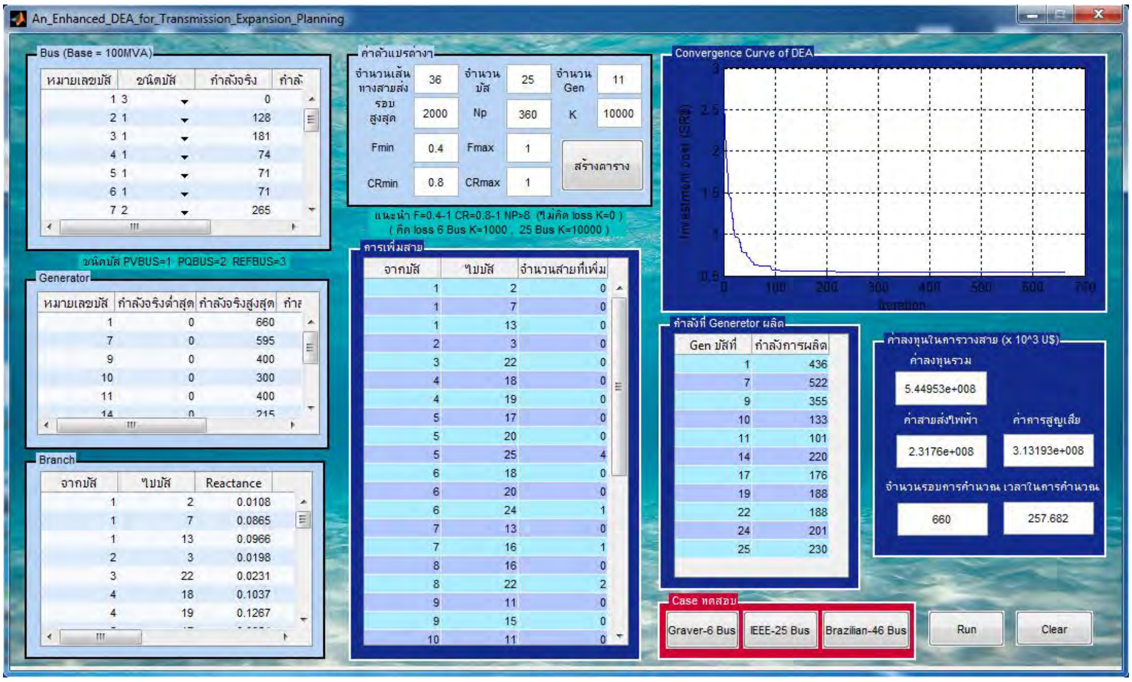

Figure 2 An example of the SaDEA optimization program for TEP problem with line losses consideration

6.3 Test Systems and Numerical Test Results

In the simulation, the proposed SaDEA procedure has been implemented in MATLAB and tested its performance on two electrical transmission systems as shown in appendix A. These two test networks are the Garver's 6-bus system and IEEE 25-bus system, which all significant data are also available in [17] and [27]. In this work, the TEP problem is included system losses consideration. In addition, the TEP problem has been investigated in two cases that are with and without power generation resizing considerations. The simulation results of the proposed SaDEA technique have been compared to conventional genetic algorithm (CGA), tabu search (TS), artificial neural networks (ANNs), hybrid artificial intelligent techniques and summarized in this report.

6.3.1 Garver 6-bus System

The first test system of this simulation is a well-known Garver's system, which comprises 6 buses, 9 possible branches, and 760 MW of power demand. The electrical system data; transmission line, load, and generation data are available in [17]. From this test system configuration, bus-6 is a new generation bus and needs to be connected to the existing network. A maximum of four parallel lines is permitted in each branch. In this simulation case, power losses consideration is included in objective function where the loss coefficient, *K*, was selected as 1000. A per-unit base in DC-load flow analysis is 100 MVA while the cost base is 10^5. The estimated lifetime of transmission lines was assumed to be 25 years and the cost of one kWh was assumed to be 0.005 monetary units/kWh found in [31]. The best solutions of SaDEA method are summarized and compared to other techniques in table 1.

Table 1 Comparison of the Expansion Costs among Various Methods for Garver 6-Bus Test System

Types of TEP problem	K=1000			
	Methods	**Investment cost**	**Losses cost "a"**	**Saved cost "b"**
TEP without the resizing of power generation	ANNs [31]	261	448.83	904.77
	TS [31]	291	382.54	971.06
	GA [3]	291	382.54	971.06
	Hybrid ANN-TS-GA [31]	291	382.54	971.06
	SaDEA	291	382.54	971.06
TEP with the resizing of power generation	SaDEA	170	231.66	1,121.94

Note: The losses cost “a” after the new line addition is calculated for 25 years. The saved cost “b” is calculated as a difference cost between the cost of ohmic power losses before the expansion of the transmission network (1353.6 monetary units) based on a 25-year (life-time of line) and the power losses cost “a” calculated after the new line additions for the same period.

For a case study of without power generation resizing consideration, the best solution of TEP problem considering system losses on Garver’s test system as shown in table 1 was found by all algorithms except ANNs method. Although the ANNs method obtained the least investment cost compared to other methods but it had the largest value of power losses cost after the new line additions. The SaDEA method obtained the investment cost and losses cost for with power generation resizing case study cheaper than the without power generation resizing case study. In addition, the SaDEA method had the largest saved cost of minimizing ohmic power losses during planning horizon in case of with power generation resizing consideration.

6.3.2 IEEE 25-bus System

The IEEE 25-bus system is selected to test the SaDEA procedure in this work. It consists of 25 buses, 36 possible branches, and 2750 MW of total power demand. The electrical system data; transmission line, load, and generation data are available in [27] and [31]. In this simulation case, the objective function includes power losses consideration, in which the loss coefficient, *K*, was selected to be 10000. The estimated lifetime of transmission lines was assumed to be 25 years while the cost of one kWh was assumed to be 0.0112 US$/kWh [31]. In this case study, a comparison among the proposed method and other techniques from [31] is included in table 2.

For a case study of without power generation resizing consideration, the best solution of the TEP problem with system losses consideration was found by SaDEA method and an investment cost was 160.051 million US$ as shown in table 2. In addition, the SaDEA method achieved the least value of a power losses cost after the new line additions compared to other techniques. Comparison between with and without power generation resizing consideration, the SaDEA method obtained the investment cost and losses cost for with power generation resizing case study cheaper than the without power generation resizing case study. Therefore, the SaDEA technique got the largest value of a saved cost of minimizing ohmic power losses during expansion planning horizon on this test system. Overall, the best algorithmic procedure for this case is SaDEA method.

Table 2 Comparison of the Expansion Costs among Various Methods for IEEE 25-Bus Test System

Types of TEP problem	K=10000			
	Methods	**Investment cost (million US$)**	**Losses cost "a" (million US$)**	**Saved cost "b" (million US$)**
TEP without the resizing of power generation	ANNs [31]	224.178	161.995	147.979
	TS [31]	180.664	155.264	154.709
	GA [31]	162.430	171.947	138.016
	Hybrid ANN-TS-GA [31]	168.784	152.320	157.653
	SaDEA	160.051	134.251	175.722
TEP with the resizing of power generation	SaDEA	61.802	83.032	226.941

Note: The losses cost "a" after the new line addition is calculated for 25 years. The saved cost "b" is calculated as the difference cost between the cost of ohmic power losses before the expansion of the transmission system (309.973 million US$) based on a 25-year (life-time of line) and the power losses cost "a" calculated after the new line additions for the same period.

6.4 Conclusion of a Self-Adaptive DEA Method for the TEP Problem with System Losses Consideration

In this work, a SaDEA method is applied when solving the TEP problem with system losses consideration. In addition, the TEP problem is also included both with and without power generation resizing considerations. Regarding the achieved results on two test networks illustrate that the SaDEA procedure is an efficient technique for solving the transmission planning problem. As the numerical test results in table 1 and 2 indicate, the proposed method obtained the least values of an investment cost and a power losses cost compared to conventional genetic algorithm, tabu search, artificial neural networks, and hybrid artificial intelligent techniques on two test systems. In addition, the SaDEA method had the largest saved cost of ohmic power losses for both test cases as shown in table 1 and table 2. The most attractive feature of the proposed algorithm is the good computational performance. The accuracy of the results obtained in the TEP study is in very good agreement with those obtained by other researchers as found in [31]. Regarding a consequence of these successful results, the TEP problem considering the *n*-1 contingencies in single line outage or single generator outage will be investigated as future work.

7. An Enhanced DEA method for the TEP Problem with Security Constraint Consideration

An enhanced DEA method is proposed to solve the TEP problem with security constraint consideration. The proposed method can be implemented to handle such problem as following details.

7.1 An Enhanced DEA Optimization Method

After two constant values are set by user, then an initial population is generated before applying optimization process. In the TEP problem formulation, each individual vector (X_i) contains many integer-valued parameters n, where $n_{j,i}$ represents the number of candidate lines in the possible branch j of the individual i. The problem decision parameter D is the number of possible branches for expansion.

$$X_i^{(G)} = [n_{1,i}^{(G)},...,n_{j,i}^{(G)},...,n_{D,i}^{(G)}],\ \ i = 1,...,N_p \tag{6}$$

When an initial population of individuals is initialized successfully, then three DEA operators create the population of next generation $P^{(G+1)}$ by using the current population $P^{(G)}$. The optimization process is continuously repeated in search of the final solution until the maximum number of generations ($G^{\max}$) is reached or other predetermined convergence criterion (ε) is satisfied.

7.2 Fitness Function of the TEP Considering Security Constraint

A fitness function of TEP problem is used to search the optimal solution, measure the performance of candidate solutions, and check for violation of the TEP problem constraints. The TEP fitness function $F(X)$ is a combination of the objective function and two penalty functions and can be formulated according to (7) for each individual. An individual is the best solution if its fitness value $F(X)$ is highest. The penalty functions must be also included in the fitness function in order to represent violations of both the planning operational constraints without security (OPC) and the planning security constraint (SCC) of TEP problem. Regarding the proposed problem, the OPC penalty function (9) investigates all constraints of TEP problem without security criterion consideration. In addition, the SCC penalty function (10) investigates all security constraints of TEP problem. The general fitness function of the TEP problem can be assigned as follows:

$$F(X) = \frac{1}{O(X) + \omega_1 P_1(X) + \omega_2 P_2(X)} \tag{7}$$

In (7), $F(X)$ and $O(X)$ represent fitness function and objective function of the TEP problem, respectively. $P_1(X)$ and $P_2(X)$ are the constraint penalty functions. X denotes the individual vector of decision variables. In this work, ω_1 and ω_2 are penalty weighting factors and set to 0.5, respectively. For this TEP problem, the objective function and the constraint penalty functions are formulated as follows.

$$O(X) = V(X) = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} \tag{8}$$

$$P_1(X) = \begin{cases} C_1 & \text{if an individual violates the OPC of TEP problem.} \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

$$P_2(X) = \begin{cases} C_2 & \text{if an individual violates the SCC of TEP problem.} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

where C_1 and C_2 are the constraint constants, which are applied to problem when an individual violates the OPC and SCC of TEP problem, respectively. In this work, both constants C_1 and C_2 are set as 0.5 for all cases.

A computer program of the SaDEA method for application to TEP problem with security constraint consideration has been designed as shown in figure 3.

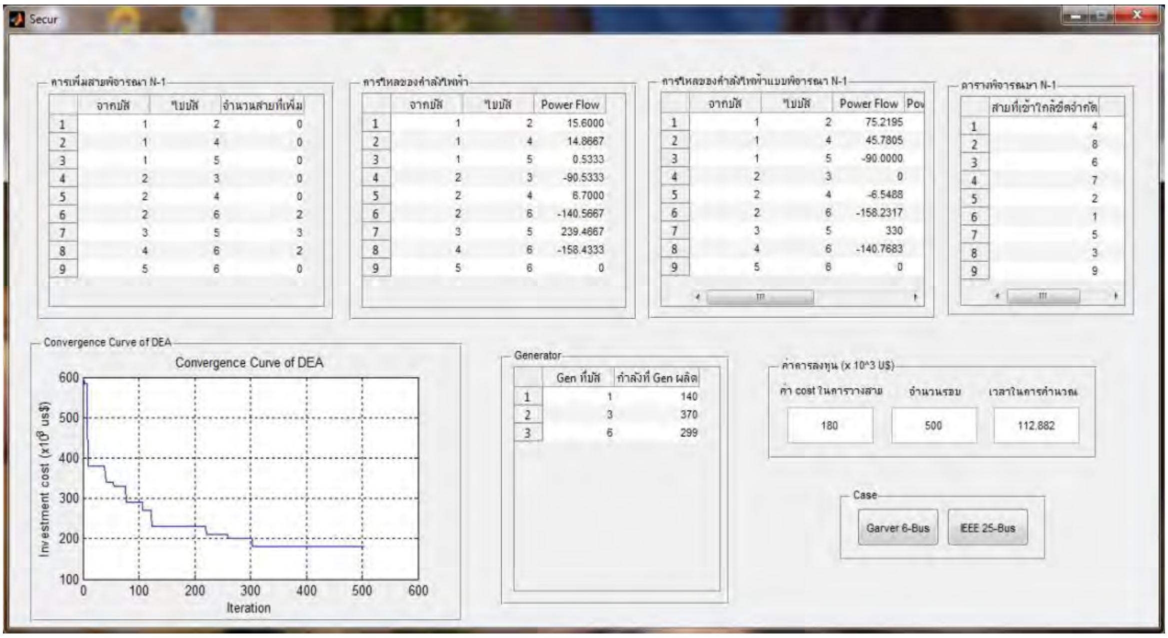

Figure 3 Example of the SaDEA optimization program for TEP problem with security constraint consideration

7.3 Test Systems and Numerical Test Results

In the simulation, the proposed enhanced DEA procedure is implemented in MATLAB and has been tested its performance on three electrical transmission systems as reported in appendix A. These three test networks are the Garver's 6-bus system, the Brazilian 46-bus system, and the IEEE 25-bus system and all required data are also available in [17], [25], and [27], respectively.

Table 3 Results comparison of TEP problem with security constraint consideration

Methods	Best cost (x10^3 US$)		
	Garver 6-bus system	IEEE 25-bus system	Brazilian 46-bus system
SaDEA	180	19,131	168,042
Chu-Beasley GA (CBGA) [36]	180	-	213,000
Ant Colony Search Algorithm (ACSA) [38]	298	248,943	-
Conventional DEA [38]	298	210,818	-

The obtained results of TEP problem with security constraint and power generation resizing considerations are summarized in table 3, where the best investment costs of expansion corresponding to the proposed SaDEA method are compared to other algorithms. As indicated by the results in table 3, SaDEA and CBGA methods found the optimal solution on Gaver 6-bus system. For IEEE 25-bus system and the Brazilian 46-bus system, the SaDEA method could find the optimal solution as shown the cheapest investment cost.

7.4 Conclusion of an Enhanced DEA method for the TEP Problem with Security Constraint Consideration

In this work, an enhanced DEA method is proposed to deal with the TEP problem with *n*-1 security criterion consideration. A single line outage is investigated in such TEP problem for reliability issue. From obtained results of Garver 6-bus system, IEEE 25-bus system, and the Brazilian 46-bus system, the SaDEA procedure is an acceptable optimization technique and minimizes effectively the total investment cost of TEP problem with security constraint consideration on realistically transmission systems. As the empirical solutions of these test cases indicate, total investment costs of the SaDEA method are less expensive than other methods on three test networks. The most attractive feature of the proposed algorithm is good computational performance and simple implementation. Regarding a consequence of the successful results, a distribution system planning problem will be investigated as future work.

8. Project Conclusions & Future Work

Cost-effective transmission expansion planning (TEP) is a major challenge with regard to electrical power system optimization problems as its main goal is to achieve an optimal expansion plan. The planning solution has to meet technical requirements while offering economical investment. Furthermore, transmission planning should specify new transmission facilities that must be added to an existing network to ensure adequate operation over a specified planning horizon.

Over past few decades, a number of optimization methods have been applied to solve the TEP problem in many issues. These proposed methods are as follows: mathematical optimization methods (e.g. linear programming, nonlinear programming, dynamic programming, integer and mixed integer programming, benders decomposition, branch & bound, etc.), heuristic methods (mostly constructive heuristics), and meta-heuristic methods (e.g. genetic algorithms, tabu search, simulated annealing, particle swarm, evolutionary algorithms, differential evolution algorithm, etc.). The details of such methods are provided in chapter 2 of this report.

A differential evolution algorithm (DEA) is an artificial intelligence technique and it was firstly presented by R. M. Storn and K. V. Price in 1995. The DEA method becomes a reliable and versatile function optimizer that is also readily applicable to a wide range of optimization problems. Although the conventional DEA method has a number of merits as described in chapter 2, it still has a drawback that is a difficult task of the DEA control parameters tuning. Regarding such disadvantage of the conventional DEA characteristic, thus it should be improved the optimization performance in this research. An enhanced DEA method is a modified version and has been proposed to solve the TEP problem with system losses and security criterion considerations in this work.

The main contribution of this research is the enhancement of a conventional DEA method and the application of proposed technique to TEP problem with system losses and security criterion considerations. First of all, design of a self-adaptive DEA (SaDEA) procedure is to develop two DEA control parameters, mutation factor (F) and crossover probability (CR), which are self-tuning parameters using probability methodology. In order to validate its searching capability and reliability, the enhanced methodology has been tested with some selected mathematical benchmark functions, namely Sphere, Rosenbrock1, Absolute, Schwefel, and Rastrigin functions.

Based on the successful results of SaDEA procedure application to selected mathematical functions, the proposed technique is subsequently implemented to solve static

TEP problem with system losses consideration, which is a real-world optimization problem, as shown in chapter 3. In chapter 3, the simulations have two different scenarios of static TEP problem that are with and without generation resizing considerations. In addition, a heuristic search method has been adopted in order to deal with static TEP considering DC based power flow model constraints. The proposed method has been implemented in Matlab7 and tested on two electrical transmission networks as found in appendix A1-A2. The obtained results indicate that SaDEA method performs effectively to handle the static TEP problem considering system losses on Graver 6-bus system and IEEE 25-bus system. The most attractive feature of the proposed algorithm is the good computational performance. The accuracy of the results obtained in the TEP study is in very good agreement with obtained by other researchers as presented in chapter 3. Regarding a consequence of the successful results, the TEP problem considering *n*-1 contingencies in single line outage has been investigated in chapter 4.

Given its effectiveness for solving the TEP problem with system losses consideration, the proposed methodology is then applied to deal with the TEP problem with *n*-1 security criterion consideration, which is more complex and difficult than the previous work. In this study, such TEP problem based on DC power flow model has been analyzed. The proposed method application to handle the TEP problem with *n*-1 security criterion consideration is tested on three transmission systems that are Graver 6-bus system, IEEE 25-bus system, and the Colombian 93-bus system, as found in appendix A1-A3. The obtained results of three networks illustrate that the SaDEA technique is good efficient and effectively minimizes the total investment cost of TEP problem on such systems.

Overall, the SaDEA procedure performs superior to other classical evolutionary algorithms (EAs) in terms of simple implementation with high quality of solution. Meanwhile, it requires less control parameters while being independent from initialization. In addition, its convergence is stable and robust as SaDEA procedure uses rather greedy selection and less stochastic approach to solve optimization problems than other classical EAs.

As a consequence of the successful results in this research, the SaDEA method will be applied to solve a problem of distribution system planning in future work. Moreover, an economical solution of the TEP problem under the current deregulatory environment remains a significant issue in electrical power system analysis. Therefore, such topic should be further investigated in future research. Some issues for market-based transmission expansion planning, i.e. the losses of social welfare and the expansion flexibility in the system should be investigated and included in the TEP problem.

CHAPTER 1

INTRODUCTION

1.1 Background and Problem Statement

In general, electric power transmission lines are constructed to link remote generating power plants to load centers, thus permitting power plants to be located in regions that are more economical and environmentally suitable. Regarding systems grew, meshed networks of transmission lines have emerged, providing alternative paths for electric power flows from generating sites to load centers that enhance the reliability of continuous supply. In regions where generation resources or load patterns are imbalanced, transmission interconnection eases the requirement for additional generation. Additional transmission capability is justified whenever there is a need to connect cheaper generation to meet growing load demand or enhance system reliability or both.

Transmission expansion planning (TEP) has always been a rather complicated task especially for large-scale real-world transmission systems. First of all, electricity demand changes across both area and time. The change in demand is met by the appropriate dispatching of generation resources. As an electric power system must obey physical laws, the effect of any change in one part of network (e.g. changing the load at a node, raising the output of a generator, switching on/off a transmission line or a transformer) will spread instantaneously to other parts of the interconnected network, hence altering the loading conditions on all transmission lines. The ensuing consequences may be more marked on some transmission lines than others, depending on electrical characteristics of the lines and interconnection.

The TEP problem involves determining the least investment cost of the power system expansion and technical operating through the timely addition of electric transmission facilities in order to guarantee that the constraints of the transmission system are satisfied over the defined planning horizon. Transmission system planners are entrusted with ensuring the above-stated goals are best met whilst utilizing all the available resources. Therefore the purpose of transmission network planning is to determine the timing and type of new transmission facilities. The facilities are required in order to provide adequate transmission capacity to cope with future additional generation and power flow requirements. The transmission plans may require the introduction of higher voltage levels, the installation of new transmission elements and new substations. Transmission network planners tend to use many techniques to solve such problem. The planners utilize automatic expansion models to determine an optimum expansion network by minimizing the mathematical objective function subject to a number of constraints.

Normally, the TEP problem can be categorized as static or dynamic according to the treatment of the study period [1]. In static planning, the planners consider only one planning horizon and determine the number of suitable lines that should be installed to each branch of transmission system. Investment is carried out at the beginning of planning horizon time. In dynamic or multistage planning, the planners consider not only the optimal number and location of additional lines but also the most appropriate times to carry out such expansion investments. Therefore the continuing growth of the demand and generation is always assimilated by the system in an optimized way. The planning horizon is divided into various stages and the transmission lines must be installed at each stage of the planning horizon.

Many optimization techniques have been employed to solve the TEP problem. These techniques range from expert engineering judgements to powerful mathematical programming methods. The engineering judgements depend on human expertise and knowledge of the system. The most applied approaches in the TEP problem can be classified into three groups that are mathematical optimization methods (e.g. linear programming, nonlinear programming, dynamic programming, integer and mixed integer programming, benders decomposition and branch and bound, etc.), heuristic methods (mostly constructive heuristics) and meta-heuristic methods (e.g. genetic algorithms, tabu search, simulated annealing, particle swarm, evolutionary algorithms, differential evolution algorithm, etc.).

Over the past decade, algorithms inspired by the observation of natural phenomena when solving complex combinatorial problems have been gaining increasing interest because they perform efficiently for solving the optimization problems [2]. Such algorithms have successfully applied to a number of power system problems [3-4], for example power system scheduling, power system planning and power system control.

In recent years, a differential evolution algorithm (DEA) method has been attracting increasing attention for a wide variety of engineering applications including electrical power system engineering. There have been many researches that applied DEA for solving electrical power system problems such as power system transfer capability assessment [5], power system planning [6], economic power dispatch [7-9], distribution network reconfiguration problem [10], short-term hydrothermal scheduling problem [11], optimal reactive power flow [12-13] and optimal power flow [14]. Moreover, the conventional DEA method has been successfully solved static and dynamic transmission expansion planning problems by the author in [15] where the DEA method performed superior to conventional genetic algorithm (CGA) in terms of simple implementation with high quality of solution and good computation performance. Meanwhile, DEA requires less control parameters while being independent from initialization. In addition, its convergence is stable as DEA procedure uses rather greedy selection and less stochastic approach to solve optimization problems than other CGA. Unfortunately, there remains a drawback of DEA procedure that is a tedious task of the DEA control parameters tuning due to complex relationship among problem's parameters. The optimal parameter settings of the DEA method may not be found and the final result may be trapped in a local minimum.

It is important to note that few algorithms have been practically applied to solve the TEP problem at present [1]. Although the method proposed in [15] by the author was successfully solved many cases of TEP problem, it was not yet sufficiently robust for practical use for industry. The conventional DEA method proposed in [15] has the notable limitation of DEA control parameter tuning due to a complex interaction of parameters as above mentioned. Therefore, a further improvement of the novel DEA method is essentially required before it can be generally adopted for practical use in industry.

The TEP problem as studied in [15] is called a basic planning, in which the security criterion has not been considered. In other words, the optimal expansion plan is determined without considering the *n*-1 contingencies caused by a transmission line or generator outage. The *n*-1 security criterion is an important index in power system reliability study as it states that the system should be expanded in such a way that, if a single line or generator is withdrawn, the expanded system should still operate adequately. Moreover, the TEP with system loss consideration is a significant issue that should be included in the planning problem for enhancing the result accuracy. Therefore, the proposed TEP problem has been investigated in both *n*-1 security criterion and system losses considerations in this research work.

1.2 Objectives of Research Project

The ultimate goal of undertaken research is to take advantage of computational simulations more effectively in an overall planning study and consequently determine an appropriate transmission network expansion plan. The main objectives of this project are:

- To enhance a conventional DEA method for solving a wide variety of mathematical and real-world optimization problems;
- To apply the proposed technique, a self-adaptive DEA method, for solving power system optimization problems, especially the TEP problem with security constraint and system losses considerations;

- To use the obtained results of planning study in order to design future transmission network and test its performance;
- To use the novel knowledge from this research for application to the author's teaching on a course of electric power system analysis and a course of electric power system operation & design.

1.3 Scopes of Research Work

- A conventional DEA method is improved its performance and then it is tested with some selected mathematical benchmark functions before applying real-world optimization problems.
- An enhanced DEA method is further employed to handle a real-world optimization problem, which is the TEP using DC power flow-based model.
- Such investigated issue is the TEP problem with system power losses and *n*-1 security constraint considerations.
- The efficiency of the proposed method is demonstrated via the analysis of low, medium and high complexity transmission network test cases.

1.4 Contributions of Research Work

The major contributions of this research are the development of a conventional DEA method and the investigation of the applicability of an enhanced DEA technique when applied to TEP problem with security constraint and system losses considerations. In addition, a detailed comparison of the enhanced DEA method and the conventional DEA procedure used for solving the TEP problem is presented. The most significant original contributions presented and investigated in this report are outlined as follows:

- Firstly, a novel methodology is proposed in this research where the conventional DEA procedure is further improved its performance by reducing a tedious task of control parameters tuning. In order to validate its searching capability and reliability, the proposed methodology has been tested with some selected mathematical benchmark test functions before applied to real-world optimization problems.
- Regarding the effectiveness of an enhanced DEA method as tested on several numerical benchmark test functions, the proposed technique is successfully implemented to solve a real-world optimization problem, which is the TEP problem with losses

consideration. For this study, two test networks, Garver's 6-bus system and IEEE 25-bus system, have been investigated and explained in this report.

- Finally, this research utilizes the proposed effective technique to deal with the TEP problem with *n*-1 security criterion consideration, which is more complex and difficult when compared to the basic TEP problem as shown in [15]. In this work, the TEP problem considering *n*-1 contingency constraint has been analyzed and it is an especially difficult task with regard to large-scale real-world transmission system. The enhanced DEA method as applied to solve the TEP problem with *n*-1 contingency criterion consideration is tested on three transmission systems that are the Garver's 6-bus system, IEEE 25-bus system, and Colombian 46-bus system.

1.5 Report Outline

- Chapter 1 presents an introduction to the TEP problem with *n*-1 security criterion and system losses considerations. In addition, research objectives and contributions of the proposed DEA method application to TEP problem are included in this chapter.
- Chapter 2 presents an overview of the TEP problem including problem formulation and literature survey. Moreover, reviews of the DEA methodology and optimization process are also provided in this chapter.
- Chapter 3 provides implementation and development of the proposed algorithm for solving the TEP problem with system losses consideration. The experimental results and comments are discussed in this chapter.
- Chapter 4 presents implementation of the proposed technique for solving the TEP problem with *n*-1 security constraint consideration. The numerical test results for realistic transmission systems and discussions are included in this chapter.
- Chapter 5 presents overall conclusions of this research and the further possible research directions are also indicated.
- Chapter 6 presents output of this research project. In addition, the proposed articles are also presented in this chapter.

CHAPTER 2

FUNDAMENTALS OF TRANSMISSION EXPANSION PLANNING PROBLEM AND DIFFERENTIAL EVOLUTION ALGORITHM

2.1 Introduction

Cost-effective transmission expansion planning (TEP) is a major challenge with regard to power system operation and planning, which is a complicated nonlinear constrained optimization problem. Generally, the main purpose of solving TEP problem is to specify addition of transmission facilities that provide adequate capacity and in the meantime maintain operating performance of electric transmission system [16]. To achieve effective plan, exact location, capacity, timing, and type of new transmission equipment must be thoroughly determined to meet demand growth, generation addition, and increased power flow.

To find an optimal solution of TEP over a planning horizon, extensive parameters are required; such as candidate circuits, electricity demand forecast, generation forecast, investment constraints, transmission losses data, etc. This would consequently impose more complexity in solving the TEP problem. Given the above information, in–depth knowledge on problem formulation and computation techniques for TEP is crucial and therefore, this chapter aims essentially at presenting fundamental information of these issues.

The organization of this chapter is as follows: section 2.2 presents overview and formulation of DC power flow model. Section 2.3 presents problem formulation and mathematical model of the basic TEP problem. Section 2.4 presents overview of the conventional DEA method and its optimization process. Finally, solution methods for the TEP problem found in the international technical literature are reviewed in section 2.5.

2.2 DC Power Flow

For a long-term TEP study, some assumptions are invented and proposed for solving such planning problem, for example, a consideration of the reactive power allocation is neglected in the first moment of the planning. In this stage, the main concern is to identify the principal power corridors that probably will become part of the expanded system. There are several types of the mathematical model employed for representing the transmission network in the TEP study; AC power flow model, DC power flow model, transportation model, hybrid model, and disjunctive model as discussed in [17].

Basically, the DC power flow model is widely adopted to the TEP problem and it is frequently considered as a reference because in general, networks synthesized by this model satisfy the basic conditions stated by operation planning studies. The planning results found in this phase will be further investigated by operation planning tools such as AC power flow analysis, transient and dynamic stability analysis and short-circuit analysis for obtaining the accurate result [3].

The formulation of DC power flow is obtained from the modification of a general representation of AC power flow, which can be illustrated by the following equations.

$$P_i = |V_i| \sum_{k=1}^{N} |V_k| [G_{ik} \cos(\theta_i - \theta_k) + B_{ik} \sin(\theta_i - \theta_k)] \tag{2.1}$$

$$Q_i = |V_i| \sum_{k=1}^{N} |V_k| [G_{ik} \sin(\theta_i - \theta_k) - B_{ik} \cos(\theta_i - \theta_k)] \tag{2.2}$$

where P_i and Q_i are real and reactive power of bus *i*, respectively. $|V_i|$ and θ_i are voltage magnitude and voltage phase angle of bus *i,* respectively. $|V_k|$ is voltage magnitude at bus *k*. G_{ik} and B_{ik} are real and imaginary parts of element (*i*,*k*) of bus admittance matrix, respectively. *N* is total number of buses in the system.

To modify AC power flow model to the DC power flow based model, the following assumptions are normally considered [18]:

- Bus voltage magnitude at each bus bar is approximate one per unit ($|V_i|$ = 1 p.u. for all *i* buses);
- Line conductance at each path is neglected (G_{ik} = 0), or on the other hand only line susceptance (B_{ik}) is considered in the DC model;
- Some trigonometric terms of AC model in equations (2.1) and (2.2) can be approximated as following terms: sin (θ_i - θ_k) ≈ θ_i - θ_k and cos (θ_i - θ_k) ≈ 1

Given these assumptions, the AC power flow equation in (2.1) is therefore simplified to yield the DC power flow equation as follows:

$$P_i = \sum_{k=1}^{N} B_{ik} (\theta_i - \theta_k) \quad , i = 1, ..., N \tag{2.3}$$

where B_{ik} is the line susceptance between bus *i* and *k*.

2.3 Basis of Transmission Expansion Planning Problem

In this section, the TEP is formulated as a mathematical problem. The goal of solving such problem is typically to fulfill the required planning function in terms of investment and operation restriction. Normally, the TEP problem can be mathematically formulated by applying DC power flow model, which is a nonlinear mixed-integer problem with high complexity, especially for large-scale real-world transmission networks. There are several alternatives to the DC model such as the transportation, hybrid, and disjunctive models. Detailed reviews of the main mathematical models for the TEP problem were presented in [17].

2.3.1 The Objective Function

The objective of TEP problem is to minimize total expansion cost while satisfying operational and economical constraints. In this research, the classical DC power flow model is applied to solve the TEP problem. Mathematically, the problem can be formulated as follows:

$$\min \quad v = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} \tag{2.4}$$

where v, c_{ij} and n_{ij} represent transmission investment cost, cost of a candidate circuit for addition to the branch *i-j* and the number of circuits added to the branch *i-j*, respectively. Here Ω is set of all candidate branches for expansion.

2.3.2 Problem Constraints

The objective function (2.4) represents a capital cost of newly installed transmission lines, which has some restrictions. These constraints must be included into mathematical model to ensure that the optimal solution satisfies transmission planning requirements. These constraints are described as follows:

- **DC Power Flow Node Balance Constraint**

This linear equality constraint represents the conservation of power at each node.

$$g = d + B\theta \tag{2.5}$$

where g, d and B are real power generation vector in existing power plants, real load demand vector in all network nodes, and susceptance matrix of the existing and added lines in the network, respectively. Here θ is the bus voltage phase angle vector.

- **Power Flow Limit on Transmission Lines Constraint**

The following inequality constraint is applied to transmission expansion planning in order to limit the power flow for each path.

$$\left| f_{ij} \right| \leq (n_{ij}^{0} + n_{ij})\, f_{ij}^{\max} \qquad (2.6)$$

In DC power flow model, each element of the branch power flow in constraint (2.6) can be calculated by using equation (2.7):

$$f_{ij} = \frac{(n_{ij}^{0} + n_{ij})}{x_{ij}} \times (\theta_i - \theta_j) \qquad (2.7)$$

where f_{ij}, $f_{ij}^{\max}$, n_{ij}, n_{ij}^{0} and x_{ij} represent, respectively, total branch power flow in branch *i-j*, maximum branch power flow in branch *i-j*, number of circuits added to branch *i-j*, number of circuits in original base system, and reactance of the branch *i-j*. Here θ_i and θ_j is voltage phase angle of terminal buses *i* and *j* respectively.

- **Power Generation Limit Constraint**

For transmission expansion planning problem, power generation limit must be included into the problem constraints. This can be mathematically represented as follows:

$$g_i^{\min} \leq g_i \leq g_i^{\max} \qquad (2.8)$$

where g_i, $g_i^{\min}$ and $g_i^{\max}$ are real power generation at node *i*, the lower and upper real power generation limits at node *i,* respectively.

- **Right-of-way Constraint**

It is essential to find an accurate TEP solution, thus planners need to know an exact capacity of newly required circuits. Therefore this constraint must be considered in such planning problem. Mathematically, this constraint defines location and maximum number of circuits, which can be installed in a specified location. It can be represented as follows.

$$0 \leq n_{ij} \leq n_{ij}^{\max} \qquad (2.9)$$

where n_{ij} and $n_{ij}^{\max}$ represent the total integer number of circuits added to the branch *i-j* and the maximum number of added circuits in the branch *i-j* respectively.

- **Bus Voltage Phase Angle Limit Constraint**

While a DC power flow model is employed to the TEP problem, thus bus voltage magnitude is not a factor in this analysis. The bus voltage phase angle could be included as a TEP constraint to be increase an accurate solution in technical issue. The calculated phase angle ($\theta_{ij}^{\mathrm{cal}}$) should be less than the predefined maximum phase angle ($\theta_{ij}^{\max}$). Such constraint can be represented as the following mathematical expression.

$$\left|\theta_{ij}^{\mathrm{cal}}\right| \leq \left|\theta_{ij}^{\max}\right| \tag{2.10}$$

2.4 Basis of Differential Evolution Algorithm Methodology

Evolutionary algorithms (EAs) are heuristic, stochastic optimization techniques based on the principles of natural evolution theory. The field of investigation, concerning all EAs, is known as “evolutionary computation”. The origins of evolutionary computation can be traced back to the late 1950’s and a variety of EAs have been developed independently by a number of researchers until now. A variety of algorithms have been developed within the field of evolutionary computation. The most popular algorithms are genetic algorithms (GAs), evolutionary programming (EP), evolution strategies (ESs), and differential evolution algorithms (DEA). These approaches attempt to discover the optimal solution of an optimization problem via a simplified model of evolutionary processes observed in nature and they are based on concept of a population of individuals that evolve and improve their fitness through probabilistic operators via processes of recombination, mutation, and selection. The individuals are evaluated with regard to their fitness and the individuals, with superior fitness, are selected to compose the population in next generation. After several generations of the optimization procedure, the fitness of individuals should be improved while current individuals explore the solution space for the optimal value.

A DEA method is an evolutionary computation algorithm as it uses real-coded variables and typically relies on mutation as the search operator. The DEA method was originally introduced by R. M. Storn and K. V. Price in 1995 [19] and further developed to be a reliable and versatile function optimizer that is also readily applicable to a wide range of optimization problems [20]. More recently, the DEA method has evolved to share many features with conventional genetic algorithm (CGA) [21]. The major similarity between these two types of algorithm is that they both maintain populations of potential solutions and use a selection mechanism for choosing the best individuals from the population. The main differences between the CGA method and the DEA technique were summarized in [22].

- DEA operates directly on floating point vectors while CGA relies mainly on binary strings;
- CGA relies mainly on recombination to explore the search space, while DEA uses a special form of mutation as the dominant operator;
- DEA is an abstraction of evolution at individual behavioural level, stressing the behavioural link between an individual and its offspring, while CGA maintains the genetic link.

The DEA method has a number of significant advantages when applying to optimization problems and these merits were discussed by Price in [23].

- Ability to find the true global minimum regardless of the initial parameter values;
- Fast and simple with regard to application and modification;
- Requires few control parameters;
- Parallel processing nature and fast convergence;
- Capable of providing multiple solutions in a single run;
- Effective on integer, discrete and mixed parameter optimization;
- Ability to find the optimal solution for a nonlinear constrained optimization problem with penalty functions.

A DEA is a parallel direct search technique that employs a population *P* of size N_P, consisted of floating point encoded individuals or candidate solutions (2.11). At every generation *G* during the optimization process, the DEA maintains population $P^{(G)}$ of N_P vectors of candidate solutions to the problem at hand.

$$P^{(G)} = [X_1^{(G)}, \ldots, X_i^{(G)}, \ldots, X_{N_P}^{(G)}] \tag{2.11}$$

Each candidate solution X_i is a *D*-dimensional vector, containing as many real-valued parameters (2.12) as the problem decision parameters *D*.

$$X_i^{(G)} = [x_{1,i}^{(G)}, \ldots, x_{j,i}^{(G)}, \ldots, x_{D,i}^{(G)}], \quad i = 1, \ldots, N_p \tag{2.12}$$

2.4.1 Initialization Step

In the first step of the DEA procedure, population of candidate solutions must be initialized. Typically, each decision parameter in every vector of the initial population is assigned a randomly chosen value from within its corresponding feasible bounds.

$$x_{j,i}^{(G=0)} = x_j^{\min} + \mathrm{rand}_j[0,1].(x_j^{\max} - x_j^{\min}) \tag{2.13}$$

where i = 1,…,N_P and j = 1,…,D. Here $x_{j,i}^{(G=0)}$ is an initial value of the j^{th} parameter of the i^{th} individual vector. $x_j^{\min}$ and $x_j^{\max}$ are the lower and upper bounds of the j^{th} decision parameter, respectively. Once every vector of the population has been initialized, its corresponding fitness value is calculated and stored for future reference.

2.4.2 Mutation Step

After the population of candidate solutions is successfully initialized, the next step of DEA optimization process is carried out by applying three basic genetic operations; mutation, crossover, and selection. These three operators create the population of next generation $P^{(G+1)}$ by using current population $P^{(G)}$. At every generation G, each vector in the population has to serve once as a target vector $X_i^{(G)}$, the parameter vector has chosen vector index i, and it is compared with a mutant vector. The mutation operator generates mutant vectors ($V_i^{(G)}$) by perturbing a randomly selected vector (X_{r1}) with the difference of two other randomly selected vectors (X_{r2} and X_{r3}).

$$V_i^{(G)} = X_{r1}^{(G)} + F\left(X_{r2}^{(G)} - X_{r3}^{(G)}\right), \quad i = 1, ..., N_P \tag{2.14}$$

The vector indices $r1$, $r2$ and $r3$ are randomly selected, in which $r1$, $r2$ and $r3$ $\in$ {1,…,N_P} and $r1 \neq r2 \neq r3 \neq i$. X_{r1}, X_{r2} and X_{r3} are selected anew for each parent vector. F is a user-defined constant known as the "scaling mutation factor", which is typically chosen from within the range [0,1$^+$].

2.4.3 Crossover Step

In this step, a crossover or recombination process is also applied in the DEA procedure because it helps to increase the diversity among mutant parameter vectors. At the generation G, crossover operation creates trial vectors (U_i) by mixing the parameters of the mutant vectors (V_i) with the target vectors (X_i) according to a selected probability distribution.

$$U_i^{(G)} = u_{j,i}^{(G)} = \begin{cases} v_{j,i}^{(G)} & \text{if} \quad \text{rand}_j(0,1) \leq CR \quad or \quad j = s \\ x_{j,i}^{(G)} & \text{otherwise} \end{cases} \tag{2.15}$$

The crossover constant CR is a user-defined value (known as the "crossover probability"), which is usually selected from within the range [0,1]. The crossover constant controls the diversity of the population and aids algorithm to escape from local optima. The "rand$_j$" is a uniformly distributed random number within the range (0,1) generated anew for each value of j. "s" is the trial parameter with randomly chosen index $\in$ {1,…,D}, which ensures that the trial vector gets at least one parameter from the mutant vector.

2.4.4 Selection Step

Finally, a selection operator is applied in the last stage of the DEA procedure. The selection operator selects the vectors that are going to compose the population in next generation. This operator compares the fitness of trial vector and corresponding target vector and then selects the one that provides the best solution. The fitter of two vectors is allowed to advance into the next generation according to (2.16).

$$X_i^{(G+1)} = \begin{cases} U_i^{(G)} & \text{if} \quad f(U_i^{(G)}) \le f(X_i^{(G)}) \\ X_i^{(G)} & \text{otherwise} \end{cases} \tag{2.16}$$

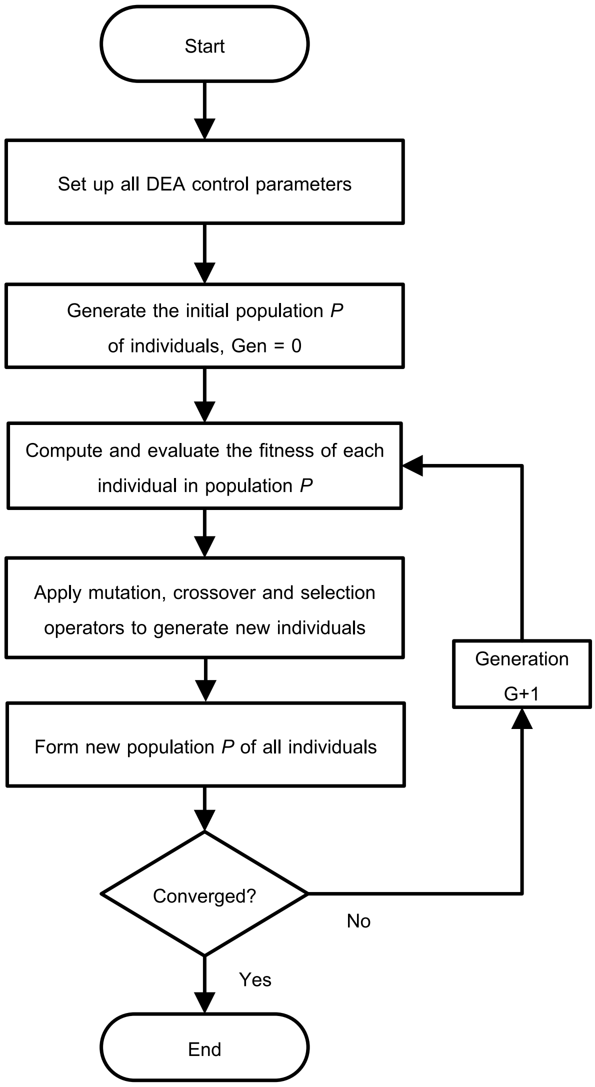

Figure 2.1 The main flowchart of the conventional DEA optimization process

The DEA optimization process is repeated continually across generations to improve the fitness of individuals. The overall optimization process is stopped whenever maximum number of generations is reached or any other predetermined convergence criterion is satisfied. The main concept of a conventional DEA optimization process is illustrated in figure 2.1.

2.5 Review of Solution Methods for Transmission Expansion Planning Problem

Over the last few decades, there were a number of conventional methods applied to solve the TEP problem, for instance, linear programming [24], branch and bound [25], dynamic programming [26], interactive method [27], nonlinear programming [28], mixed integer programming [29], and etc.

In 1970, Garver proposed a linear programming method to solve the TEP problem [24]. This original method was applied to long-term planning of electrical power systems and produced a feasible transmission network with near-minimum circuit miles using as input any existing network plus a load forecast and generation schedule. Two main steps of the method, in which the planning problem was formulated as load flow equations and new circuit selection could be searched based on the system overloads, were described in detail.

An interactive method was applied in order to optimize the TEP problem and reported in 1984 [27]. The method was based on a single-stage optimization procedure using sensitivity analysis and the adjoint network approach to transmit power from a new generating station to a loaded AC system. The non-linear programming technique of gradient projection followed by a round-off procedure was used for this optimization method.

Recently, many methods based on artificial intelligence (AI) techniques have been also proposed to solve the TEP problem. These AI techniques include genetic algorithms (GAs) [30-31], simulated annealing (SA) [32], tabu search (TS) [33], and artificial neural networks (ANNs) [31]. In 2002, several types of AI techniques, which are GAs, TS and ANNs with linear and quadratic programming models, were applied to solve the TEP problem both with and without system losses consideration by Al-Saba and El-Amin [31]. The purpose of the TEP was to minimize the investment costs needed to handle the increased load and the additional generation requirements in terms of circuit additions and power losses. The TEP results reported in [31] are used to compare to the obtained results of this research project.

A differential evolution based method for power system planning problem was presented by Dong et al. [6]. The planning aimed at locating the minimum cost of additional transmission lines that must be added to satisfy the forecasted load in a power system. The planning in [6] considered several objectives including expansion investment cost, the reliability objective-expected energy not supplied, the social welfare objective-expected economical losses and the system expansion flexibility objective. Differential evolution could show its capability on handling integer variables and non-linear constrained multi-objective optimization problem.

In addition, a conventional differential evolution algorithm was successfully applied to static and dynamic transmission expansion planning by the author as shown in [15]. There were ten variations of DEA strategies to be employed for optimization. Overall, the DEA method performed superior to CGA for finding the optimal solutions and computational times in all study cases. Unfortunately, the conventional DEA method still has a drawback that is a tedious task of the DEA control parameters tuning due to complex relationship among problem's parameters. Therefore, the further research should be proposed for enhancing the conventional DEA performance.

CHAPTER 3

A SELF-ADAPTIVE DIFFERENTIAL EVOLUTION ALGORITHM FOR TRANSMISSION EXPANSION PLANNING WITH SYSTEM LOSSES CONSIDERATION

3.1 Introduction

Although a conventional DEA method has a number of merits as described in chapter 2, it still has a drawback that is a difficult task of the DEA control parameters tuning. Regarding such disadvantage of the conventional DEA characteristic, thus it should be enhanced the optimization performance in this research. A self-adaptive DEA (SaDEA) method is a modified version and has been proposed to solve the TEP problem with system losses consideration in this chapter. Several transmission expansion costs; an investment cost, a power losses cost, and a saved cost of the proposed SaDEA technique are compared to conventional genetic algorithm, tabu search, artificial neural networks, and hybrid artificial intelligent techniques reported in [31] on the Garver 6-bus test system and IEEE 25-bus test system.

The organization of this chapter is as follows: section 3.2 presents a formulation of TEP problem with system losses consideration. A SaDEA method is an enhanced version of the conventional DEA method and proposed in section 3.3. Section 3.4 states the implementation of the SaDEA method to handle the TEP problem with system losses consideration. Section 3.5 shows significant data of two selected electrical transmission systems to be tested the proposed algorithm. Meanwhile, the experimental results of these test systems are also included in the same section. Subsequently, these results are discussed and further analyzed in section 3.6. Finally, section 3.7 provides summary of this chapter.

3.2 Primal Transmission Expansion Planning with System Losses Consideration

A main purpose of solving the TEP problem with system losses consideration is to minimize the total expansion cost while satisfying technical and economical constraints. In this task, a classical DC power flow model is adopted to solve the TEP problem [31]. Mathematically, an objective function of such problem can be formulated as follows:

$$\text{Minimize } v = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} + K \sum_{m=1}^{NL} I_m^2 R_m \qquad (3.1)$$

where v, c_{ij} and n_{ij} represent transmission expansion cost, cost of a candidate circuit for addition to the branch *i-j*, and the number of circuits added to the branch *i-j,* respectively. Here Ω is the set of all candidate branches for expansion. In addition, K is a loss coefficient (calculated using K=8760$\times$ *NYE*$\times$ *C*kwh); *NYE* is an estimated life time of the expansion network (years); *C*kWh: is a cost of one kWh (US$/kWh); R_m is a resistance of the *m*th line; I_m is the flow on the *m*th line; and *NL* is the number of the existing lines.

The first term of objective function represents the capital cost of installed lines and the second term represents the cost of ohmic power losses after new line additions. The system power flow and losses are changed due to a result of line additions. The loss coefficient (K) depends upon number of years of transmission system operation and the kWh cost. The DC load flow is used in the problem formulation where current (I) is approximately equal to the power flow and voltage is assumed to be unity at all buses.

The objective function (3.1) of TEP problem with system losses consideration represents the expansion cost of newly installed transmission lines, which has some restrictions. These constraints must be included into mathematical model to ensure that the optimal solution satisfies transmission planning requirements. The TEP problem constraints are described in subsection 2.3.2 and can be formulated as following equations (2.5)-(2.10) in chapter 2.

3.3 An Enhanced Differential Evolution Algorithm Method

According to a difficult task of the DEA control parameters tuning due to complex relationship among problem's parameters has been a drawback of the conventional DEA method. Therefore, a further improvement of the conventional DEA method is essentially required before it can be generally adopted for practical use in industry. In this research, the conventional DEA method has been developed its optimization procedure. A self-adaptive DEA technique is proposed and explained in this section. The design of SaDEA optimization procedure is to develop two DEA control parameters, mutation factor (F) and crossover probability (CR), which are self-tuning parameters using probability methodology. This enhanced method is called "Method 2jDE" as found in [34].

As such proposed method, users must define two constant values (T_1 and T_2) that are the indices of control parameters (F and CR) changing, respectively. The user-defined values T_1 and T_2 are usually selected from within the range [0,1] and they are set as 0.1 in this research for avoiding local optimum trapping. The control parameters F and CR are updated in their setting bounds when the uniformly distributed random numbers within the range (0,1) are less than T_1 and T_2. The overall procedures of the SaDEA method can be summarized as follows:

Step 1: Set up all control parameters of the SaDEA method (F^{min}, F^{max}, CR^{min}, CR^{max}, T_1, T_2, N_P and D);

Step 2: Generate the initial values of the SaDEA control parameters (F and CR) to be applied to mutation and crossover processes;

Step 3: Initialize the population P of all individuals according to (2.13);

Step 4: Evaluate an initial population as initialized from step 3;

Step 5: Create mutant vectors from the population P using mutation operation;

Step 6: Create trial vectors using crossover operation;

Step 7: Evaluate the trial vectors as created from step 6;

Step 8: Select vector providing the best solution in present generation using selection operation for next computational generation;

Step 9: Update control parameter F, the F value is essential to update when a random value $rand_1$ (0,1) $<$ T_1;

Step 10: Updating control parameter CR, the CR value is essential to update when a random value $rand_2$ (0,1) $<$ T_2;

Step 11: Repeat the SaDEA optimization process from step 5 until step 10 across generations to improve the fitness values of candidate solutions;

Step 12: Verification of stop criterion, the overall optimization process is stopped whenever maximum number of generations is reached or any other predetermined convergence criterion is satisfied.

The main concept of a self-adaptive DEA optimization process is illustrated in figure 3.1.

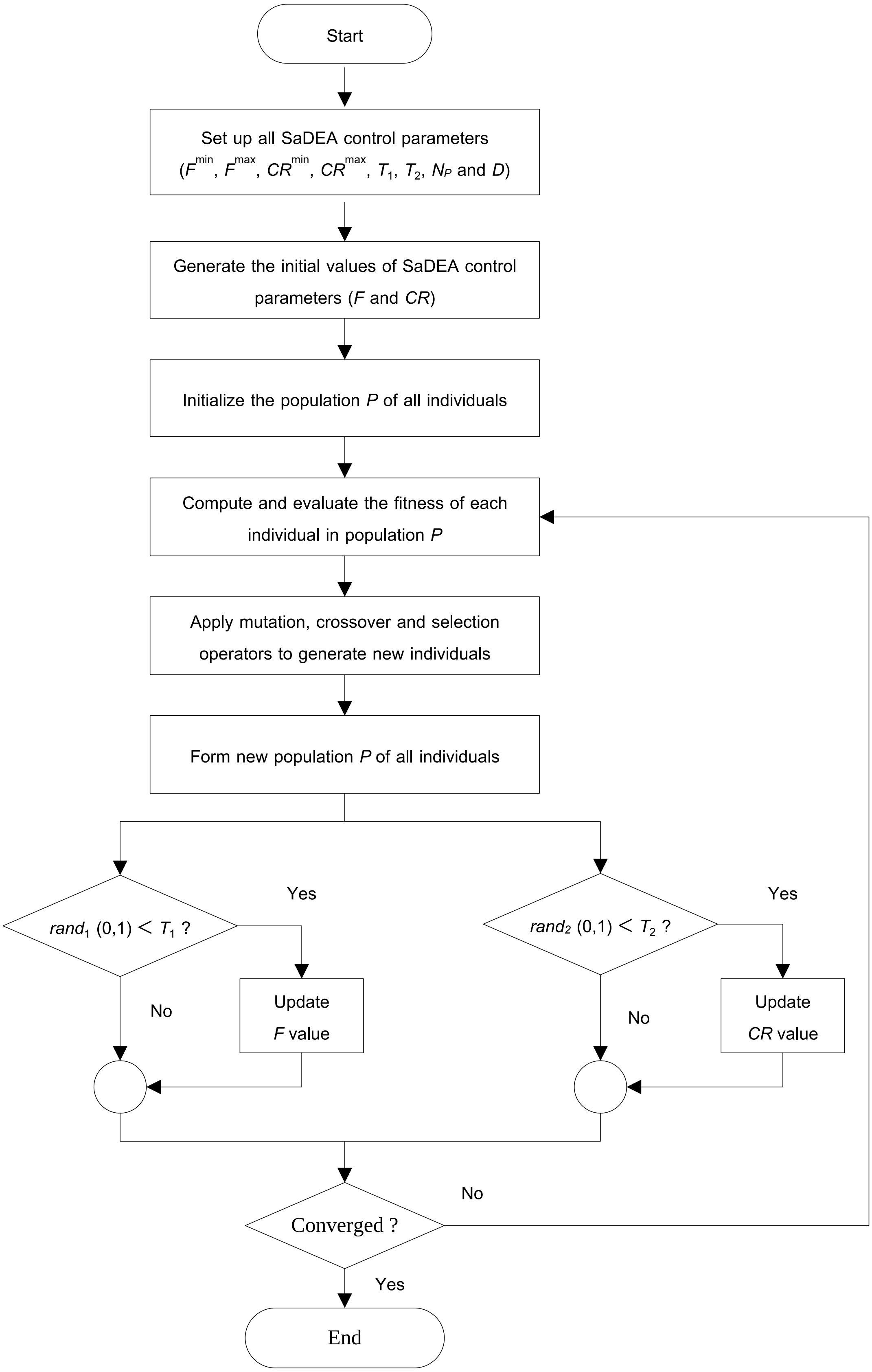

Figure 3.1 The main flowchart of a self-adaptive DEA optimization process

3.4 Implementation of a Self-Adaptive DEA Method for the TEP Problem with System Losses Consideration

Regarding a conventional differential evolution algorithm (CDEA) method (described in chapter 2) has the notable limitation of CDEA control parameter tuning due to a complex interaction of parameters. The SaDEA procedure is proposed to enhance the performance of conventional DEA method by reducing a tedious task of control parameters tuning. In addition, the SaDEA technique was successfully adopted to solve an economic dispatch problem in the previous author's work [35]. From the achieved successful results, the SaDEA method is proposed to solve the TEP problem with transmission system losses consideration in this research work.

3.4.1 The SaDEA Optimization Procedure

In the first step of SaDEA optimization process, users have to define two constant values (T_1 and T_2) that are the indices of control parameters (F and CR) changing. The user-defined values T_1 and T_2 are usually selected from within the range [0,1] and they are set as 0.1 in this work for avoiding local optimum trapping. The control parameters F and CR are updated in their setting bounds when the uniformly distributed random numbers within the range (0,1) are less than T_1 and T_2.

In the next step, an initial population is generated according to (2.13). For the TEP problem formulation, each individual vector (X_i) contains many integer-valued parameters n, where $n_{j,i}$ represents number of candidate lines in the possible branch j of the individual i. The problem decision parameter D is number of possible branches for expansion.

$$X_i^{(G)} = [n_{1,i}^{(G)}, ..., n_{j,i}^{(G)}, ..., n_{D,i}^{(G)}], \quad i = 1, ..., N_p \tag{3.2}$$

After new individuals are initialized successfully, then they are created by applying mutation (2.14), crossover (2.15), and selection (2.16) operators, respectively. The optimization process is repeated in search of the final solution until the maximum number of generations (G^{max}) is reached or other predetermined convergence criterion (ε) is satisfied.

3.4.2 Fitness Function of the TEP Problem Considering Line Losses

In this work, a fitness function $F(X)$ of the TEP problem is assigned according to (3.3) for each individual. The fitness function is a combination of an objective function and two penalty functions. The fitness function is adopted to find an optimal solution, measure the performance of candidate solutions, and check for violation of the TEP problem constraints.

An individual is the best solution if its fitness value $F(X)$ is highest. The penalty functions are also included in the fitness function in order to represent violations of both equality and inequality constraints. For the TEP problem, an equality constraint penalty function (3.5) considers the DC power flow node balance constraint and an inequality constraint penalty function (3.6) considers the constraints of power flow limit on each transmission line, power generation limit, bus voltage phase angle limit, and right-of-way, respectively. A general fitness function of the TEP problem can be formulated as follows:

$$F(X) = \frac{1}{O(X) + \omega_1 P_1(X) + \omega_2 P_2(X)} \tag{3.3}$$

$F(X)$ and $O(X)$ are fitness function and objective function of the TEP problem, respectively. $P_1(X)$ and $P_2(X)$ are the equality and inequality constraint penalty functions, respectively. X denotes the individual vector of decision variables. ω_1 and ω_2 are penalty weighting factors that are set to 0.5 in this work. For this TEP problem, the objective function and penalty functions are formulated as follows.

$$O(X) = V(X) = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} + K \sum_{m=1}^{NL} I_m^2 R_m \tag{3.4}$$

$$P_1(X) = \sum_{k=1}^{nb} \left| d_k + B_k \theta_k - g_k \right| \tag{3.5}$$

$$P_2(X) = \begin{cases} C & \text{if an individual violates the TEP} \\ & \text{inequality constraints.} \\ 0 & \text{otherwise} \end{cases} \tag{3.6}$$

where C is an inequality constraint constant that is used when an individual violates the inequality constraints. In this work, the constant C is set as 0.5 for all cases.

3.4.3 Control Parameters Setting

A proper selection of the SaDEA control parameters is very essential to algorithm performance and success when searching optimal solution. In this simulation, the setting ranges of the SaDEA control parameters used in the TEP problem are as follows: F = [0.4,1], CR = [0.8,1] and N_P = [5*D,10*D]. The maximum predetermined convergence criterion (ε) is set to $1\text{x}10^{-4}$ and the maximum number of generations (G^{max}) is set to $1\text{x}10^{3}$.

3.4.4 Overall Procedures of the SaDEA Optimization Program for TEP Problem

The overall procedures of the SaDEA method for solving the TEP problem can be summarized as follows:

Step 1: Read all required system data;

Step 2: Set up two constant values T_1 and T_2 for simulation;

Step 3: Set iteration G = 0 for an initialization step of the SaDEA procedure;

Step 4: Initialize the SaDEA control parameters F and CR;

Step 5: Initialize the population P of all individuals according to (2.13);

Step 6: Evaluate the fitness function according to (3.3) and then check violations of all constraints for each individual using (3.5) and (3.6);

Step 7: Rank all individuals according to their fitness;

Step 8: Updating control parameter F, the F value is essential to updated when a random value $rand_1\ (0,1) < T_1$;

Step 9: Updating control parameter CR, the CR value is essential to updated when a random value $rand_2\ (0,1) < T_2$;

Step 10: Set iteration G = 1 for the next step of the SaDEA optimization process;

Step 11: Apply mutation, crossover, and selection operations to create new individuals;

Step 12: Evaluate the fitness function by using (3.3) and then check violations of all constraints for each new individual using (3.5) and (3.6);

Step 13: Rank new individuals according to their fitness;

Step 14: Updating F, the F value is updated when a random value $rand_1\ (0,1) < T_1$;

Step 15: Updating CR, the CR value is updated when random value $rand_2\ (0,1) < T_2$;

Step 16: Verification of stop criterion, if $\left|F(X)^{G} - F(X)^{G-1}\right| > \varepsilon$ or $G < G^{max}$, set $G = G + 1$ and return to step 11 for repeating to search the final solution. Otherwise, stop to calculate and go to step 17;

Step 17: Compute and display the final solutions, which are an investment cost, a system losses cost, and a total expansion cost.

A computer program of the SaDEA method application to TEP problem with system losses consideration has been designed and performed as above procedures. This proposed computational program is illustrated in figure 3.2.

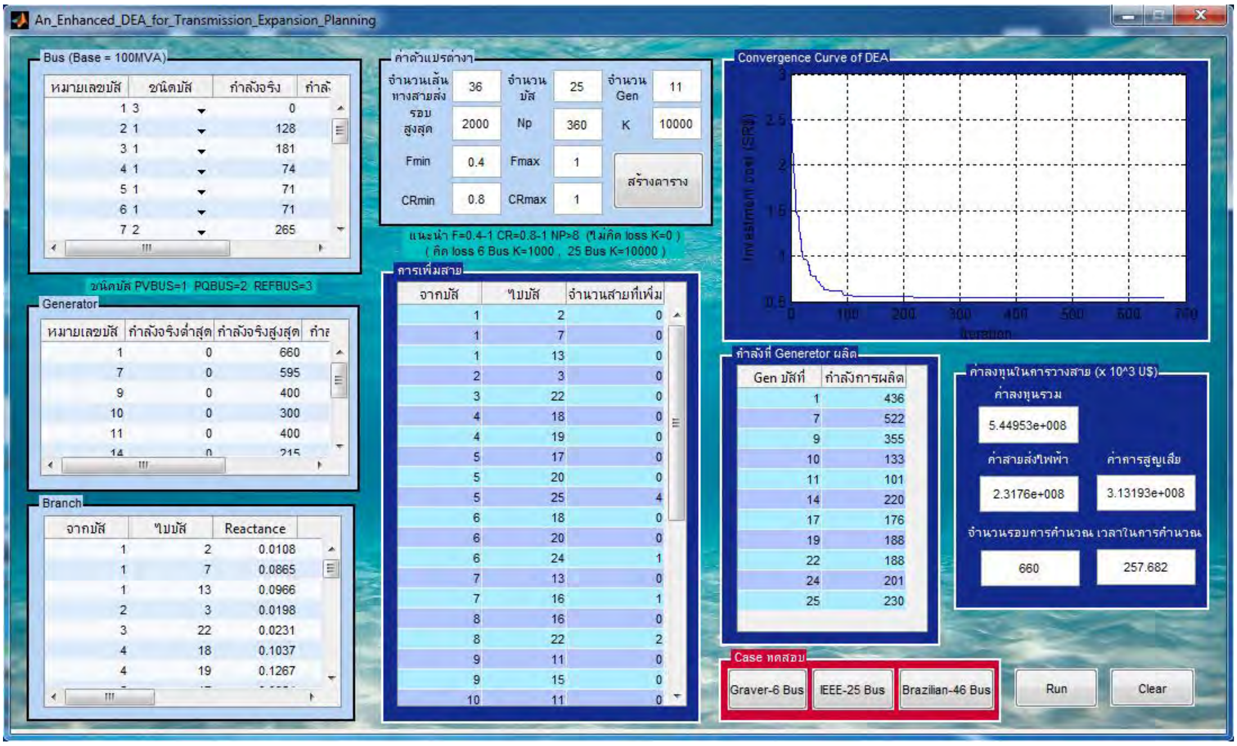

Figure 3.2 Example of the SaDEA optimization program for TEP problem with line losses consideration

3.5 Test Systems and Numerical Test Results

In the simulation, the proposed SaDEA procedure has been implemented in MATLAB and tested its performance on two electrical transmission systems as shown in appendix A. These two test networks are Garver's 6-bus system and IEEE 25-bus system, which all significant data are also available in [17] and [27]. In this work, the TEP problem is analyzed including system losses consideration. In addition, the TEP problem has been investigated in two cases that are with and without power generation resizing considerations. In case of with generation resizing consideration, the generated MW power at each generator varies between g_i^{min} and g_i^{max}, of which the details are explained in section 2.3. For the experiment, the values of g_i^{min} are set to “0” MW for all generating units in two test systems. Meanwhile, setting data of g_i^{max} are referred to as presented in appendix A. The simulation results of the proposed SaDEA technique have been compared to conventional genetic algorithm (CGA), tabu search (TS), artificial neural networks (ANNs), hybrid artificial intelligent techniques and summarized in this chapter.

3.5.1 Garver 6-bus System

The first test system of this simulation is a well-known Garver's system, which comprises 6 buses, 9 possible branches, and 760 MW of power demand. The electrical system data; transmission line, load, and generation data are available in [17]. From this test system configuration, bus-6 is a new generation bus and needs to be connected to the existing network. A maximum of four parallel lines is permitted in each branch. In this simulation case, the power losses consideration is included in the objective function where the loss coefficient, *K*, was selected as 1000. The per-unit base in the DC-load flow analysis is 100 MVA while the cost base is 10^5. The estimated lifetime of transmission lines was assumed to be 25 years and the cost of one kWh was assumed to be 0.005 monetary units/kWh found in [31]. Numerical test results of the proposed method are shown in table 3.1-3.2 for each case and then the best solutions of SaDEA method are summarized and compared to other techniques in table 3.3.

3.5.1.1 Without Generation Resizing Consideration - Garver's System

For the Graver's 6-bus test system, the obtained results of TEP problem considering line losses in case of without generation resizing are presented in table 3.1 and figure 3.3.

Table 3.1 Summary results of Garver 6-bus system without generation resizing case

Results of the TEP with line losses consideration (without power gen resizing)	The SaDEA method
Best total cost	673.54
Average total cost	686.79
Worst total cost	739.83
% Difference between best and worst	9.84
Standard deviation	27.95
Average CPU time (second)	2.78
Line additions for the best result	$n_{2\text{-}6}$ = 4, $n_{3\text{-}5}$ = 1, $n_{4\text{-}6}$ = 3 and $n_{5\text{-}6}$ = 1

The achieved results of this case are discussed as follows:

- In the first case, the total TEP cost (investment cost + losses cost) of the optimal solution equals to 673.54 with the following topology: $n_{2\text{-}6}$ = 4, $n_{3\text{-}5}$ = 1, $n_{4\text{-}6}$ = 3 and $n_{5\text{-}6}$ = 1.
- A convergence curve of SaDEA method to obtain the optimal solution is illustrated in figure 3.3, where the optimal solution was found by SaDEA method at the 12^{nd} iteration.
- An average computational time of the proposed method is 2.78 second in this test case.

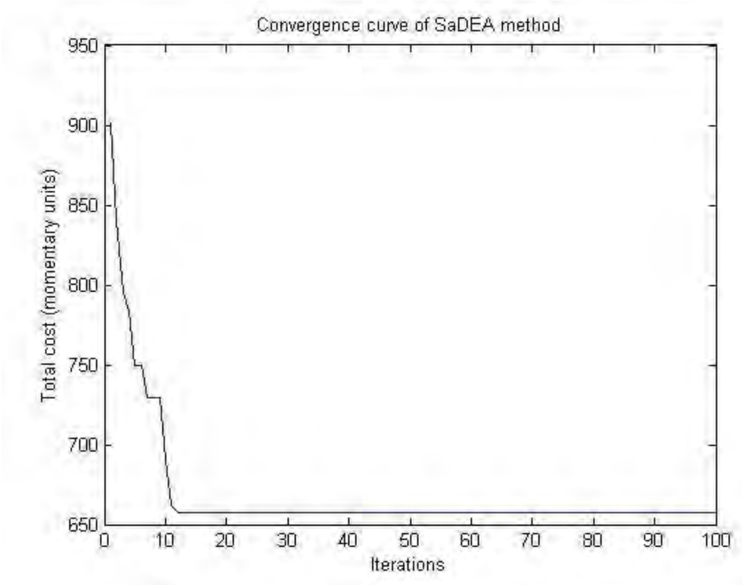

Figure 3.3 A convergence curve of SaDEA method for Garver 6-bus system without generation resizing case

3.5.1.2 With Generation Resizing Consideration - Garver's System

In the second case, test results of TEP problem on the Graver's 6-bus system are shown in table 3.2 and figure 3.4.

Table 3.2 Summary results of Garver 6-bus system with generation resizing case

Results of the TEP with line losses consideration (with power gen resizing)	The SaDEA method
Best total cost	401.66
Average total cost	403.32
Worst total cost	413.98
% Difference between best and worst	3.07
Standard deviation	2.27
Average CPU time (second)	38.94
Line additions for the best result	$n_{2\text{-}3}$ = 2, $n_{3\text{-}5}$ = 2 and $n_{4\text{-}6}$ = 3

The obtained results of the TEP with generation resizing case are explained as follows:

- Regarding an optimal solution of the TEP problem with power generation resizing consideration, the total TEP cost equals to 401.66 at the following topology: $n_{2\text{-}3}$ = 2, $n_{3\text{-}5}$ = 2 and $n_{4\text{-}6}$ = 3.

- A convergence curve of the SaDEA method to obtain the best solution is illustrated in figure 3.4. In this case, the optimal solution was found by SaDEA method at the 155th iteration.
- According to obtained results in table 3.2, a performance of SaDEA method is very robust to find the solution, as suggested by small values of a standard deviation and percent difference between best and worst results.
- In this case, an average CPU time of the proposed method is 38.94 second.

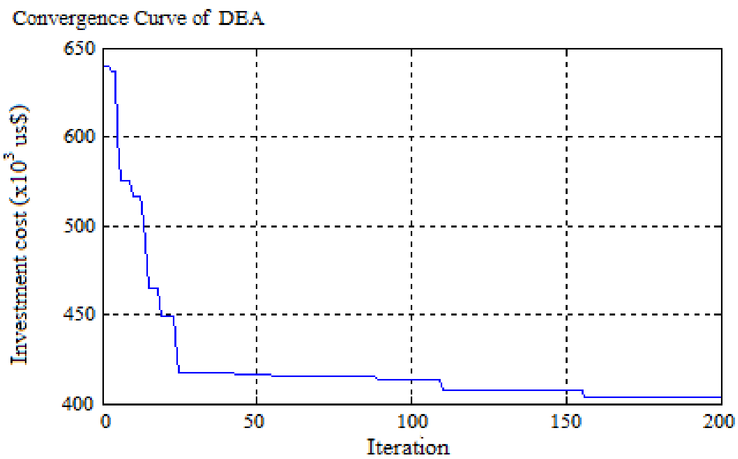

Figure 3.4 A convergence curve of SaDEA method for Garver 6-bus system with generation resizing case

Table 3.3 Comparison of Expansion Costs among Various Methods for Garver 6-Bus Test System

Types of TEP problem	K=1000			
	Methods	**Investment cost**	**Losses cost “a”**	**Saved cost “b”**
TEP without the resizing of power generation	ANNs [31]	261	448.83	904.77
	TS [31]	291	382.54	971.06
	GA [3]	291	382.54	971.06
	Hybrid ANN-TS-GA [31]	291	382.54	971.06
	SaDEA	291	382.54	971.06
TEP with the resizing of power generation	SaDEA	170	231.66	1,121.94

Note: The losses cost “a” after the new line addition is calculated for 25 years. The saved cost “b” is calculated as a difference cost between the cost of ohmic power losses before the expansion of the transmission network (1353.6 monetary units) based on a 25-year (life-time of line) and the power losses cost “a” calculated after the new line additions for the same period.

For a case study of without power generation resizing consideration, the best solution of TEP problem considering system losses on Garver’s test system as shown in table 3.3 was found by all algorithms except ANNs method. Although the ANNs method obtained the least investment cost compared to other methods but it had the largest value of power losses cost after the new line additions. The SaDEA method obtained the investment cost and losses cost for with power generation resizing case study cheaper than the without power generation resizing case study. In addition, the SaDEA method had the largest saved cost of minimizing ohmic power losses during planning horizon in case of with power generation resizing consideration.

3.5.2 IEEE 25-bus System

The IEEE 25-bus system is selected to test the SaDEA procedure in this work. It consists of 25 buses, 36 possible branches, and 2750 MW of total power demand. The electrical system data; transmission line, load, and generation data are available in [27] and [31]. A new bus of this system is bus-25 that is prepared for connecting to bus-5 and/or bus-24. A maximum of four parallel lines is permitted to install in each branch. In this simulation case, the objective function includes power losses consideration, in which the loss coefficient, K, was selected to be 10000. The estimated lifetime of the transmission lines was assumed to be 25 years while the cost of one kWh was assumed to be 0.0112 US$/kWh [31]. In this case study, numerical test results of the SaDEA method are put in table 3.4-3.6 where the comparisons among the proposed method and other techniques from [31] are also included in table 3.6.

3.5.2.1 Without Generation Resizing Consideration - IEEE 25-System

According to the TEP problem without generation resizing consideration, the results of testing the proposed algorithm to IEEE 25-bus system are shown in table 3.4. These results are discussed as follows:

- In this case, the best solution of TEP problem without power generation resizing consideration was found by the SaDEA method and a total TEP cost was 294.302 million US$ as shown in table 3.4, with the addition of the following lines to the base topology: $n_{7\text{-}13} = 2$, $n_{8\text{-}22} = 3$, $n_{11\text{-}14} = 2$, $n_{12\text{-}14} = 2$, $n_{12\text{-}23} = 3$, $n_{13\text{-}18} = 2$, $n_{13\text{-}20} = 3$, $n_{16\text{-}18} = 3$, $n_{16\text{-}20} = 3$, $n_{20\text{-}21} = 1$, $n_{5\text{-}25} = 3$ and $n_{24\text{-}25} = 2$.
- In this case, the optimal solution was found by SaDEA method at the 88th iteration and an average CPU time of the proposed method is 84.58 second.

Table 3.4 Summary results of IEEE 25-bus system without generation resizing case

Results of the TEP with line losses consideration (without power gen resizing)	The SaDEA method
Best total cost (million US$)	294.302
Average total cost (million US$)	305.023
Worst total cost (million US$)	321.104
% Difference between best and worst	9.11
Standard deviation (million US$)	13.840
Average CPU time (second)	84.58
Line additions for the best result	$n_{7\text{-}13}$ = 2, $n_{8\text{-}22}$ = 3, $n_{11\text{-}14}$ = 2, $n_{12\text{-}14}$ = 2, $n_{12\text{-}23}$ = 3, $n_{13\text{-}18}$ = 2, $n_{13\text{-}20}$ = 3, $n_{16\text{-}18}$ = 3, $n_{16\text{-}20}$ = 3, $n_{20\text{-}21}$ = 1, $n_{5\text{-}25}$ = 3 and $n_{24\text{-}25}$ = 2

3.5.2.2 With Generation Resizing Consideration - IEEE 25-System

The obtained results of IEEE 25-bus system in case of with power generation resizing consideration can be shown in table 3.5 including the result discussion as follows:

Table 3.5 Summary results of IEEE 25-bus system with generation resizing case

Results of the TEP with line losses consideration (with power gen resizing)	The SaDEA method
Best total cost (million US$)	144.834
Average total cost (million US$)	145.1536
Worst total cost (million US$)	146.432
% Difference between best and worst	1.10
Standard deviation (million US$)	0.673776
Average CPU time (second)	237.29
Line additions for the best result	$n_{5\text{-}25}$ = 4, $n_{6\text{-}24}$ = 1, $n_{7\text{-}16}$ = 1, $n_{8\text{-}22}$ = 2, $n_{12\text{-}23}$ = 1, $n_{13\text{-}18}$ = 3, $n_{13\text{-}20}$ = 2, $n_{16\text{-}18}$ = 1 and $n_{24\text{-}25}$ = 1

- The necessary total expansion cost of the TEP problem with generation resizing consideration for this test system is 144.834 million US$ and the following lines are added: $n_{5\text{-}25}$ = 4, $n_{6\text{-}24}$ = 1, $n_{7\text{-}16}$ = 1, $n_{8\text{-}22}$ = 2, $n_{12\text{-}23}$ = 1, $n_{13\text{-}18}$ = 3, $n_{13\text{-}20}$ = 2, $n_{16\text{-}18}$ = 1 and $n_{24\text{-}25}$ = 1.

- In this case, the best solution was found by SaDEA method at the 226th iteration and an average calculation time of the proposed method is 237.29 second.

Table 3.6 Comparison of Expansion Costs among Various Methods for IEEE 25-Bus Test System

Types of TEP problem	**K=10000**			
	Methods	**Investment cost (million US$)**	**Losses cost "a" (million US$)**	**Saved cost "b" (million US$)**
TEP without the resizing of power generation	ANNs [31]	224.178	161.995	147.979
	TS [31]	180.664	155.264	154.709
	GA [31]	162.430	171.947	138.016
	Hybrid ANN-TS-GA [31]	168.784	152.320	157.653
	SaDEA	160.051	134.251	175.722
TEP with the resizing of power generation	SaDEA	61.802	83.032	226.941

Note: The losses cost "a" after the new line addition is calculated for 25 years. The saved cost "b" is calculated as the difference cost between the cost of ohmic power losses before the expansion of the transmission system (309.973 million US$) based on a 25-year (life-time of line) and the power losses cost "a" calculated after the new line additions for the same period.

For a case study of without power generation resizing consideration, the best solution of the TEP problem with system losses consideration was found by SaDEA method and an investment cost was 160.051 million US$ as shown in table 3.6. In addition, the SaDEA method achieved the least value of a power losses cost after the new line additions compared to other techniques. Comparison between with and without power generation resizing consideration, the SaDEA method obtained the investment cost and losses cost for with power generation resizing case study cheaper than the without power generation resizing case study. Therefore the SaDEA got the largest value of a saved cost of minimizing ohmic power losses during expansion planning horizon in this test system. Overall, the best algorithmic procedure for this case is SaDEA method.

3.6 Discussion on the Results

All obtained results in table 3.3 and 3.6 clearly indicate that SaDEA method can be efficiently applied to the TEP problem with line losses consideration. The proposed technique shows better overall performance especially in robustness than other algorithms in the optimization of the TEP problem both with and without generation resizing investigations. The proposed algorithm was tested 50 times to find the best results in each case and the control parameters were set as explained in section 3.4.3.

3.7 Conclusion

In this chapter, a SaDEA method is applied when solving the TEP problem with system losses consideration. In addition, the TEP problem is also included both with and without power generation resizing considerations. Regarding the achieved results on two test networks illustrate that the SaDEA procedure is an efficient technique for solving the transmission planning problem. As the numerical test results in table 3.3 and 3.6 indicate, the proposed method obtained the least values of an investment cost and a power losses cost compared to the conventional genetic algorithm, the tabu search, the artificial neural networks, and the hybrid artificial intelligent techniques on two test systems. In addition, the SaDEA method had the largest saved cost of ohmic power losses for both test cases as shown in table 3.3 and table 3.6. The most attractive feature of the proposed algorithm is the good computational performance. The accuracy of the results obtained in the TEP study is in very good agreement with those obtained by other researchers as found in [31]. Regarding a consequence of these successful results, the TEP problem considering the *n*-1 contingencies in single line outage or single generator outage will be investigated as future work.

CHAPTER 4

AN ENHANCED DIFFERENTIAL EVOLUTION ALGORITHM APPLICATION TO TRANSMISSION EXPANSION PLANNING WITH SECURITY CONSTRAINT CONSIDERATION

4.1 Introduction

Regarding a previous work in chapter 3, an enhanced DEA methodology, called a self-adaptive DEA (SaDEA) procedure, is directly applied to DC power flow based model in order to solve the TEP problem with system losses consideration. The SaDEA method performed well with regard to both low and medium complex transmission networks as demonstrated on Garver six-bus system and IEEE 25-bus system, respectively. As a consequence of these successful results obtained from solving such TEP problem, the SaDEA technique has been implemented again to deal with a TEP problem with security criterion consideration, which is more complex and difficult to be solved than basic TEP problem. The TEP problem considering security constraint is determined not only the optimal number of new transmission lines and their locations but also the most reliable planning when a single line is outage. In this research, the effectiveness of the proposed enhancement is initially demonstrated by the analyses of low, medium, and highly complex transmission test systems. The analyses are performed within a mathematical programming environment of MATLAB using both the enhanced DEA and the conventional DEA methods and a detailed comparison of accuracy and performance is also presented in this chapter.

An outline of this chapter is as follows: Section 4.2 presents formulation of TEP problem with *n*-1 security criterion consideration. Section 4.3 explains implementation of SaDEA procedure for solving the proposed TEP problem, and then all details of the SaDEA optimization program for approaching this planning problem are also included in the same section. The significant data of selected test systems are given in section 4.4 and the achieved experimental results are also reported in this section. Finally, the discussion and conclusion of test results are given in section 4.5 and 4.6, respectively.

4.2 Primal Transmission Expansion Planning with Security Constraint Consideration

The main purpose of solving the TEP problem with *n*-1 security criterion consideration is to minimize total expansion cost while satisfying economical, technical, and reliable constraints. In this work, a classical DC power flow model is adopted to solve the TEP problem with security constraints consideration as found in [36]. Mathematically, an objective function of such problem can be formulated as follows:

$$\min \quad v = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} \tag{4.1}$$

Subject to

$$n = \{n_{ij}\} \in \text{OPC} \tag{4.2}$$

$$n = \{n_{ij}\} \in \text{SCC} \tag{4.3}$$

where Ω is set of all candidate branches for expansion. The OPC represents the planning operational constraints without security as explained in subsection 2.3.2 and can be formulated as following equations (2.5)-(2.10). Moreover, the SCC represents the security constraints including in the TEP problem. In this chapter, the TEP problem is investigated that the system operates with security and satisfied *n*-1 criterion. In this context, the SCC constraints to the problem with *nl* paths to expansion presents the following equations:

- **DC Power Flow Node Balance Constraint**

This linear equality constraint represents the conservation of power at each node.

$$g^{p} = d + [B\theta]^{p} \tag{4.4}$$

where g^p, *d*, and *B* are real power generation vector in existing power plants, real load demand vector in all network nodes, and susceptance matrix of the existing and added lines in the network, respectively. Here θ is the bus voltage phase angle vector.

- **Power Flow Limit on Transmission Lines Constraint**

The following inequality constraint is applied to TEP problem with security criterion consideration in order to limit the power flow for each path.

$$\left| f_{ij}^{p} \right| \le (n_{ij}^{0} + n_{ij}) f_{ij}^{\max} \quad \forall (i,j) \in 1,2,...,nl; \quad \text{and } (i,j) \ne p \tag{4.5}$$

$$\left| f_{ij}^{p} \right| \le (n_{ij}^{0} + n_{ij} - 1) f_{ij}^{\max} \quad \text{for } (i,j) = p \tag{4.6}$$

In DC power flow model, each element of branch power flow in constraints (4.5) and (4.6) can be calculated using (4.7) and (4.8), respectively:

$$f_{ij}^{p} = \frac{(n_{ij}^{0} + n_{ij})}{x_{ij}} \times (\theta_i^p - \theta_j^p) \quad \forall (i,j) \in 1,2,...,nl; \quad \text{and } (i,j) \ne p \tag{4.7}$$

$$f_{ij}^{p} = \frac{(n_{ij}^{0} + n_{ij} - 1)}{x_{ij}} \times (\theta_i^p - \theta_j^p) \quad (i,j) = p \tag{4.8}$$

where f_{ij}^{p}, $f_{ij}^{\max}$, n_{ij}, n_{ij}^{0} and x_{ij} represent total branch power flow in branch *i-j*, maximum branch power flow in branch *i-j*, number of circuits added to branch *i-j*, number of circuits in original base system, and reactance of the branch *i-j*, respectively. Here θ_i^p and θ_j^p are voltage phase angle of the terminal buses *i* and *j*, respectively.

- **Power Generation Limit Constraint**

In the TEP problem, power generation limit must be included into the problem constraints. This can be mathematically represented as follows:

$$g_i^{\min} \le g_i^{p} \le g_i^{\max} \tag{4.9}$$

where g_i^{p}, $g_i^{\min}$ and $g_i^{\max}$ are real power generation at node *i*, the lower and upper real power generation limits at node *i,* respectively.

- **Right-of-way Constraint**

Mathematically, this constraint defines location and maximum number of circuits, which can be installed in a specified location. It can be represented as follows:

$$0 \le n_{ij} \le n_{ij}^{\max} \tag{4.10}$$

where n_{ij} and $n_{ij}^{\max}$ represent total integer number of circuits added to the branch *i-j* and maximum number of added circuits in the branch *i-j,* respectively.

- **Bus Voltage Phase Angle Limit Constraint**

A calculated phase angle (θ_{ij}^{cal}) should be less than a predefined maximum phase angle ($\theta_{ij}^{\max}$). Such constraint can be represented as the following mathematical expression.

$$\left|\theta_{ij}^{\text{cal}}\right| \le \left|\theta_{ij}^{\max}\right| \tag{4.11}$$

- **Other TEP Constraint**

In this TEP problem, several significant constraints must be included as follows:

$$(n_{ij} + n_{ij}^{0} - 1) \ge 0 \quad \text{and integer for } (i, j) = p \tag{4.12}$$

$$n_{ij} \ge 0 \quad \text{and integer } \forall (i, j) \in 1,2,...,nl; \quad \text{and } (i, j) \ne p \tag{4.13}$$

$$f_{ij}^{p} \text{ and } \theta_{\mathrm{j}}^{\mathrm{p}} \quad \text{unbounded} \tag{4.14}$$

$$(i, j) \in \Omega \quad \text{and } p = 1, 2, ..., nl \tag{4.15}$$

For this problem formulation, there are *nl* sets of operational variables, a set to each contingency when it is considered all paths $p = (i,j) \in \Omega$.

4.3 Implementation of an Enhanced DEA Method for the TEP Problem with Security Constraint Consideration

An enhanced DEA method is proposed to solve the TEP problem with security constraint consideration as formulated in previous section. The proposed method can be implemented to handle such problem as following details.

4.3.1 An Enhanced DEA Optimization Method

In this research, a design of a SaDEA procedure is to develop two DEA control parameters, mutation factor (F) and crossover probability (CR), which are self-tuning parameters using probability methodology. This enhanced method is called “Method 2jDE” as found in [34]. In the first step of SaDEA optimization process, users must determine two constant values (T_1 and T_2), which are the indices of control parameters (F and CR) changing. The user-defined values T_1 and T_2 are usually chosen from within the range [0,1] and set as 0.1 in this work for avoiding local optimum trapping. These control parameters F and CR are updated in their setting bounds when the uniformly distributed random numbers within the range (0,1) are less than T_1 and T_2.

After two constant values are set by users, then an initial population is generated according to (2.13). In the TEP problem formulation, each individual vector (X_i) contains many integer-valued parameters n, where $n_{j,i}$ represents the number of candidate lines in the possible branch j of the individual i. The problem decision parameter D is the number of possible branches for expansion.

$$X_i^{(G)} = [n_{1,i}^{(G)}, \ldots, n_{j,i}^{(G)}, \ldots, n_{D,i}^{(G)}], \quad i = 1, \ldots, N_p \tag{4.16}$$

When an initial population of individuals is initialized successfully, then three DEA operators (2.14)-(2.16) create the population of next generation $P^{(G+1)}$ by using current population $P^{(G)}$. The optimization process is continuously repeated in search of final solution until the maximum number of generations (G^{max}) is reached or other predetermined convergence criterion (ε) is satisfied.

4.3.2 Fitness Function of the TEP Considering Security Constraint

A fitness function of TEP problem is applied to search the optimal solution, measure the performance of candidate solutions, and check for violation of the TEP problem constraints. The TEP fitness function $F(X)$ is a combination of an objective function and two penalty functions and can be formulated according to (4.17) for each individual. An individual is the best solution if its fitness value $F(X)$ is highest. The penalty functions must be also included in the fitness function in order to represent violations of both planning operational constraints without security (OPC) and the planning security constraints (SCC) of TEP problem. Regarding the proposed problem, the OPC penalty function (4.19) investigates all constraints of TEP problem without security criterion consideration. In addition, the SCC penalty function (4.20) investigates all security constraints of TEP problem. The general fitness function of the TEP problem can be assigned as follows:

$$F(X) = \frac{1}{O(X) + \omega_1 P_1(X) + \omega_2 P_2(X)} \tag{4.17}$$

In (4.17), $F(X)$ and $O(X)$ represent fitness function and objective function of the TEP problem, respectively. $P_1(X)$ and $P_2(X)$ are the constraint penalty functions. X denotes the individual vector of decision variables. In this work, ω_1 and ω_2 are penalty weighting factors and set to 0.5, respectively. For this TEP problem, the objective function and the constraint penalty functions are formulated as follows.

$$O(X) = V(X) = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} \tag{4.18}$$

$$P_1(X) = \begin{cases} C_1 & \text{if an individual violates the OPC of TEP problem.} \\ 0 & \text{otherwise} \end{cases} \tag{4.19}$$

$$P_2(X) = \begin{cases} C_2 & \text{if an individual violates the SCC of TEP problem.} \\ 0 & \text{otherwise} \end{cases} \tag{4.20}$$

where C_1 and C_2 are the constraint constants, which are applied to problem when an individual violates the OPC and SCC of TEP problem, respectively. In this work, both constants C_1 and C_2 are set as 0.5 for all cases.

4.3.3 Control Parameters Setting

The SaDEA optimization performance depends on the suitable values of control parameters. In this simulation, the setting ranges of SaDEA control parameters used in the TEP problem are as follows: F = [0.5,1], CR = [0.6,1] and N_P = [5*D,10*D]. The maximum predetermined convergence criterion (ε) is set to $1\text{x}10^{-4}$ and the maximum number of generations (G^{max}) is set to $3\text{x}10^{3}$.

4.3.4 Overall Procedures

The overall procedures of the SaDEA method application to TEP problem with n-1 security criterion consideration can be summarized as follows:

Step 1: Read all required transmission system data;

Step 2: Set up all control parameters of the SaDEA method (F^{min}, F^{max}, CR^{min}, CR^{max}, T_1, T_2, N_P and D);

Step 3: Create the initial values of the SaDEA control parameters (F and CR) to be applied to mutation and crossover operators;

Step 4: Set initial iteration G = 0 for an initialization step of the SaDEA procedure;

Step 5: Initialize the population P of all individuals according to (2.13);

Step 6: Evaluate the fitness function according to (4.17) and then check violations of all constraints for each individual using (4.19) and (4.20);

Step 7: Check n-1 security criterion for all constraints (4.4)-(4.15);

Step 8: Rank all individuals according to their fitness;

Step 9: Updating F, the F value is updated when a random value $rand_1$ (0,1) $<$ T_1;

Step 10: Updating CR, the CR value is updated when a random value $rand_2$ (0,1) $<$ T_2;

Step 11: Set iteration G = 1 for the next step of the SaDEA optimization process;

Step 12: Apply mutation, crossover and selection operations to create new individuals;

Step 13: Evaluate the fitness function by using (4.17) and then check violations of all constraints for each new individual using (4.19) and (4.20);

Step 14: Check n-1 security criterion for all constraints (4.4)-(4.15);

Step 15: Rank new individuals according to their fitness;

Step 16: Updating F, the F value is updated when a random value $rand_1$ (0,1) $<$ T_1;

Step 17: Updating CR, the CR value is updated when random value $rand_2$ (0,1) $<$ T_2;

Step 18: Verification of stop criterion, if $\left|F(X)^{G} - F(X)^{G-1}\right| > \varepsilon$ or $G < G^{max}$, set $G = G + 1$ and return to step 12 for repeating to search the final solution. Otherwise, stop to calculate and go to step 19;

Step 19: Compute and display the final solutions, which are an investment cost and a convergence curve.

A computer program of the SaDEA method for application to TEP problem with security constraint consideration has been designed and performed as above procedures. This proposed computational program is illustrated in figure 4.1.

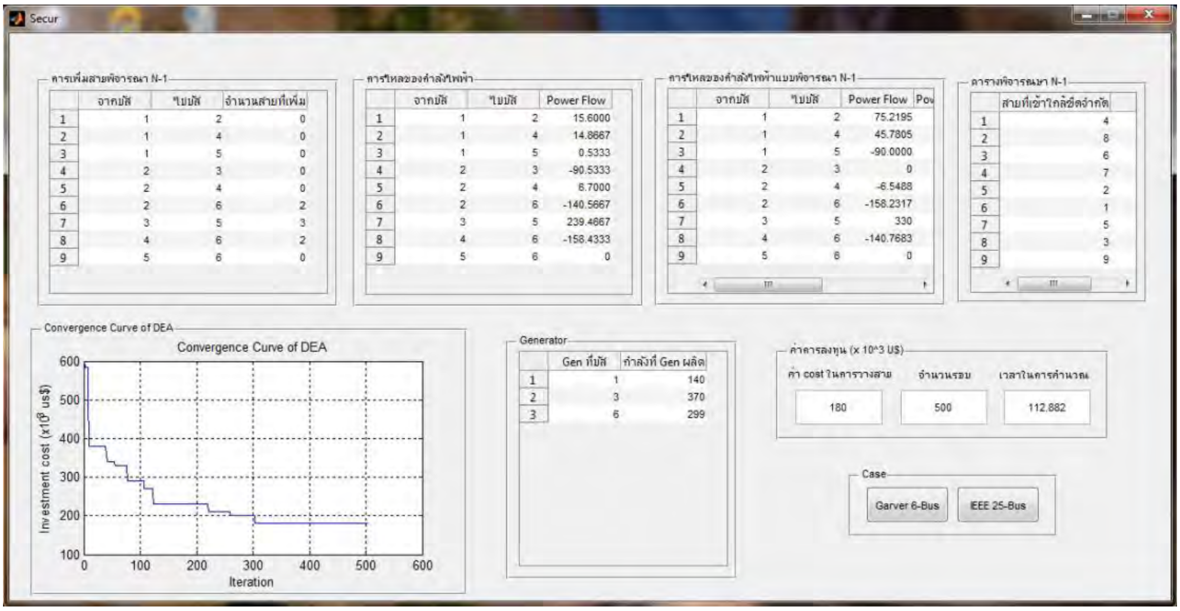

Figure 4.1 Example of the SaDEA optimization program for TEP problem with security constraint consideration

4.4 Test Systems and Numerical Test Results

In the simulation, the proposed enhanced DEA procedure is implemented in MATLAB and has been tested its performance on three electrical transmission systems as reported in appendix A. These three test networks are the Garver's 6-bus system, the Brazilian 46-bus system, and the IEEE 25-bus system and all required data are also available in [17], [25] and [27], respectively. In this chapter, the proposed method is applied to handle the TEP problem considering security constraint that is more difficult for solving than the basic TEP problem.

Moreover, such TEP problem includes an issue of power generation resizing consideration. The numerical results of proposed SaDEA technique are compared to conventional differential evolution algorithm (DEA), ant colony search algorithm (ACSA), Chu-Beasley genetic algorithm (CBGA) and also summarized in this section.

4.4.1 Garver 6-bus System

In this research, Garver's system is the first test network employed for investigation. It consists of 6 buses, 9 possible branches, and 760 MW of demand. The electrical system data; transmission line, load, and generation data are available in [17]. In this test system, bus-6 is a new generation bus that needs to be connected to the existing network. The dotted lines represent new possible line additions and solid lines are the existing lines as shown in figure A1. A maximum of four parallel transmission lines is allowed to install in each branch.

The achieved results of SaDEA method on the Garver 6-bus system can be tabulated in table 4.1 including the discussion of these results as follows:

- For the first case, a total expansion cost of the best solution equals to 180,000 US$ with the following topology: $n_{2\text{-}6} = 2$, $n_{3\text{-}5} = 3$, and $n_{4\text{-}6} = 2$.
- A convergence curve of SaDEA method to obtain the best solution is illustrated in figure 4.2, where the optimal solution was found by SaDEA method at the 152nd iteration.
- An average computational time of the proposed method is 64.03 second in this test case.

Table 4.1 Summary results of Garver 6-bus system

Results of the TEP with security constraint consideration	The SaDEA method
Best total cost (x10^3 US$)	180
Average total cost (x10^3 US$)	187
Worst total cost (x10^3 US$)	210
% Difference between best and worst	16.67
Standard deviation (x10^3 US$)	11.60
Average CPU time (second)	64.03
Line additions for the best result	$n_{2\text{-}6} = 2$, $n_{3\text{-}5} = 3$, and $n_{4\text{-}6} = 2$

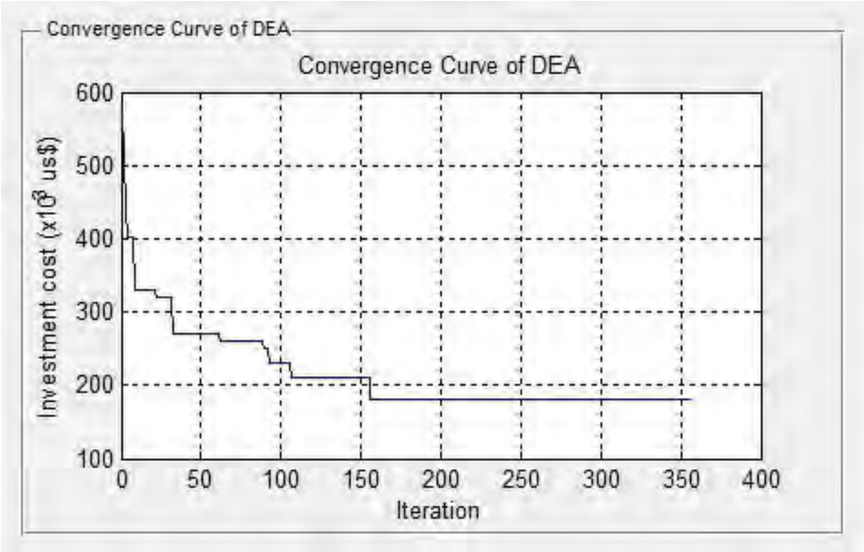

Figure 4.2 A convergence curve of SaDEA method for Garver 6-bus system

Table 4.2 Summary power flow at each right-of-way of Garver 6-bus system (Before considering *n*-1 security criterion)

Line path between buses	Power Flow (MW)	Max Power Flow (MW)
2-3	82.1675	100
4-6	157.7034	200
2-6	143.2966	200
3-5	225.8325	400
1-4	16.894	80
1-2	19.9385	100
1-5	14.1675	100
2-4	5.4026	100
5-6	0	0

Table 4.3 Summary power flow at each right-of-way of Garver 6-bus system (After considering *n*-1 security criterion, when a line between buses 2-3 is outage.)

Line path between buses	Power Flow (MW)	Max Power Flow (MW)
2-3	0	0
4-6	141.6707	200
2-6	159.3293	200
3-5	308	400
1-4	44.9512	80
1-2	74.0488	100
1-5	68	100
2-4	6.622	100
5-6	0	0

In tables 4.2 and 4.3, real power flow and maximum real power flow at each right-of-way are presented. Form obtained results in table 4.2, a line path between buses 2-3 is the most critical because it has the lowest gap between power flow and maximum power flow compared to other path on this system. Therefore, real power flow and maximum real power flow at each path are selected to show in table 4.3, when a line between buses 2-3 is outage. Regarding results in table 4.3, the power flow are not over the maximum power flow for each path.

4.4.2 IEEE 25-bus System

The IEEE 25-bus system is tested the performance of SaDEA procedure in this work. For the second test system, it has 25 buses, 36 possible branches, and 2750 MW of total demand. The electrical system data; transmission line, load, and generation data are available in [27] and [31]. A new bus of this system is bus-25 that is prepared for connecting to bus-5 and/or bus-24. The dotted lines represent new possible line additions and solid lines are the existing lines as shown in figure A2. A maximum of four parallel lines is permitted to install in each branch.

Table 4.4 Summary results of IEEE 25-bus system

Results of the TEP with security constraint consideration	The SaDEA method
Best total cost (x10^3 US$)	19131
Average total cost (x10^3 US$)	25050
Worst total cost (x10^3 US$)	30020
% Difference between best and worst	56.92
Standard deviation (x10^3 US$)	4060.30
Average CPU time (second)	654.52
Line additions for the best result	$n_{5\text{-}20}$ = 1, $n_{5\text{-}25}$ = 4, $n_{6\text{-}24}$ = 1, $n_{13\text{-}18}$ = 1, $n_{13\text{-}20}$ = 1, $n_{16\text{-}20}$ = 1, and $n_{24\text{-}25}$ = 1

The obtained results of SaDEA method on the IEEE 25-bus system can be tabulated in table 4.4 and the discussion of these results are as follows:

- For the second test system, total expansion cost of the best solution equals to 19.131 million US$ with the following topology: $n_{5\text{-}20}$ = 1, $n_{5\text{-}25}$ = 4, $n_{6\text{-}24}$ = 1, $n_{13\text{-}18}$ = 1, $n_{13\text{-}20}$ = 1, $n_{16\text{-}20}$ = 1, and $n_{24\text{-}25}$ = 1.
- A convergence curve of SaDEA method to obtain the best solution is illustrated in

figure 4.3, where the best solution was found by SaDEA method at the 584th iteration.

- An average computational time of the proposed method is 654.52 second in this test case.

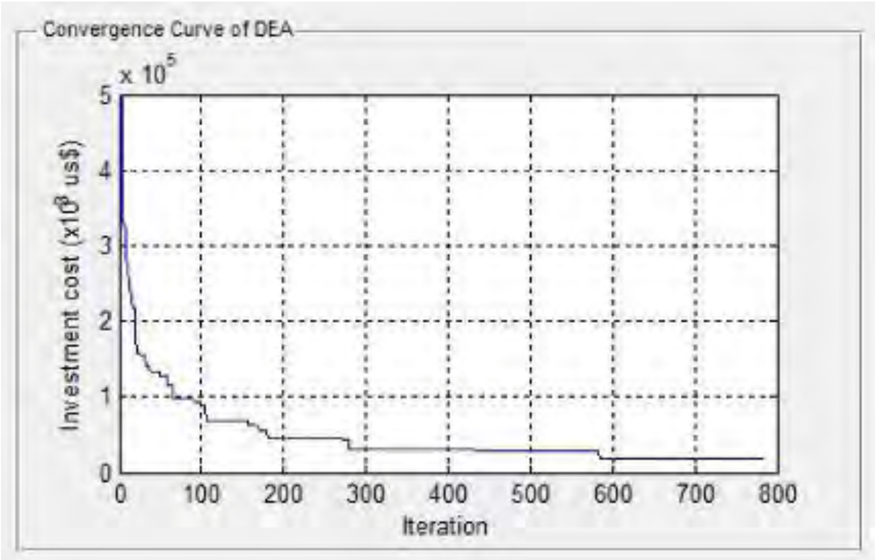

Figure 4.3 A convergence curve of SaDEA method for IEEE 25-bus system

4.4.3 Brazilian 46-Bus System

The third test network is the Brazilian 46-bus system as depicted in figure A3. The system comprises 46 buses, 79 circuits, and 6880 MW of total demand. The electrical system data, which consist of transmission line, load, and generation data including generation resizing range in MW, are available in [25]. This system represents a good test to the proposed approach because it is a real-world transmission system. In figure A3, solid lines represent existing circuits in the base case topology and dotted lines represent the possible addition of new transmission lines. The addition of parallel transmission lines to existing lines is again allowed in this case with a limit of 4 lines for each branch.

The obtained results of SaDEA method on the IEEE 46-bus system can be tabulated in table 4.5 and the discussion of these results are as follows:

- For this test system, total expansion cost of the best solution equals to 168.042 million US$ with the following topology: $n_{2\text{-}3}$ = 2, $n_{3\text{-}46}$ = 1, $n_{19\text{-}25}$ = 1, $n_{20\text{-}21}$= 1, $n_{23\text{-}24}$ = 1, $n_{24\text{-}25}$ = 2, $n_{26\text{-}29}$ = 3, $n_{28\text{-}30}$ = 1, $n_{29\text{-}30}$ = 2, $n_{31\text{-}32}$ = 1 and $n_{42\text{-}43}$ = 2.
- In this case, the best solution was found by SaDEA method at the 728th iteration and an average CPU time of the proposed method is 1962.43 second.

Table 4.5 Summary results of IEEE 46-bus system

Results of the TEP with security constraint consideration	The SaDEA method
Best total cost (x10^3 US$)	168042
Average total cost (x10^3 US$)	185372
Worst total cost (x10^3 US$)	208870
% Difference between best and worst	24.30
Standard deviation (x10^3 US$)	17152
Average CPU time (second)	1962.43
Line additions for the best result	$n_{2\text{-}3}$ = 2, $n_{3\text{-}46}$ = 1, $n_{19\text{-}25}$ = 1, $n_{20\text{-}21}$ = 1, $n_{23\text{-}24}$ = 1, $n_{24\text{-}25}$ = 2, $n_{26\text{-}29}$ = 3, $n_{28\text{-}30}$ = 1, $n_{29\text{-}30}$ = 2, $n_{31\text{-}32}$ = 1, and $n_{42\text{-}43}$ = 2

Table 4.6 Results comparison of TEP problem with security constraint consideration

Methods	Best cost (x10^3 US$)		
	Garver 6-bus system	IEEE 25-bus system	Brazilian 46-bus system
SaDEA	180	19,131	168,042
Chu-Beasley GA (CBGA) [36]	180	-	213,000
Ant Colony Search Algorithm (ACSA) [38]	298	248,943	-
Conventional DEA [38]	298	210,818	-

All obtained results of TEP problem with security constraint and power generation resizing considerations are summarized in table 4.6, where the best investment costs of expansion corresponding to the proposed method are compared to other algorithms. As indicated by the results in table 4.6, SaDEA and CBGA methods found the optimal solution on Gaver 6-bus system. For IEEE 25-bus system and the Brazilian 46-bus system, the SaDEA method could find the optimal solution as shown the cheapest investment cost.

4.5 Discussion on the Results

The achieved numerical results clearly indicate that SaDEA method can be efficiently applied to TEP problem with *n*-1 security constraint consideration on three test systems. From the results in table 4.6, SaDEA technique could find the best solution cheaper than other methods in all cases. The proposed algorithm was tested 30 times to find the best result in each case and the control parameters were set as suggestion in subsection 4.3.3.

The performance of SaDEA method depends upon selection of proper control parameters. In this research, the control parameters of SaDEA procedures (*F* and *CR*) were automatically tuned in their setting bounds. According to experiments, the scaling mutation factor *F* is much more sensitive than crossover probability *CR*. Therefore, *CR* is more useful as a fine tuning parameter.

4.6 Conclusion

In this chapter, an enhanced DEA method is proposed to deal with the TEP problem with *n*-1 security criterion consideration. A single line outage is investigated in such TEP problem for reliability issue. From obtained results of Garver six-bus system, IEEE 25-bus system, and the Brazilian 46-bus system, the SaDEA procedure is an acceptable optimization technique and minimizes effectively the total investment cost of TEP problem with security constraint consideration on realistically transmission systems. As the empirical solutions of these test cases indicate, total investment costs of the SaDEA method are less expensive than other methods on three test networks. The most attractive feature of the proposed algorithm is good computational performance and simple implementation. Regarding a consequence of the successful results, a distribution system planning problem will be investigated as future work.

CHAPTER 5
CONCLUSIONS AND FUTURE WORK

5.1 Project Conclusions

Cost-effective transmission expansion planning (TEP) is a major challenge with regard to electrical power system optimization problems as its main goal is to achieve an optimal expansion plan. The planning solution has to meet technical requirements while offering economical investment. Furthermore, transmission planning should specify new transmission facilities that must be added to an existing network to ensure adequate operation over a specified planning horizon.

Over past few decades, a number of optimization methods have been applied to solve the TEP problem in many issues. These proposed methods are as follows: mathematical optimization methods (e.g. linear programming, nonlinear programming, dynamic programming, integer and mixed integer programming, benders decomposition, branch & bound, etc.), heuristic methods (mostly constructive heuristics), and meta-heuristic methods (e.g. genetic algorithms, tabu search, simulated annealing, particle swarm, evolutionary algorithms, differential evolution algorithm, etc.). The details of such methods are provided in chapter 2 of this report.

A differential evolution algorithm (DEA) is an artificial intelligence technique and it was firstly presented by R. M. Storn and K. V. Price in 1995. The DEA method becomes a reliable and versatile function optimizer that is also readily applicable to a wide range of optimization problems. In addition, the DEA method has been employed to optimize a wide variety of problems in electrical power system, for example, economic power dispatch, short-term scheduling of hydrothermal power system, power system planning, optimal reactive power flow, etc. In a number of cases, the DEA method has proved to be more accurate, reliable as it can provide optimum solutions within acceptable computational times.

Although a conventional DEA method has a number of merits as described in chapter 2, it still has a drawback that is a difficult task of the DEA control parameters tuning. Regarding such disadvantage of the conventional DEA characteristic, thus it should be improved the optimization performance in this research. An enhanced DEA method is a modified version and has been proposed to solve the TEP problem with system losses and security criterion considerations in this work.

The main contribution of this research is the enhancement of a conventional DEA method and the application of proposed technique to TEP problem with system losses and security criterion considerations. First of all, the design of a self-adaptive DEA (SaDEA) procedure is to develop two DEA control parameters, mutation factor (*F*) and crossover probability (*CR*), which are self-tuning parameters using probability methodology. In order to validate its searching capability and reliability, the enhanced methodology has been tested with some selected mathematical benchmark functions, namely Sphere, Rosenbrock1, Absolute, Schwefel, and Rastrigin functions.

Based on the successful results of SaDEA procedure application to selected mathematical functions, the proposed technique is subsequently implemented to solve static TEP problem with system losses consideration, which is a real-world optimization problem, as shown in chapter 3. In chapter 3, the simulations have two different scenarios of static TEP problem that are with and without generation resizing considerations. In addition, a heuristic search method has been adopted in order to deal with static TEP considering DC based power flow model constraints. The proposed method has been implemented in Matlab7 and tested on two electrical transmission networks as shown in appendix A1-A2. The obtained results indicate that SaDEA method performs effectively to handle the static TEP problem considering system losses on Graver 6-bus system and IEEE 25-bus system. The most attractive feature of the proposed algorithm is the good computational performance. The accuracy of the results obtained in the TEP study is in very good agreement with obtained by other researchers as presented in chapter 3. Regarding a consequence of the successful results, the TEP problem considering *n*-1 contingencies in single line outage has been investigated in chapter 4.

Given its effectiveness for solving the TEP problem with system losses consideration, the proposed methodology is then applied to deal with the TEP problem with *n*-1 security criterion consideration, which is more complex and difficult than the previous work. In this study, such TEP problem based on DC power flow model has been analyzed. The proposed method application to handle the TEP problem with *n*-1 security criterion consideration is tested on three transmission systems that are Graver 6-bus system, IEEE 25-bus system, and the Colombian 93-bus system, as shown in appendix A1-A3. From chapter 4, the obtained results of three networks illustrate that the SaDEA technique is good efficient and effectively minimizes the total investment cost of TEP problem on such systems.

Overall, the SaDEA procedure performs superior to other classical evolutionary algorithms (EAs) in terms of simple implementation with high quality of solution. Meanwhile, it requires less control parameters while being independent from initialization. In addition, its convergence is stable and robust as SaDEA procedure uses rather greedy selection and less stochastic approach to solve optimization problems than other classical EAs.

5.2 Future Work

As a consequence of the successful results in this research, the SaDEA method will be applied to solve a problem of distribution system planning in future work. Moreover, an economic solution of the TEP problem under the current deregulatory environment remains a significant issue in electrical power system analysis. Therefore, such topic should be further investigated in future research. Some issues for market-based transmission expansion planning, i.e. the losses of social welfare and the expansion flexibility in the system should be investigated and included in the modern TEP problem.

CHAPTER 6

OUTPUTS OF THE RESEARCH PROJECT

6.1 Summary of Research Project Outputs

From this research work, a conventional DEA methodology is enhanced its computational performance until the optimization procedures are acceptable and reliable. The main goal of undertaken research is to take advantage of computational simulations more effectively in an overall planning study and consequently determine an appropriate transmission network expansion plan. In this research, a self-adaptive DEA (SaDEA) method is applied to solve a wide variety of mathematical and real-world optimization problems, especially transmission planning considering line losses and *n*-1 security criterion. Regarding the obtained results, the SaDEA method is an optimization technique for application to handle such problems. In addition, these successful results of planning study will be used in order to design future transmission network of Thailand. The novel knowledge from this research, the author has employed to his teaching on a course of electric power system analysis and a course of electric power system operation & design. Several topics, which are an artificial intelligence (AI) application to power system optimization problems, power system planning, and etc., are included in the author's lecture notes.

The significant outputs of this project, three articles were submitted for publication. In December 2012, the first article namely "A self-adaptive differential evolution algorithm for transmission network expansion planning with system losses consideration" was published and presented at the 2012 IEEE International Conference on Power and Energy (PECON 2012), Kota Kinabalu, Malaysia. At the conference, the author had opportunity to share novel knowledge with other researchers from many countries. During May until June 2013, the second article namely "An enhanced differential evolution algorithm application to transmission network expansion planning with security constraint consideration" was prepared and submitted to a journal of IET Proceeding Generating Transmission Distribution, United Kingdom. In this paper, all obtained results of SaDEA method applied to TEP considering *n*-1 security criterion has been presented and discussed on three test systems. The reliability of system operation is considered when the transmission plan is employed to future expansion. In addition, the third article namely "An enhanced differential evolution algorithm for transmission expansion planning with system losses consideration" was published and presented at the 9th Naresuan and Tao-Ngam Research Conferences, Phitsanulok, Thailand in July 2013.

From these successful works, the proposed methodology application to solve the transmission planning and other power system optimization problems will be presented as an invited paper to electrical engineers and researchers at the 2014 International Electrical Engineering Congress (*i*EECON 2014), Pattaya City, on 19th -21st March 2014.

6.2 List of Publications

Arising from this research project, two conference papers were presented and published in conference proceedings. In addition, a journal paper has been submitted in a selected international journal. The papers are listed as follows:

6.2.1 Refereed Journal Paper: Submitted

- T. Sum-Im and W. Ongsakul, “An enhanced differential evolution algorithm application to transmission network expansion planning with security constraint consideration,” *IET Proc. Gener. Transm. Distrib.*, Current Impact Factor 1.414 (Submitted 2013).

6.2.2 Refereed International Conference Paper: Published

- T. Sum-Im and W. Ongsakul, “A self-adaptive differential evolution algorithm for transmission network expansion planning with system losses consideration,” *Proc. 2012 IEEE International Conference on Power and Energy* (*PECON 2012*), Kota Kinabalu, Malaysia, pp. 153-158, 2nd-5th Dec. 2012.

6.2.3 Refereed National Conference Paper: Published

- Thanathip Sum-Im, “An enhanced differential evolution algorithm for transmission expansion planning with system losses consideration,” *Proc. 9th Naresuan and Tao-Ngam Research Conferences*, Phitsanulok, Thailand, pp. 3, 28th-29th Jul. 2013.

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APPENDIX A

TEST SYSTEMS DATA

A-1 Garver 6-Bus System

Table A1.1 Generation and load data for Garver 6-bus system

Bus No.	Generation, MW		Load, MW	Bus No.	Generation, MW		Load, MW
	Maximum	Level			Maximum	Level	
1	150	50	80	4	0	0	160
2	0	0	240	5	0	0	240
3	360	165	40	6	600	545	0

Table A1.2 Branch data for Garver 6-bus system

From-To	n_{ij}^{0}	Reactance x_{ij}, p.u.	f_{ij}^{max}, MW	Cost, $\times 10^{3}$ US$
1-2	1	0.4	100	40
1-4	1	0.6	80	60
1-5	1	0.2	100	20
2-3	1	0.2	100	20
2-4	1	0.4	100	40
2-6	0	0.3	100	30
3-5	1	0.2	100	20
4-6	0	0.3	100	30
5-6	0	0.61	78	61

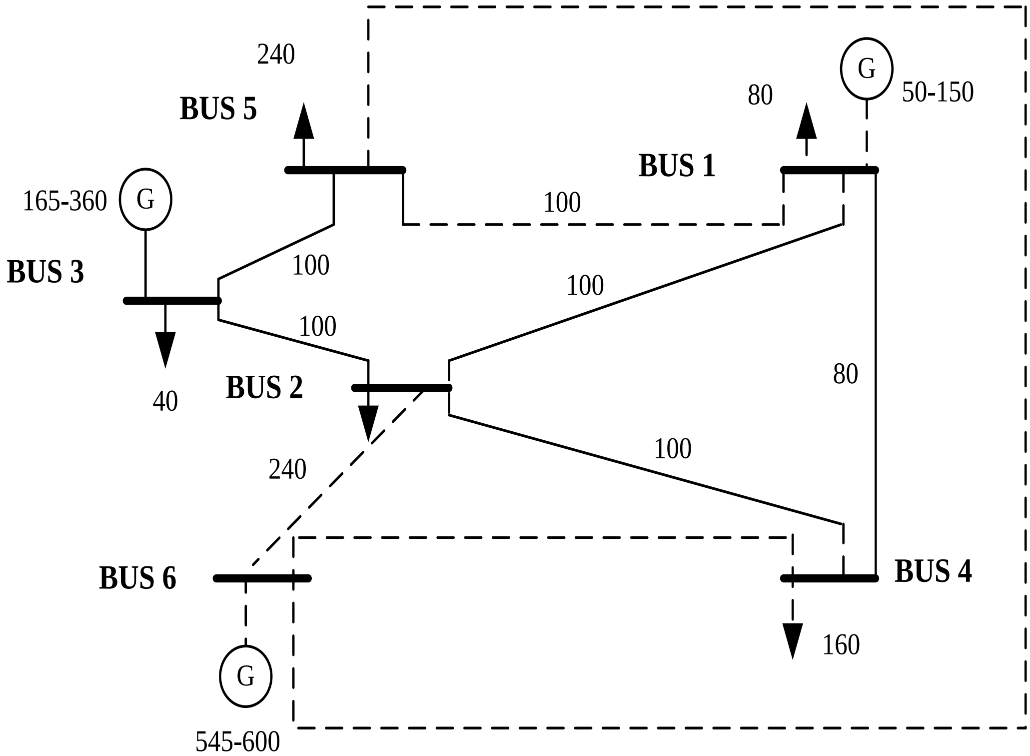

Figure A1 Garver 6-Bus System

A-2 IEEE 25-Bus System

Table A2.1 Generation and load data for IEEE 25-bus system

Bus No.	Generation, MW		Load, MW	Bus No.	Generation, MW		Load, MW
	Maximum	Level			Maximum	Level	
1	660	530	0	14	215	43	317
2	0	0	128	15	0	0	0
3	0	0	181	16	0	0	0
4	0	0	74	17	192	40	108
5	0	0	71	18	0	0	175
6	0	0	71	19	192	40	97
7	595	594	265	20	0	0	195
8	0	0	194	21	0	0	136
9	400	400	333	22	155	155	100
10	300	300	0	23	0	0	180
11	400	400	0	24	300	60	125
12	0	0	0	25	660	330	0
13	0	0	0				

Table A2.2 Branch data for IEEE 25-bus system

From-To	n_{ij}^{0}	Reactance x_{ij}, p.u.	f_{ij}^{max}, MW	Cost, $\times 10^{3}$ US$
1-2	1	0.0108	800	3760
1-7	1	0.0865	65	27808
1-13	1	0.0966	100	30968
2-3	1	0.0198	500	7109
3-22	1	0.0231	200	8187
4-18	1	0.1037	1000	4907
4-19	1	0.1267	250	5973
5-17	1	0.0854	800	3987
5-20	1	0.0883	940	4171
5-25	0	0.0902	220	1731
6-18	1	0.1651	440	7776
6-20	1	0.1651	280	7776
6-24	1	0.0614	1080	2944
7-13	1	0.0476	250	16627
7-16	1	0.0476	90	16627
8-16	1	0.0418	490	14792
8-22	1	0.0389	65	13760
9-11	1	0.0129	260	4587
9-15	1	0.0144	250	5112
10-11	1	0.0678	800	21909
10-15	1	0.1053	250	33920
11-14	1	0.0245	700	8507
12-14	1	0.0519	100	16915
12-23	1	0.0839	70	675
13-18	1	0.0839	100	675
13-20	1	0.0839	250	675
14-22	1	0.0173	200	5963
15-22	1	0.0259	360	9243
16-18	1	0.0839	250	675
16-20	1	0.0839	564	675
17-19	1	0.0139	400	493
17-23	1	0.2112	350	8880
18-23	1	0.1190	150	5605
19-21	1	0.1920	110	9045
20-21	1	0.0605	180	2245
24-25	0	0.1805	220	3067

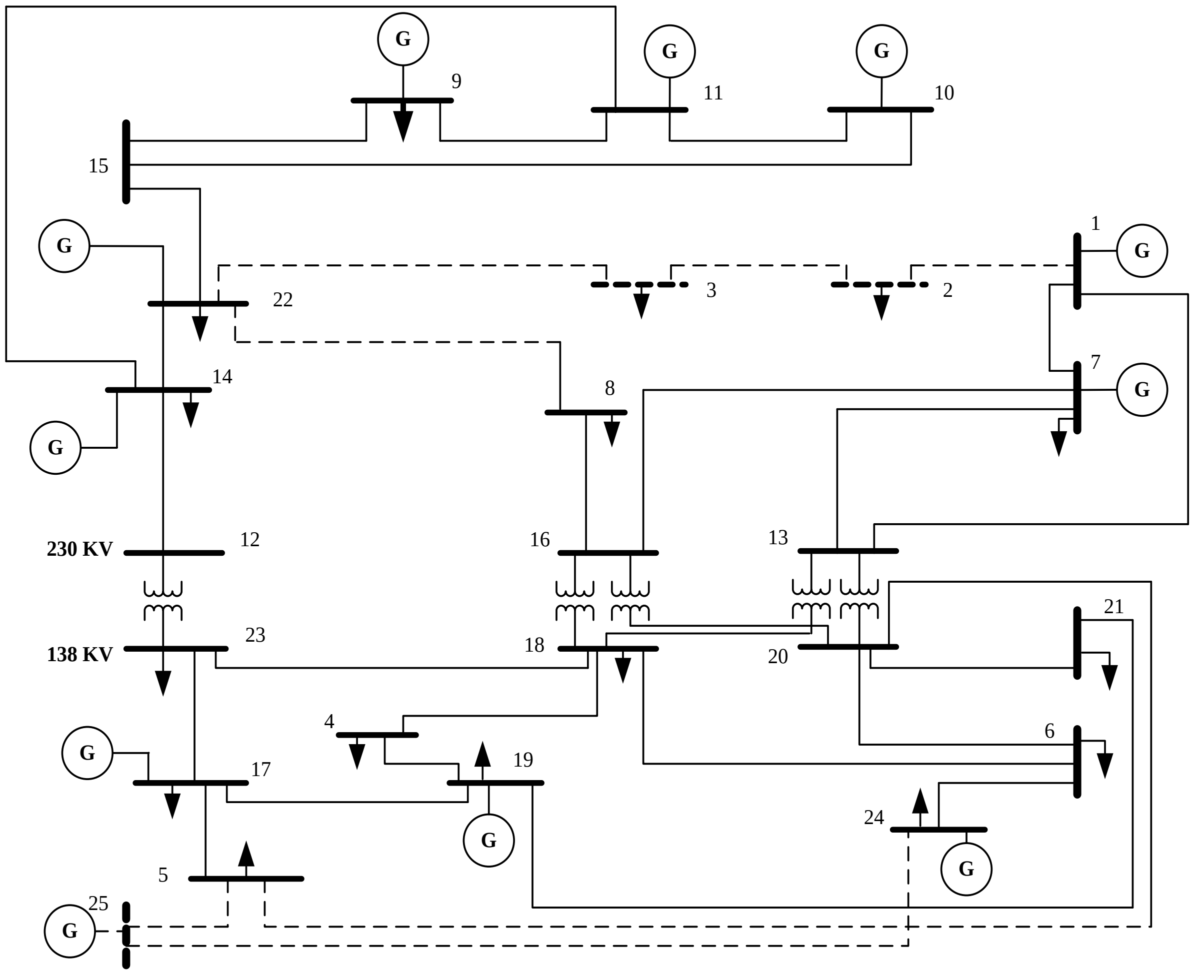

Figure A2 IEEE 25-Bus System

A-3 Brazilian 46-Bus System

Table A3.1 Generation and load data for Brazilian 46-bus system

Bus No.	Generation, MW		Load, MW	Bus No.	Generation, MW		Load, MW
	Maximum	Level			Maximum	Level	
1	0	0	0	24	0	0	478.2
2	0	0	443.1	25	0	0	0
3	0	0	0	26	0	0	231.9
4	0	0	300.7	27	220	54	0
5	0	0	238	28	800	730	0
6	0	0	0	29	0	0	0
7	0	0	0	30	0	0	0
8	0	0	72.2	31	700	310	0
9	0	0	0	32	500	450	0
10	0	0	0	33	0	0	229.1
11	0	0	0	34	748	221	0
12	0	0	511.9	35	0	0	216
13	0	0	185.8	36	0	0	90.1
14	1257	944	0	37	300	212	0
15	0	0	0	38	0	0	216
16	2000	1366	0	39	600	221	0
17	1050	1000	0	40	0	0	262.1
18	0	0	0	41	0	0	0
19	1670	773	0	42	0	0	1607.9
20	0	0	1091.2	43	0	0	0
21	0	0	0	44	0	0	79.1
22	0	0	81.9	45	0	0	86.7
23	0	0	458.1	46	700	599	0

Table A3.2 Branch data for Brazilian 46-bus system

From-To	n_{ij}^{0}	Reactance x_{ij}, p.u.	f_{ij}^{max}, MW	Cost, $\times 10^{3}$ US$	From-To	n_{ij}^{0}	Reactance x_{ij}, p.u.	f_{ij}^{max}, MW	Cost, $\times 10^{3}$ US$
1-2	2	0.1065	270	7076	20-21	1	0.0125	600	8178
1-7	1	0.0616	270	4349	20-23	2	0.0932	270	6268
2-3	0	0.0125	600	8178	21-25	0	0.0174	2000	21121
2-4	0	0.0882	270	5965	22-26	1	0.0790	270	5409
2-5	2	0.0324	270	2581	23-24	2	0.0774	270	5308
3-46	0	0.0203	1800	24319	24-25	0	0.0125	600	8178
4-5	2	0.0566	270	4046	24-33	1	0.1448	240	9399
4-9	1	0.0924	270	6217	24-34	1	0.1647	220	10611
4-11	0	0.2246	240	14247	25-32	0	0.0319	1400	37109
5-6	0	0.0125	600	8178	26-27	2	0.0832	270	5662
5-8	1	0.1132	270	7480	26-29	0	0.0541	270	3894
5-9	1	0.1173	270	7732	27-29	0	0.0998	270	6672
5-11	0	0.0915	270	6167	27-36	1	0.0915	270	6167
6-46	0	0.0128	2000	16005	27-38	2	0.2080	200	13237
7-8	1	0.1023	270	6823	28-30	0	0.0058	2000	8331
8-13	1	0.1348	240	8793	28-31	0	0.0053	2000	7819
9-10	0	0.0125	600	8178	28-41	0	0.0339	1300	39283
9-14	2	0.1756	220	11267	28-43	0	0.0406	1200	46701
10-46	0	0.0081	2000	10889	29-30	0	0.0125	600	8178
11-46	0	0.0125	600	8178	31-32	0	0.0046	2000	7052
12-14	2	0.0740	270	5106	31-41	0	0.0278	1500	32632
13-18	1	0.1805	220	11570	32-41	0	0.0309	1400	35957
13-20	1	0.1073	270	7126	32-43	1	0.0309	1400	35957

Table A3.2 Branch data for Brazilian 46-bus system (Contd.)

From-To	n_{ij}^0	Reactance x_{ij}, p.u.	f_{ij}^{max}, MW	Cost, $\times 10^3$ US$	From-To	n_{ij}^0	Reactance x_{ij}, p.u.	f_{ij}^{max}, MW	Cost, $\times 10^3$ US$
14-15	0	0.0374	270	2884	33-34	1	0.1265	270	8288
14-18	2	0.1514	240	9803	34-35	2	0.0491	270	3591
14-22	1	0.0840	270	5712	35-38	1	0.1980	200	12631
14-26	1	0.1614	220	10409	36-37	1	0.1057	270	7025
15-16	0	0.0125	600	8178	37-39	1	0.0283	270	2329
16-17	1	0.0078	2000	10505	37-40	1	0.1281	270	8389
16-28	0	0.0222	1800	26365	37-42	1	0.2105	200	13388
16-32	0	0.0311	1400	36213	38-42	3	0.0907	270	6116
16-46	1	0.0203	1800	24319	39-42	3	0.2030	200	12934
17-19	1	0.0061	2000	8715	40-41	0	0.0125	600	8178
17-32	0	0.0232	1700	27516	40-42	1	0.0932	270	6268
18-19	1	0.0125	600	8178	40-45	0	0.2205	180	13994
18-20	1	0.1997	200	12732	41-43	0	0.0139	2000	17284
19-21	1	0.0278	1500	32632	42-43	1	0.0125	600	8178
19-25	0	0.0325	1400	37748	42-44	1	0.1206	270	7934
19-32	1	0.0195	1800	23423	44-45	1	0.1864	200	11924
19-46	1	0.0222	1800	26365					

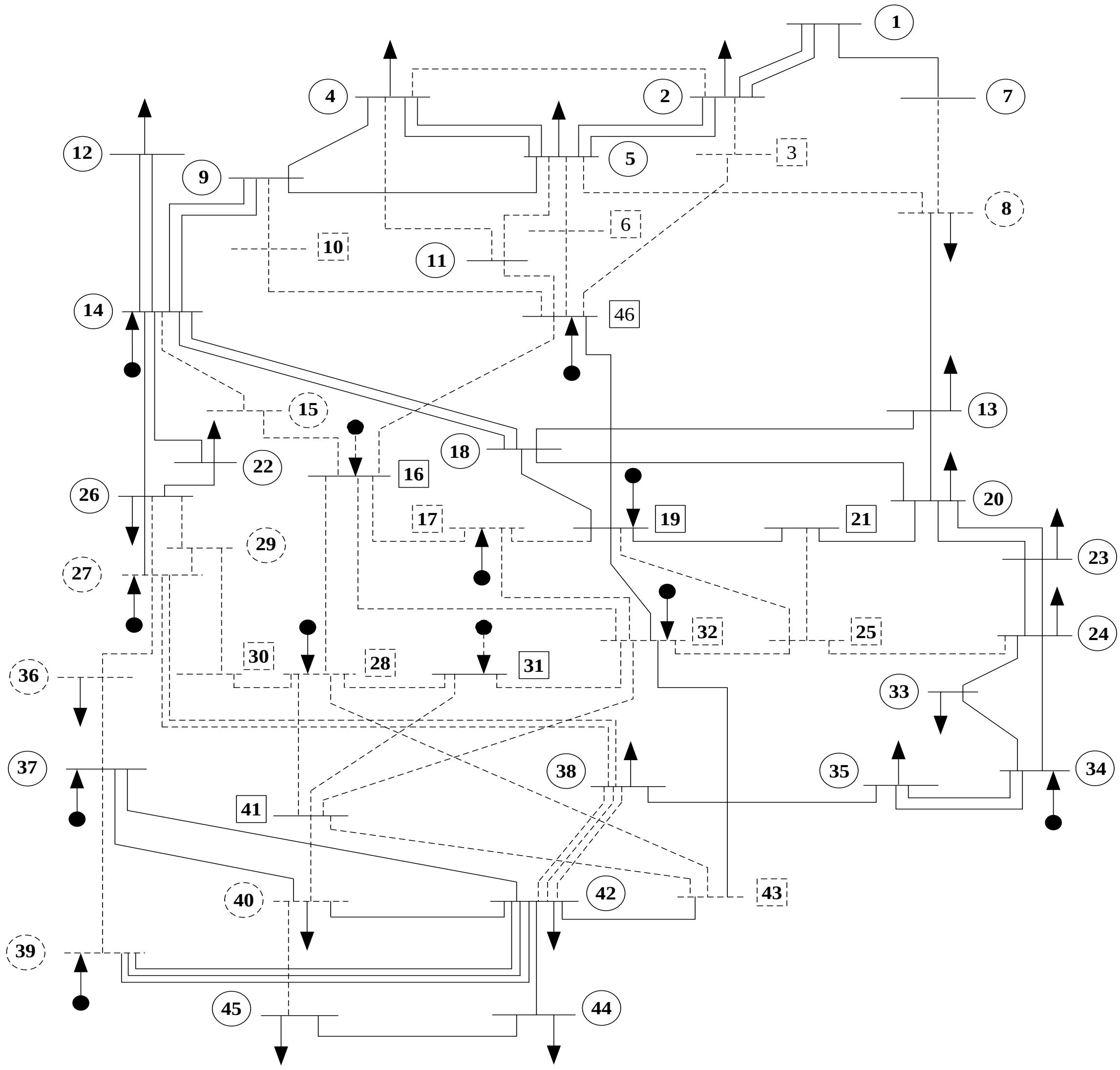

Figure A3 Brazilian 46-Bus System

APPENDIX B

LIST OF PUBLICATIONS

B-1 A self-adaptive differential evolution algorithm for transmission network expansion planning with system losses consideration

A Self-Adaptive Differential Evolution Algorithm for Transmission Network Expansion Planning with System Losses Consideration

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Abstract—**In this paper, a self-adaptive differential evolution algorithm (SaDEA) is applied directly to the DC power flow based model in order to efficiently solve transmission network expansion planning (TNEP) problem. The purpose of TNEP is to minimize the transmission investment cost associated with the technical operation and economical constraints. The TNEP problem is a large-scale, complex and nonlinear combinatorial problem of mixed integer nature where the number of candidate solutions to be evaluated increases exponentially with system size. In addition, the TNEP problem with system losses consideration is also investigated in this paper. The efficiency of the proposed method is initially demonstrated via the analysis of low and medium complexity transmission network test cases. A detailed comparative study among conventional genetic algorithm (CGA), tabu search (TS), artificial neural networks (ANNs), hybrid artificial intelligent techniques and the proposed method is presented. From the obtained experimental results, the proposed technique provides the accurate solution, the feature of robust computation, the simple implementation and the satisfactory computational time.**

Keywords-Transmission network expansion planning; self-adaptive differential evolution algorithm; transmission line losses

I. INTRODUCTION

In general, the main purpose of solving the transmission network expansion planning (TNEP) problem is to specify addition of transmission facilities that provide adequate capacity and in the mean time maintain operating performance of electric transmission system [1]. To achieve effective plan, exact location, capacity, timing and type of new transmission equipment must be thoroughly determined to meet demand growth, generation addition and increased power flow. However, cost-effective TNEP becomes one of the major challenges in power system optimization due to the nature of the problem that is complex, large-scale, difficult and nonlinear. Meanwhile, mixed integer nature of TNEP results in an exponentially increased number of possible solutions when system size is enlarged.

Normally, TNEP can be categorized as static or dynamic according to the treatment of the study period [2]. In static planning; the planner considers only one planning horizon and determines the number of suitable circuits that should be installed to each branch of the transmission system. Investment is carried out at the beginning of the planning horizon time. In dynamic or multistage planning; the planner considers not only the optimal number and location of added lines and type of investments but also the most appropriate times to carry out such expansion investments. Therefore the continuing growth of the demand and generation is always assimilated by the system in an optimized way. The planning horizon is divided into various stages and the transmission lines must be installed at each stage of the planning horizon.

Over the last few decades, a number of optimization methods have been applied when solving the TNEP problem. In 1970, Garver proposed a linear programming method to solve the TNEP problem [3]. This original method was applied to long-term planning of electrical power systems and produced a feasible transmission network with near-minimum circuit miles using as input any existing network plus a load forecast and generation schedule. Two main steps of the method, in which the planning problem was formulated as load flow estimation and new circuit selection could be searched based on the system overloads, were presented in [3].

In addition to mathematical optimization methods, heuristic and meta-heuristic methods become the current alternative to solve the TNEP problem. These heuristic and meta-heuristic techniques are efficient algorithms to optimize the transmission planning problem. There have been many applications of heuristic and meta-heuristic optimization methods to solve the TNEP problem, for example heuristic algorithms [1], tabu search [4], simulated annealing [5], genetic algorithms [6-8], artificial neural networks [9], hybrid artificial intelligent techniques [9] and differential evolution algorithm [10].

Recently, a differential evolution algorithm (DEA) method has been attracting increasing attention for a wide variety of science and engineering applications including electrical power system problems. There have been many researches that applied DEA for solving power system optimization problems, for instance, power system planning [11], short-term hydrothermal scheduling problem [12], optimal reactive power flow [13-14], optimal power flow [15], transmission expansion planning, [10], economic dispatch [16], etc. The DEA method was successfully employed to solve both static and dynamic transmission expansion planning problems by the author in [10] where the DEA method performed superior to a conventional genetic algorithm (CGA) in terms of simple implementation with high quality of solution and good computational performance. In addition, a self-adaptive differential evolution algorithm (SaDEA) method was modified and also applied for solving the economic dispatch problem considering transmission losses by the author in [16]. The results obtained on the IEEE 30-bus system illustrated that the SaDEA procedure is an efficient technique when solving the economic dispatch problem. Considering such advantages with regard to SaDEA performance, the authors propose the SaDEA method to solve the TNEP problem with system losses consideration in this paper. The various transmission expansion costs; an investment cost, a power losses cost and a saved cost of the proposed SaDEA technique are compared to CGA, tabu search, artificial neural networks and hybrid artificial intelligent techniques reported in [9] on the Garver 6-bus system and IEEE 25-bus system.

II. THE TNEP PROBLEM FORMULATION

In general, the TNEP problem can be mathematically formulated by applying DC power flow model, which is a nonlinear mixed-integer problem with high complexity, especially for large-scale real-world transmission networks. There are several alternatives to the DC model such as the transportation, hybrid and disjunctive models. Detailed reviews of the main mathematical models for the TNEP problem were presented in [17].

A. The Objective Function

The goal of TNEP problem with system losses consideration is to minimize the total expansion cost while satisfying technical and economical constraints. In this paper, a classical DC power flow model is employed to solve the TNEP problem [9]. Mathematically, the problem can be formulated as follows:

$$\text{Minimize} \quad v = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} + K \sum_{m=1}^{NL} I_m^2 R_m \tag{1}$$

where v, c_{ij} and n_{ij} represent, respectively, transmission expansion cost, cost of a candidate circuit for addition to the branch *i-j* and the number of circuits added to the branch *i-j*. Here Ω is the set of all candidate branches for expansion. In addition, K is a loss coefficient (calculated using K=8760× NYE× Ckwh); NYE is an estimated life time of the expansion network (years); CkWh: is a cost of one kWh (US$/kWh); R_m is a resistance of the mth line; I_m is the flow on the mth line; and NL is the number of the existing lines.

The first term of an objective function represents the capital cost of the installed lines and the second term represents the cost of ohmic power losses after the new line additions. The system power flow and losses are changed due to a result of line additions. The loss coefficient (K) depends upon the number of years of transmission system operation and the kWh cost. The DC load flow is used in the problem formulation where the current (I) is approximately equal to the power flow and voltage is assumed to be unity at all buses.

B. Problem Constraints

The objective function (1) represents the expansion cost of the newly installed transmission lines, which has some restrictions. These constraints must be included into mathematical model to ensure that the optimal solution satisfies transmission planning requirements. These constraints are described and formulated as following (2)-(7).

- *DC Power Flow Node Balance Constraint*

This linear equality constraint represents the conservation of power at each node.

$$g = d + B\theta \tag{2}$$

where g, d and B are real power generation vector in existing power plants, real load demand vector in all network nodes, and susceptance matrix of the existing and added lines in the network, respectively. Here θ is the bus voltage phase angle vector.

- *Power Flow Limit on Transmission Lines Constraint*

The following inequality constraint is applied to TNEP problem in order to limit the power flow for each path.

$$\left|f_{ij}\right| \le (n_{ij}^0 + n_{ij}) f_{ij}^{\max} \tag{3}$$

In DC power flow model, each element of the branch power flow in constraint (3) can be calculated by using equation (4):

$$f_{ij} = \frac{(n_{ij}^0 + n_{ij})}{x_{ij}} \times (\theta_i - \theta_j) \tag{4}$$

where f_{ij}, $f_{ij}^{\max}$, n_{ij}, n_{ij}^0 and x_{ij} represent, respectively, total branch power flow in branch *i-j*, maximum branch power flow in branch *i-j*, number of circuits added to branch *i-j*, number of circuits in original base system and reactance of the branch *i-j*. Here θ_i and θ_j are voltage phase angle of the terminal buses i and j respectively.

- *Power Generation Limit Constraint*

In TNEP problem, power generation limit must be included into the problem constraints. This can be mathematically represented as follows:

$$g_i^{\min} \le g_i \le g_i^{\max} \tag{5}$$

where g_i, $g_i^{\min}$ and $g_i^{\max}$ are real power generation at node i, the lower and upper real power generation limits at node i, respectively.

- *Right-of-way Constraint*

It is important to an accurate TNEP solution that planner needs to know the exact capacity of the newly required circuits. Therefore this constraint must be included into the consideration of planning problem. Mathematically, this constraint defines the new circuit location and the maximum number of circuits that can be installed in a specified location. It can be represented as follows:

$$0 \le n_{ij} \le n_{ij}^{\max} \tag{6}$$

where n_{ij} and $n_{ij}^{\max}$ represent the total integer number of circuits added to the branch *i-j* and the maximum number of added circuits in the branch *i-j*, respectively.

- *Bus Voltage Phase Angle Limit Constraint*

The voltage phase angle is also included as a TNEP constraint and a calculated phase angle (θ_{ij}^{cal}) should be less than a predefined maximum phase angle (θ_{ij}^{max}). This can be represented as the following mathematical expression.

$$\left|\theta_{ij}^{\mathrm{cal}}\right| \leq \left|\theta_{ij}^{\max}\right| \tag{7}$$

III. Basis of Differential Evolution Algorithm Methodology

A differential evolution algorithm (DEA) is an evolutionary computation method as it uses real-coded variables and typically relies on mutation as the search operator. The DEA method was originally introduced by R. Storn and K. Price in 1995 [18] and further developed to be a reliable and versatile function optimizer that is also readily applicable to a wide range of optimization problems [19]. More recently the DEA method has evolved to share many features with CGA [20]. The major similarity between these two types of algorithm is that they both maintain populations of potential solutions and use a selection mechanism for choosing the best individuals from the population. The main differences between the CGA method and the DEA technique were summarized in [21].

A DEA is a parallel direct search technique that employs a population P of size N_P, consisted of floating point encoded individuals or candidate solutions (8). At every generation G during the optimization process, the DEA maintains population $P^{(G)}$ of N_P vectors of candidate solutions to the problem at hand.

$$P^{(G)} = [X_1^{(G)}, ..., X_i^{(G)}, ..., X_{N_P}^{(G)}] \tag{8}$$

Each candidate solution X_i is a D-dimensional vector, containing as many real-valued parameters (9) as the problem decision parameters D.

$$X_i^{(G)} = [x_{1,i}^{(G)}, ..., x_{j,i}^{(G)}, ..., x_{D,i}^{(G)}], \quad i = 1, ..., N_p \tag{9}$$

A. Initialization Step

In the first step of the DEA procedure, the population of candidate solutions must be initialized. Typically, each decision parameter in every vector of the initial population is assigned a randomly chosen value from within its corresponding feasible bounds.

$$x_{j,i}^{(G=0)} = x_j^{\min} + \mathrm{rand}_j[0,1].(x_j^{\max} - x_j^{\min}) \tag{10}$$

where $i = 1,\ldots,N_P$ and $j = 1,\ldots,D$. $x_{j,i}^{(G=0)}$ are the initial value of the j^{th} parameter of the i^{th} individual vector. x_j^{min} and x_j^{max} are the lower and upper bounds of the j^{th} decision parameter, respectively. Once every vector of the population has been initialized, its corresponding fitness value is calculated and stored for future reference.

B. Mutation Step

After the population of candidate solutions is successfully initialized, the next step of DEA optimization process is carried out by applying three basic genetic operations; mutation, crossover and selection. These three operators create the population of next generation $P^{(G+1)}$ by using the current population $P^{(G)}$. At every generation G, each vector in the population has to serve once as a target vector $X_i^{(G)}$, the parameter vector has chosen vector index i, and it is compared with a mutant vector. The mutation operator generates mutant vectors ($V_i^{(G)}$) by perturbing a randomly selected vector (X_{r1}) with the difference of two other randomly selected vectors (X_{r2} and X_{r3}).

$$V_i^{(G)} = X_{r1}^{(G)} + F\left(X_{r2}^{(G)} - X_{r3}^{(G)}\right), \quad i = 1, ..., N_P \tag{11}$$

Vector indices $r1$, $r2$ and $r3$ are randomly selected, which $r1$, $r2$ and $r3 \in \{1,\ldots,N_P\}$ and $r1 \neq r2 \neq r3 \neq i$. X_{r1}, X_{r2} and X_{r3} are selected anew for each parent vector. F is a user-defined constant known as the "scaling mutation factor", which is typically chosen from within the range $[0,1^+]$.

C. Crossover Step

In this step, a crossover or recombination process is also applied in the DEA procedure because it helps to increase the diversity among the mutant parameter vectors. At the generation G, the crossover operation creates trial vectors (U_i) by mixing the parameters of the mutant vectors (V_i) with the target vectors (X_i) according to a selected probability distribution.

$$U_i^{(G)} = u_{j,i}^{(G)} = \begin{cases} v_{j,i}^{(G)} & \text{if } \mathrm{rand}_j(0,1) \leq CR \;\; or \;\; j = s \\ x_{j,i}^{(G)} & \text{otherwise} \end{cases} \tag{12}$$

The crossover constant CR is a user-defined value (known as the "crossover probability"), which is usually selected from within the range [0,1]. The crossover constant controls the diversity of the population and aids the algorithm to escape from local optima. The "rand_j" is a uniformly distributed random number within the range (0,1) generated anew for each value of j. "s" is the trial parameter with randomly chosen index $\in \{1,\ldots,D\}$, which ensures that the trial vector gets at least one parameter from the mutant vector.

D. Selection Step

Finally, the selection operator is applied in the last stage of the DEA procedure. The selection operator selects the vectors that are going to compose the population in the next generation. This operator compares the fitness of the trial vector and the corresponding target vector and selects the one that provides the best solution. The fitter of the two vectors is then allowed to advance into the next generation according to (13).

$$X_i^{(G+1)} = \begin{cases} U_i^{(G)} & \text{if } \; f(U_i^{(G)}) \leq f(X_i^{(G)}) \\ X_i^{(G)} & \text{otherwise} \end{cases} \tag{13}$$

The DEA optimization process is repeated across generations to improve the fitness of individuals. The overall optimization process is stopped whenever maximum number of generations is reached or any other predetermined convergence criterion is satisfied.

IV. Implementation of SaDEA Method for TNEP Problem with System Losses Consideration

Regarding a conventional differential evolution algorithm (CDEA) method (described in the previous section) has the notable limitation of CDEA control parameter tuning due to a complex interaction of parameters. The SaDEA procedure is proposed to enhance the performance of CDEA method by reducing a tedious task of control parameters tuning. In addition, the SaDEA technique was successfully adopted to solve an economic dispatch problem in the previous author's work [16]. From the achieved successful results, the SaDEA method is proposed to solve the TNEP problem with transmission system losses consideration in this paper.

A. The SaDEA Optimization Procedure

In the first step of SaDEA optimization procedure, the user has to define two constant values (T_1 and T_2) that are the indices of control parameters (F and CR) changing. The user-defined values T_1 and T_2 are usually selected from within the range [0,1] and they are set as 0.1 in this work for avoiding local optimum trapping. The control parameters F and CR are updated in their setting bounds when the uniformly distributed random numbers within the range (0,1) are less than T_1 and T_2.

In the next step, an initial population is generated according to (10). For the TNEP problem formulation, each individual vector (X_i) contains many integer-valued parameters n, where $n_{j,i}$ represents the number of candidate lines in the possible branch j of the individual i. The problem decision parameter D is the number of possible branches for expansion.

$$X_i^{(G)} = [n_{1,i}^{(G)}, ..., n_{j,i}^{(G)}, ..., n_{D,i}^{(G)}], \;\; i = 1, ..., N_p \tag{14}$$

After new individuals are initialized successfully then they are created by applying mutation (11), crossover (12) and selection (13) operators. The optimization process is repeated in search of the final solution until the maximum number of generations ($G^{\max}$) is reached or other predetermined convergence criterion (ε) is satisfied.

B. Fitness Function of TNEP Problem

In this work, a fitness function $F(X)$ of the TNEP problem is assigned according to (15) for each individual. The fitness function is a combination of an objective function and two penalty functions. The fitness function is adopted to find the optimal solution, measure the performance of candidate solutions and check for violation of the TNEP problem constraints. An individual is the best solution if its fitness value $F(X)$ is highest. The penalty functions are also included in the fitness function in order to represent violations of both equality and inequality constraints. For the TNEP problem, an equality constraint penalty function (17) considers the DC power flow node balance constraint and an inequality constraint penalty function (18) considers the constraints of power flow limit on each transmission line, power generation limit, bus voltage phase angle limit and right-of-way, respectively. The general fitness function of the TNEP problem can be formulated as follows:

$$F(X) = \frac{1}{O(X) + \omega_1 P_1(X) + \omega_2 P_2(X)} \tag{15}$$

$F(X)$ and $O(X)$ are a fitness function and an objective function of the TNEP problem, respectively. $P_1(X)$ and $P_2(X)$ are the equality and inequality constraint penalty functions respectively. X denotes the individual vector of decision variables. ω_1 and ω_2 are penalty weighting factors that are set to 0.5 in this paper. For the TNEP problem, the objective function and penalty functions are formulated as follows.

$$O(X) = V(X) = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} + K \sum_{m=1}^{NL} I_m^2 R_m \tag{16}$$

$$P_1(X) = \sum_{k=1}^{nb} \left| d_k + B_k \theta_k - g_k \right| \tag{17}$$

$$P_2(X) = \begin{cases} C & \text{if an individual violates the TNEP} \\ & \text{inequality constraints.} \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

where C is an inequality constraint constant that is used when an individual violates the inequality constraints. In this work, the constant C is set as 0.5 for all cases.

C. Control Parameters Setting

A proper selection of the SaDEA control parameters is very significant for the algorithm performance and success when searching optimal solution. In this simulation, the setting ranges of the SaDEA control parameters used in the TNEP problem are as follows: F = [0.4,1], CR = [0.8,1] and N_P = [5*D,10*D]. The maximum predetermined convergence criterion (ε) is set to 10^{-4} and the maximum number of generations ($G^{\max}$) is set to 10^3.

D. Overall Procedures

The overall procedures of the SaDEA method for solving the TNEP problem can be summarized as follows:

Step 1: Read all required system data;

Step 2: Set up two constant values T_1 and T_2 for simulation;

Step 3: Set iteration G = 0 for an initialization step of the SaDEA procedure;

Step 4: Initialize the SaDEA control parameters F and CR;

Step 5: Initialize the population P of all individuals according to (10);

Step 6: Evaluate the fitness function according to (15) and then check violations of all constraints for each individual using (17) and (18);

Step 7: Rank all individuals according to their fitness;

Step 8: Updating F, the F value is updated when a random value $rand_1$ (0,1) < T_1;

Step 9: Updating CR, the CR value is updated when a random value $rand_2$ (0,1) < T_2;

Step 10: Set iteration G = 1 for the next step of the SaDEA optimization process;

Step 11: Apply mutation, crossover and selection operations to create new individuals;

Step 12: Evaluate the fitness function by using (15) and then check violations of all constraints for each new individual using (17) and (18);

Step 13: Rank new individuals according to their fitness;

Step 14: Updating F, the F value is updated when a random value $rand_1$ (0,1) < T_1;

Step 15: Updating CR, the CR value is updated when random value $rand_2$ (0,1) < T_2;

Step 16: Verification of stop criterion, if $|F(X)^G - F(X)^{G-1}| > \varepsilon$ or $G < G^{\max}$, set $G = G + 1$ and return to step 11 for repeating to search the final solution. Otherwise, stop to calculate and go to step 17;

Step 17: Compute and display the final solutions, which are an investment cost, a system losses cost and a total expansion cost.

V. TEST SYSTEMS AND NUMERICAL RESULTS

In the simulation, the proposed SaDEA procedure is implemented in MATLAB and tested its performance on two electrical transmission systems reported in [17] and [22]. These two test networks are the Garver's 6-bus system and IEEE 25-bus system, which all significant data are also available in [17] and [22]. In this work, the TNEP problem is investigated including system losses consideration. The simulation results of the proposed SaDEA technique have been compared to conventional genetic algorithm (CGA), tabu search (TS), artificial neural networks (ANNs), hybrid artificial intelligent techniques and summarized in this paper.

Garver 6-bus System

In this paper, the first test system is a well-known Garver's system, which comprises 6 buses, 9 possible branches and 760 MW of demand. The electrical system data; transmission line, load and generation data are available in [17]. In this test system, bus 6 is a new generation bus and needs to be connected to the existing network. A maximum of four parallel lines is permitted in each branch. In this simulation case, the power losses consideration is included in the objective function where the loss coefficient, K, was selected as 1000. The per-unit base in the DC-load flow analysis is 100 MVA while the cost base is 10^5. The estimated lifetime of the transmission lines was assumed to be 25 years and the cost of one kWh was assumed to be 0.005 monetary units/kWh as found in [9].

Regarding the results of Garver's test system as shown in table 1, the best solution of the TNEP problem with system losses consideration was found by all algorithms except ANNs method with the following topology: $n_{2\text{-}6} = 4$, $n_{3\text{-}5} = 1$, $n_{4\text{-}6} = 3$ and $n_{5\text{-}6} = 1$. Although the ANNs method obtained the least investment cost compared to other methods but it had the largest value of power losses cost after the new line additions. In addition, the ANNs method had the smallest saved cost of minimizing ohmic power losses during planning horizon. The convergence curve of SaDEA technique to obtain the best solution is illustrated in Fig. 1, where the best solution was found at the 12nd generation.

TABLE I. COMPARISON OF THE EXPANSION COSTS AMONG VARIOUS METHODS FOR GARVER 6-BUS TEST SYSTEM

K=1000			
Methods	**Investment cost**	**Losses cost "a"**	**Saved cost "b"**
ANNs [9]	261	448.83	904.77
TS [9]	291	382.54	971.06
GA [9]	291	382.54	971.06
Hybrid ANN-TS-GA [9]	291	382.54	971.06
SaDEA	291	382.54	971.06

Note: The losses cost "a" after the new line addition is calculated for 25 years. The saved cost "b" is calculated as a difference cost between the cost of ohmic power losses before the expansion of the transmission network (1353.6 monetary units) based on a 25-year (life-time of line) and the power losses cost "a" calculated after the new line additions for the same period.

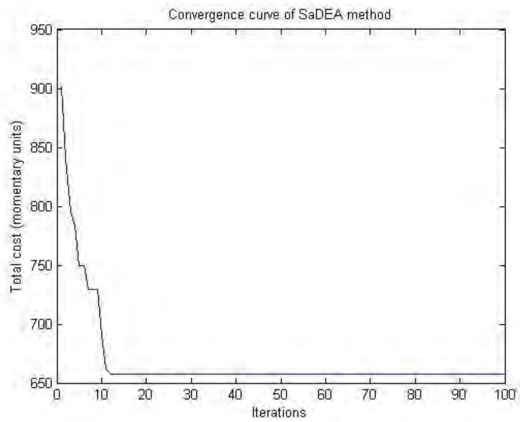

Figure 1. A convergence curve of SaDEA method for Garver 6-bus system

IEEE 25-bus System

The IEEE 25-bus system is selected for testing the SaDEA procedure in this work. It consists of 25 buses, 36 possible branches and 2750 MW of total demand. The electrical system data; transmission line, load and generation data are available in [9] and [22]. A new bus of this system is bus 25 that is prepared for connecting to bus 5 and/or bus 24. A maximum of four parallel lines is permitted to install in each branch. In this simulation case, the objective function includes the power losses consideration, in which the loss coefficient, K, was selected to be 10000. The estimated lifetime of the transmission lines was assumed to be 25 years while the cost of one kWh was assumed to be 0.0112 US$/kWh [9].

In this test case, the best solution of the TNEP problem with system losses consideration was found by SaDEA method and an investment cost was 160.051 million US$ as shown in table 2, with the addition of the following lines to the base topology: $n_{7\text{-}13} = 2$, $n_{8\text{-}22} = 3$, $n_{11\text{-}14} = 2$, $n_{12\text{-}14} = 2$, $n_{12\text{-}23} = 3$, $n_{13\text{-}18} = 2$, $n_{13\text{-}20} = 3$, $n_{16\text{-}18} = 3$, $n_{16\text{-}20} = 3$, $n_{20\text{-}21} = 1$, $n_{5\text{-}25} = 3$ and $n_{24\text{-}25} = 2$. In addition, the SaDEA method achieved the least value of a power losses cost after the new line additions compared to other techniques. Therefore the SaDEA had the largest value of a saved cost of minimizing ohmic power losses during expansion planning horizon in this case. Overall, the best algorithmic procedure for this case is SaDEA method.

TABLE II. COMPARISON OF THE EXPANSION COSTS AMONG VARIOUS METHODS FOR IEEE 25-BUS TEST SYSTEM

K=10000			
Methods	**Investment cost (million US$)**	**Losses cost "a" (million US$)**	**Saved cost "b" (million US$)**
ANNs [9]	224.178	161.995	147.979
TS [9]	180.664	155.264	154.709
GA [9]	162.430	171.947	138.016
Hybrid ANN-TS-GA [9]	168.784	152.320	157.653
SaDEA	160.051	134.251	175.722

Note: The losses cost "a" after the new line addition is calculated for 25 years. The saved cost "b" is calculated as the difference cost between the cost of ohmic power losses before the expansion of the transmission system (309.973 million US$) based on a 25-year (life-time of line) and the power losses cost "a" calculated after the new line additions for the same period.

VI. CONCLUSIONS

In this paper, a SaDEA methodology has been applied when solving TNEP problem with system losses consideration. Regarding the achieved results on the two test networks illustrate that the SaDEA procedure is an efficient technique for solving the transmission planning problem. As the numerical test results in table 2 indicate, the proposed method obtained the least values of an investment cost and a power losses cost compared to the conventional genetic algorithm, the tabu search, the artificial neural networks and the hybrid artificial intelligent techniques on the IEEE 25-bus system. In addition, the SaDEA method had the largest saved cost of ohmic power losses for both test cases as shown in table 1 and table 2. The most attractive feature of the proposed algorithm is the good computational performance. The accuracy of the results obtained in the TNEP study is in very good agreement with those obtained by other researchers as found in [9]. Regarding a consequence of these successful results, the TNEP problem considering the *n*-1 contingencies in single line outage or single generator outage will be investigated as future work.

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An Enhanced Differential Evolution Algorithm for Transmission Expansion Planning with System Losses Consideration

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Abstract

Cost-effective transmission expansion planning (TEP) is a major challenge with regard to electric power system optimization problems. The TEP addresses the problem of determining the optimal number of lines that should be added to an existing network in order to supply the forecasted load as economically as possible subject to the prevailing operational constraints. In this paper, an enhanced differential evolution algorithm (DEA) is applied directly to the DC power flow based model in order to solve the TEP problem with system losses consideration. In addition, such problem is also investigated both with and without the resizing of power generation. The effectiveness of the proposed enhancement is initially demonstrated via analysis of low and medium complexity transmission test systems. A detailed comparative study among conventional genetic algorithm (CGA), tabu search (TS), artificial neural networks (ANNs), hybrid artificial intelligent techniques and the proposed method is presented. Regarding the obtained experimental results, the proposed technique provides the accurate solution, the simple implementation and the satisfactory computational time.

Keywords: Transmission expansion planning; power system optimization; differential evolution algorithm; transmission line losses

I. INTRODUCTION

The main goal of solving a transmission expansion planning (TEP) problem is to determine the optimal expansion plan of the electrical power system [1]. Furthermore, transmission planning should specify new transmission facilities that must be added to an existing network to ensure adequate operation over a specified planning horizon. Usually, the TEP can be categorized as static or dynamic planning according to the treatment of the study period [2]. In static planning; the planner considers only single planning horizon and determines the number of suitable circuits that should be installed to each branch of the transmission system. Investment is carried out at the beginning of the planning horizon time. On the other hand, in dynamic planning; the planner considers not only the optimal number and location of added lines but also the most appropriate times to carry out such expansion investments. Therefore the continuing growth of the demand and generation is always assimilated by the system in an optimized way. The planning horizon is divided into multistage and the new lines must be installed at each stage of the planning horizon.

Over the last few decades, a number of optimization techniques have been applied when solving the TEP problem. In 2002, Al-Saba and El-Amin proposed the application of artificial intelligent (AI) tools that comprised genetic algorithm, tabu search and artificial neural networks (ANNs) with linear and quadratic programming models for solving TEP problem with line losses consideration as shown in [3]. The effectiveness of these AI methods in dealing with small-scale and large-scale transmission systems was tested through their applications to the Graver 6-bus system, the IEEE 24-bus system and the Saudi Arabian network. The planning work [3] aimed to obtain the optimal design using a fast automatic decision-maker. An intelligent tool started from a random state and it proceeded to allocate the calculated cost recursively until the stage of the negotiation point was reached.

In the last few years, a differential evolution algorithm (DEA) has been employed to handle a wide range of electric power system optimization problems such as power system planning [4], short-term scheduling of hydrothermal power system [5], optimal reactive power flow [6-7], optimal power flow [8], economic power dispatch [9] and transmission expansion planning [10]. In a number of case studies, the DEA has proved to be more accurate and can provide the accurate solution within an acceptable computation time. In 2009, the author applied a novel DEA method for solving TEP problem in both static and dynamic planning cases as shown in [10] where the DEA method performed superior to a conventional genetic algorithm (CGA) in terms of simple implementation with high quality of solution and good computational performance. Although the proposed DEA method [10] was successfully applied many cases of the TEP problem, it was not yet sufficiently robust for practical use for industry. Such DEA method has the notable limitation of DEA control parameter tuning due to a complex interaction of parameters. Therefore, a further improvement of the novel DEA method is essentially required before it can be generally adopted for practical use in industry. An enhanced differential evolution algorithm method is modified and then applied to handle the TEP problem with system losses consideration in this research. The various transmission expansion costs; an investment cost, a power losses cost and a saved cost of the proposed enhanced DEA method are compared to CGA, tabu search, artificial neural networks and hybrid artificial intelligent techniques reported in [3] on the Garver 6-bus system and IEEE 25-bus system.

II. THE TEP PROBLEM FORMULATION

In general, the TEP problem is mathematically formulated using DC power flow model. The used model is a nonlinear mixed-integer problem with high complexity, especially for large-scale real-world transmission systems. Regarding the TEP model, there are several alternatives to the DC model, for example the transportation, hybrid and disjunctive models. Detailed reviews of the main mathematical models applied to the TEP problem were presented in [11].

A. The Objective Function

The objective of TEP problem is to minimize the total transmission expansion cost while satisfying technical and economical constraints. In this research, a classical DC power flow model has been applied to solve the TEP problem with transmission system losses consideration as reported in [3]. Mathematically, the proposed problem can be formulated as follows:

$$\text{Minimize} \quad v = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} + K \sum_{m=1}^{NL} I_m^2 R_m \tag{1}$$

where v, c_{ij} and n_{ij} represent the transmission expansion cost, the cost of a candidate circuit for addition to branch *i-j* and the number of circuits added to branch *i-j*, respectively. Here Ω is the set of all candidate branches for expansion. In addition, K is a loss coefficient (calculated using K=8760× NYE× Ckwh); NYE is an estimated life time of the expansion network (years); CkWh: is a cost of one kWh (US$/kWh); R_m is a resistance of the mth line; I_m is the flow on the mth line; and NL is the number of the existing lines. In the first term of an objective function, the capital cost of the added lines is represented and the second term represents the cost of ohmic power losses after the new line additions. The system power flow and losses are changed due to a result of line additions. The loss coefficient (K) depends upon the number of years of transmission system operation and the kWh cost. The used DC load flow model in the problem formulation, a current (I) is approximately equal to the power flow and voltage is assumed to be unity at all buses.

B. Problem Constraints

The objective function (1) represents the capital cost of newly installed transmission lines and the cost of ohmic power losses while it has some technical restrictions. The problem’s constraints must be included into mathematical model to ensure that the optimal solution satisfies the TEP requirements. These problem’s constraints are described and formulated as following (2)-(7).

- *DC Power Flow Node Balance Constraint*

  This linear equality constraint represents the conservation of power at each node and can be formulated as in (2).

$$g = d + B\theta \tag{2}$$

where g, d and B are real power generation vector in existing power plants, real load demand vector in all network nodes, and susceptance matrix of the existing and added lines in the network, respectively. Here θ is the bus voltage phase angle vector.

- *Power Flow Limit on Transmission Lines Constraint*

  The following inequality constraint is applied to TEP problem in order to check the limit power flow for each path.

$$\left| f_{ij} \right| \le (n_{ij}^0 + n_{ij})\, f_{ij}^{\max} \tag{3}$$

In DC power flow model, each element of the branch power flow in constraint (3) can be calculated by using (4):

$$f_{ij} = \frac{(n_{ij}^0 + n_{ij})}{x_{ij}} \times (\theta_i - \theta_j) \tag{4}$$

where f_{ij}, $f_{ij}^{\max}$, n_{ij}, n_{ij}^0 and x_{ij} represent, respectively, total branch power flow in branch *i-j*, maximum branch power flow in branch *i-j*, number of circuits added to branch *i-j*, number of circuits in original base system and reactance of the branch *i-j*. Here θ_i and θ_j are voltage phase angle of the terminal buses i and j respectively.

- *Power Generation Limit Constraint*

  For the TEP problem with power generation resizing consideration, a power generation limit must be included into the problem constraints. This can be mathematically represented as follows:

$$g_i^{\min} \le g_i \le g_i^{\max} \tag{5}$$

where g_i, $g_i^{\min}$ and $g_i^{\max}$ are real power generation at node i, the lower and upper real power generation limits at node i, respectively.

- *Right-of-way Constraint*

  It is essential to obtain the accurate TEP solution, thus planner needs to know an exact capacity of newly required circuits. Therefore a right-of-way constraint is also included into such problem. Mathematically, this constraint defines new circuit location and maximum number of circuit that can be installed in a specified location. It can be represented as follows:

$$0 \le n_{ij} \le n_{ij}^{\max} \tag{6}$$

where n_{ij} and $n_{ij}^{\max}$ represent the total integer number of circuits added to the branch *i-j* and the maximum number of added circuits in the branch *i-j*, respectively.

- *Bus Voltage Phase Angle Limit Constraint*

A voltage phase angle should be included as a TEP constraint and a calculated phase angle (θ_{ij}^{cal}) must be less than a predefined maximum phase angle ($\theta_{ij}^{\max}$). This constraint can be represented as the following mathematical expression.

$$\left|\theta_{ij}^{\text{cal}}\right| \le \left|\theta_{ij}^{\max}\right| \tag{7}$$

III. BASIS OF DIFFERENTIAL EVOLUTION ALGORITHM METHODOLOGY

A differential evolution algorithm (DEA) is a novel evolutionary algorithm as it employs real-coded variables and typically relies on mutation as the search operator. More recently the DEA has evolved to share many features with a conventional genetic algorithm (CGA) as found in [12]. Regarding the major similarity between these two types of algorithm, they both maintain populations of potential solutions and use a selection mechanism for choosing the best individuals from the population. The features of DEA method are different from CGA in several aspects [13].

The DEA method is a parallel direct search technique that employs a population P of size N_P, consisted of floating point encoded individuals or candidate solutions (8). At every generation G during the optimization process, the DEA maintains population $P^{(G)}$ of N_P vectors of candidate solutions to the problem at hand.

$$P^{(G)} = [X_1^{(G)}, \ldots, X_i^{(G)}, \ldots, X_{N_P}^{(G)}] \tag{8}$$

Each candidate solution X_i is a D-dimensional vector, containing as many real-valued parameters (9) as the problem decision parameters D.

$$X_i^{(G)} = [x_{1,i}^{(G)}, \ldots, x_{j,i}^{(G)}, \ldots, x_{D,i}^{(G)}], \quad i = 1, \ldots, N_p \tag{9}$$

A. Initialization Step

In the first step of DEA procedure, the population of candidate solutions must be initialized. Typically, each decision parameter in every vector of the initial population is assigned a randomly chosen value from within its corresponding feasible bounds.

$$x_{j,i}^{(G=0)} = x_j^{\min} + \text{rand}_j[0,1].(x_j^{\max} - x_j^{\min}) \tag{10}$$

where $i = 1,\ldots,N_P$ and $j = 1,\ldots,D$. $x_{j,i}^{(G=0)}$ is an initial value of the j^{th} parameter of the i^{th} individual vector. $x_j^{\min}$ and $x_j^{\max}$ are the lower and upper bounds of the j^{th} decision parameter, respectively. Once every vector of the population has been initialized, its corresponding fitness value is calculated and stored for future reference.

B. Mutation Step

After the population of candidate solutions is successfully initialized in the first step of DEA procedure, thus the next step is carried out by applying three basic genetic operations that are mutation, crossover and selection. Several such DEA operators generate the population of next generation $P^{(G+1)}$ by using the current population $P^{(G)}$. At every generation G, each vector in the population must serve once as a target vector $X_i^{(G)}$ and the parameter vector has selected vector index i. The chosen target vector is compared with a mutant vector in the next step. The mutation operator creates mutant vectors ($V_i^{(G)}$) by perturbing a randomly selected vector (X_{r1}) with the difference of two other randomly selected vectors (X_{r2} and X_{r3}).

$$V_i^{(G)} = X_{r1}^{(G)} + F\left(X_{r2}^{(G)} - X_{r3}^{(G)}\right), \quad i = 1, \ldots, N_P \tag{11}$$

Vector indices $r1$, $r2$ and $r3$ are randomly selected, which $r1$, $r2$ and $r3 \in \{1,\ldots,N_P\}$ and $r1 \neq r2 \neq r3 \neq i$. X_{r1}, X_{r2} and X_{r3} are selected anew for each parent vector. F is a user-defined constant known as the “scaling mutation factor”, which is typically chosen from within the range $[0,1^+]$.

C. Crossover Step

In this step, the DEA procedure employs a crossover or recombination process to increase the diversity among the mutant parameter vectors. At the generation G, the crossover operation creates trial vectors (U_i) by mixing the parameters of the mutant vectors (V_i) with the target vectors (X_i) according to a selected probability distribution.

$$U_i^{(G)} = u_{j,i}^{(G)} = \begin{cases} v_{j,i}^{(G)} & \text{if} \quad \text{rand}_j(0,1) \le CR \;\; or \;\; j = s \\ x_{j,i}^{(G)} & \text{otherwise} \end{cases} \tag{12}$$

The crossover constant CR is a user-defined value (known as the “crossover probability”), which is usually selected from within the range [0,1]. The crossover constant controls the diversity of the population and aids the algorithm to escape from local optima. The “rand_j” is a uniformly distributed random number within the range (0,1) generated anew for each value of j. “s” is the trial parameter with randomly chosen index $\in \{1,\ldots,D\}$, which ensures that the trial vector gets at least one parameter from the mutant vector.

D. Selection Step

Finally, a selection operator is adopted in the last stage of the DEA procedure. The selection operator picks the vector that is going to compose the population in the next generation. This operator compares the fitness values between the trial vector and the corresponding target vector, and then it selects the one providing the best solution. The fitter of the two vectors is then permitted to advance into the next generation according to (13).

$$X_i^{(G+1)} = \begin{cases} U_i^{(G)} & \text{if} \quad f(U_i^{(G)}) \le f(X_i^{(G)}) \\ X_i^{(G)} & \text{otherwise} \end{cases} \qquad (13)$$

The DEA optimization process is repeated continuously across generations to improve the fitness of individuals. The overall optimization process is stopped whenever maximum number of generations is reached or any other predetermined convergence criterion is satisfied.

IV. Implementation of An Enhanced DEA Method for TEP Problem with System Losses Consideration

Although a conventional DEA method has a number of merits as described in section III, it still has a drawback that is a difficult task of the DEA control parameters tuning. Regarding such disadvantage of the conventional DEA characteristic, thus it should be improved the optimization performance in this research. An enhanced DEA method is a modified version and has been proposed to solve the TEP problem with system losses consideration in this paper.

A. An Enhanced DEA Optimization Method

In this research, the design of a self-adaptive DEA (SaDEA) procedure is to develop two DEA control parameters, mutation factor (F) and crossover probability (CR), which are self-tuning parameters using probability methodology. This enhanced method is called "Method 2jDE" as found in [14]. In the first step of SaDEA optimization process, user must determine two constant values (T_1 and T_2), which are the indices of control parameters (F and CR) changing. The user-defined values T_1 and T_2 are usually chosen from within the range [0,1] and set as 0.1 in this work for avoiding local optimum trapping. These control parameters F and CR are updated in their setting bounds when the uniformly distributed random numbers within the range (0,1) are less than T_1 and T_2.

After two constant values are set by user, then an initial population is generated according to (10). In the TEP problem formulation, each individual vector (X_i) contains many integer-valued parameters n, where $n_{j,i}$ represents the number of candidate lines in the possible branch j of the individual i. The problem decision parameter D is the number of possible branches for expansion.

$$X_i^{(G)} = [n_{1,i}^{(G)},\ldots,n_{j,i}^{(G)},\ldots,n_{D,i}^{(G)}], \quad i = 1,\ldots,N_p \qquad (14)$$

When an initial population of individuals is initialized successfully, then three DEA operators (11)-(13) create the population of next generation $P^{(G+1)}$ by using the current population $P^{(G)}$. The optimization process is continuously repeated in search of the final solution until the maximum number of generations ($G^{\max}$) is reached or other predetermined convergence criterion (ε) is satisfied.

The SaDEA optimization performance depends on the suitable values of control parameters. In this simulation, the setting ranges of the SaDEA control parameters used in the TEP problem are as follows: F = [0.4,1], CR = [0.8,1] and N_P = [5*D,10*D]. The maximum predetermined convergence criterion (ε) is set to 10^{-4} and the maximum number of generations ($G^{\max}$) is set to 10^3.

B. The TEP Fitness Function

A fitness function of TEP problem is used to search the optimal solution, measure the performance of candidate solutions and check for violation of the TEP problem constraints. The TEP fitness function $F(X)$ is a combination of an objective function and two penalty functions and can be formulated according to (15) for each individual. An individual is the best solution if its fitness value $F(X)$ is highest. The penalty functions must be also included in the fitness function in order to represent violations of both equality and inequality constraints of TEP problem. Regarding the proposed problem, an equality constraint penalty function (17) considers the DC power flow node balance constraint and an inequality constraint penalty function (18) considers the constraints of power flow limit on each transmission line, power generation limit, bus voltage phase angle limit and right-of-way, respectively. The general fitness function of the TEP problem can be assigned as follows:

$$F(X) = \frac{1}{O(X) + \omega_1 P_1(X) + \omega_2 P_2(X)} \qquad (15)$$

In (15), $F(X)$ and $O(X)$ represent a fitness function and an objective function of the TEP problem, respectively. $P_1(X)$ and $P_2(X)$ are the equality and inequality constraint penalty functions respectively. X denotes the individual vector of decision variables. In this work, ω_1 and ω_2 are penalty weighting factors and set to 0.5, respectively. For the TEP problem, the objective function and penalty functions are formulated as follows.

$$O(X) = V(X) = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} + K \sum_{m=1}^{NL} I_m^2 R_m \tag{16}$$

$$P_1(X) = \sum_{k=1}^{nb} \left| d_k + B_k \theta_k - g_k \right| \tag{17}$$

$$P_2(X) = \begin{cases} C & \text{if an individual violates the TEP} \\ & \text{inequality constraints.} \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

where C is an inequality constraint constant that is used when an individual violates the inequality constraints. In this work, the constant C is set as 0.5 for all cases.

C. Overall Procedures

The overall procedures of the SaDEA method application to the TEP problem with line losses consideration can be summarized as follows:

Step 1: Read all required transmission system data;
Step 2: Set up all control parameters of the SaDEA method ($F^{\min}$, $F^{\max}$, $CR^{\min}$, $CR^{\max}$, T_1, T_2, N_P and D);
Step 3: Create the initial values of the SaDEA control parameters (F and CR) to be applied to mutation and crossover operators;
Step 4: Set initial iteration $G = 0$ for an initialization step of the SaDEA procedure;
Step 5: Initialize the population P of all individuals according to (10);
Step 6: Evaluate the fitness function according to (15) and then check violations of all constraints for each individual using (17) and (18);
Step 7: Rank all individuals according to their fitness;
Step 8: Updating F, the F value is updated when a random value $rand_1$ (0,1) < T_1;
Step 9: Updating CR, the CR value is updated when a random value $rand_2$ (0,1) < T_2;
Step 10: Set iteration $G = 1$ for the next step of the SaDEA optimization process;
Step 11: Apply mutation, crossover and selection operations to create new individuals;
Step 12: Evaluate the fitness function by using (15) and then check violations of all constraints for each new individual using (17) and (18);
Step 13: Rank new individuals according to their fitness;
Step 14: Updating F, the F value is updated when a random value $rand_1$ (0,1) < T_1;
Step 15: Updating CR, the CR value is updated when random value $rand_2$ (0,1) < T_2;
Step 16: Verification of stop criterion, if $|F(X)^G - F(X)^{G-1}| > \varepsilon$ or $G < G^{\max}$, set $G = G + 1$ and return to step 11 for repeating to search the final solution. Otherwise, stop to calculate and go to step 17;
Step 17: Compute and display the final solutions, which are an investment cost, a system losses cost and a total expansion cost.

V. Test Systems and Numerical Results

In the simulation, the proposed enhanced DEA procedure is implemented in MATLAB and tested its performance on two electrical transmission systems reported in [11] and [15]. These two test networks are the Garver's 6-bus system and IEEE 25-bus system, which all significant data are also available in [11] and [15]. For this research, the TEP problem with system losses consideration is investigated both with and without the resizing of power generation. The numerical results of the proposed SaDEA technique have been compared to conventional genetic algorithm (CGA), tabu search (TS), artificial neural networks (ANNs), hybrid artificial intelligent techniques and summarized in this section.

A. Garver 6-bus System

In this paper, a well-known Garver's system is the first test network employed for investigation. It consists of 6 buses, 9 possible branches and 760 MW of demand. The electrical system data; transmission line, load and generation data are available in [11]. A maximum of four parallel lines is permitted in each branch. In this simulation case, the power losses consideration is included in the objective function where the loss coefficient (K) is selected as 1000. The per-unit base in the DC-load flow analysis is 100

MVA while the cost base is 10^5. The estimated lifetime of the transmission lines is assumed to be 25 years and the cost of one kWh is assumed to be 0.005 monetary units/kWh as found in [3].

TABLE I. COMPARISON OF THE EXPANSION COSTS AMONG VARIOUS METHODS FOR GARVER 6-BUS TEST SYSTEM

Types of TEP problem	**K=1000**			
	Methods	**Investment cost**	**Losses cost "a"**	**Saved cost "b"**
TEP without the resizing of power generation	ANNs [3]	261	448.83	904.77
	TS [3]	291	382.54	971.06
	GA [3]	291	382.54	971.06
	Hybrid ANN-TS-GA [3]	291	382.54	971.06
	SaDEA [16]	291	382.54	971.06
TEP with the resizing of power generation	SaDEA	170	231.66	1,121.94

Note: The losses cost "a" after the new line addition is calculated for 25 years. The saved cost "b" is calculated as a difference cost between the cost of ohmic power losses before the expansion of the transmission network (1353.6 monetary units) based on a 25-year (life-time of line) and the power losses cost "a" calculated after the new line additions for the same period.

For a case study of without power generation resizing consideration, the best solution of TEP problem considering transmission system losses on Garver's test system as shown in table 1 was found by all algorithms except ANNs method with the following topology: $n_{2\text{-}6} = 4$, $n_{3\text{-}5} = 1$, $n_{4\text{-}6} = 3$ and $n_{5\text{-}6} = 1$. Although the ANNs method obtained the least investment cost compared to other methods but it had the largest value of power losses cost after the new line additions. The SaDEA method obtained the investment cost and losses cost for with power generation resizing case study cheaper than the without power generation resizing case study. In addition, the SaDEA method had the largest saved cost of minimizing ohmic power losses during planning horizon in case of with power generation resizing consideration.

B. IEEE 25-bus System

The IEEE 25-bus system is conduced to test the performance of SaDEA procedure in this paper. For the second test system, it has 25 buses, 36 possible branches and 2750 MW of total demand. The electrical system data; transmission line, load and generation data are available in [3] and [15]. A new bus of this system is bus-25 that is prepared for connecting to bus-5 and/or bus-24. A maximum of four parallel lines is permitted to install in each branch. In this simulation case, the objective function includes the power losses consideration, in which the loss coefficient (K) is selected to be 10000. The estimated lifetime of the transmission lines is assumed to be 25 years while the cost of one kWh is assumed to be 0.0112 US$/kWh [3].

TABLE II. COMPARISON OF THE EXPANSION COSTS AMONG VARIOUS METHODS FOR IEEE 25-BUS TEST SYSTEM

Types of TEP problem	**K=10000**			
	Methods	**Investment cost (million US$)**	**Losses cost "a" (million US$)**	**Saved cost "b" (million US$)**
TEP without the resizing of power generation	ANNs [3]	224.178	161.995	147.979
	TS [3]	180.664	155.264	154.709
	GA [3]	162.430	171.947	138.016
	Hybrid ANN-TS-GA [3]	168.784	152.320	157.653
	SaDEA [16]	160.051	134.251	175.722
TEP with the resizing of power generation	SaDEA	62.477	83.032	226.941

Note: The losses cost "a" after the new line addition is calculated for 25 years. The saved cost "b" is calculated as the difference cost between the cost of ohmic power losses before the expansion of the transmission system (309.973 million US$) based on a 25-year (life-time of line) and the power losses cost "a" calculated after the new line additions for the same period.

For a case study of without power generation resizing consideration, the best solution of the TEP problem considering line losses consideration was found by SaDEA method and an investment cost was 160.051 million US$ as shown in table 2, with the addition of the following lines to the base topology: $n_{7\text{-}13} = 2$, $n_{8\text{-}22} = 3$, $n_{11\text{-}14} = 2$, $n_{12\text{-}14} = 2$, $n_{12\text{-}23} = 3$, $n_{13\text{-}18} = 2$, $n_{13\text{-}20} = 3$, $n_{16\text{-}18} = 3$, $n_{16\text{-}20} = 3$, $n_{20\text{-}21} = 1$, $n_{5\text{-}25} = 3$ and $n_{24\text{-}25} = 2$. In addition, the SaDEA method achieved the least value of a power losses cost after the new line additions compared to other techniques. Comparison of two case studies, the SaDEA method obtained the investment cost and losses cost for with power generation resizing case cheaper than the without power generation resizing case. Therefore the SaDEA method got the largest value of a saved cost of minimizing ohmic power losses during expansion planning horizon in this test system. Overall, the best algorithmic procedure for this test case is SaDEA method.

VI. CONCLUSIONS

In this paper, an enhanced DEA methodology, called a self-adaptive DEA (SaDEA) procedure, has been applied when solving TEP problem considering transmission system losses. In addition, the resizing of power generation consideration is also included in such problem. According to all obtained results on two test systems illustrate that the SaDEA procedure is an efficient technique for solving the TEP problem. As the numerical test results in table 2 indicate, the proposed method found the least values of an investment cost and a power losses cost compared to the conventional genetic algorithm, the tabu search, the artificial neural networks and the hybrid artificial intelligent techniques on the IEEE 25-bus system for both with and without power generation resizing case studies. In addition, the SaDEA method had the largest saved cost of ohmic power losses for both test cases as shown in table 1 and table 2. In the simulation, the most attractive feature of the proposed algorithm is the good computational performance. The accuracy of the results obtained in the TEP study is in very good agreement with those obtained by other researchers as found in [3]. Regarding a consequence of these successful results, the TEP problem considering the n-1 contingencies in single line outage or single generator outage will be investigated as future work.

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An enhanced differential evolution algorithm application to transmission network expansion planning with security constraints consideration

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Abstract: In this article, an enhanced differential evolution algorithm (DEA) is applied directly to the DC power flow based model in order to efficiently handle a problem of transmission network expansion planning (TNEP) with *n*-1 security criterion consideration. The proposed methodology is adopted to minimise a transmission investment cost associated with economical, operational, and reliable constraints. Mathematically, long-term transmission planning using the DC model is a mixed integer nonlinear programming problem, which is a difficult task for solving in real-world transmission systems. In addition, the TNEP problem is also investigated both with and without the resizing of power generation in this work. The efficiency of the proposed technique is initially demonstrated via the analysis of low and medium complexity transmission system test cases. In this work, the analyses are performed within a mathematical programming environment of MATLAB and a detailed comparative study among conventional DEA technique, ant colony search algorithm (ACSA), Chu-Beasley genetic algorithm (CBGA), and the proposed method is presented. As numerical results, the proposed algorithm provides accurate solution, feature of robust computation, simple implementation, and satisfactory computational time.

1. Introduction

In general, cost-effective transmission network expansion planning (TNEP) is a major challenge with regard to electrical power system optimisation problems as its main goal is to achieve optimal expansion plan. The planning solution has to meet technical requirements while offering economical investment. Furthermore, good transmission expansion plan should specify new transmission facilities that must be installed in existing network to ensure adequate operation over a specified planning horizon [1].

Over past few decades, a number of optimisation techniques have been applied to deal with the TNEP problem in many issues. These proposed methods are as follows: mathematical optimization methods (e.g. linear programming, nonlinear programming, dynamic programming, integer and mixed integer programming, benders decomposition, branch & bound, etc.), heuristic methods (mostly constructive heuristics), and meta-heuristic methods (e.g. genetic algorithms, tabu search, simulated annealing, particle swarm, evolutionary algorithms, differential evolution algorithm, etc.).

In recent years, a differential evolution algorithm (DEA) has been attracting increasing attention for a wide variety of engineering applications including electrical power system optimisation problems. A large number of researches, applying DEA for solving the electrical power system optimisation problems, for instance, power system planning [2], economic power dispatch [3-5], distribution network reconfiguration problem [6], short-term hydrothermal scheduling problem [7], optimal reactive power flow [8-9], and optimal power flow [10]. In addition, the DEA method was successfully solved both static and dynamic TNEP problems by the author in [11], where the DEA method performed superior to conventional genetic algorithm (CGA) in terms of simple implementation with high quality of solution and good computation performance. Meanwhile, DEA requires less control parameters while being independent from initialization. Moreover, its convergence is stable as DEA procedure uses rather greedy selection and less stochastic approach to solve optimization problems than other CGA. Unfortunately, there remains a drawback of DEA procedure that is a tedious task of the DEA control parameters tuning due to complex relationship among problem’s parameters. The optimal parameter settings of DEA method may not be found and the final results may be trapped in a local minimum.

It is important to note that few algorithms have been practically applied to solve the TNEP problem as reported in [12]. Although the proposed DEA method [11] was successfully solved many cases of TNEP problem, it was not yet sufficiently robust for practical use in industry. The DEA method has the notable limitation of control parameter tuning due to a complex interaction of parameters as above mentioned. Therefore, a further improvement of the DEA method is essentially required before it can be generally adopted for practical use in industry.

The proposed problem as studied in [11] is a basic transmission planning, in which the security criterion has not been considered. In other words, the optimal expansion plan is determined without considering *n*-1 contingencies caused by a transmission line or generator outage. The *n*-1 security criterion is an essential index in power system reliability study as it states that the system should be expanded in such a way that, if a single line or generator is withdrawn, the expanded system should still operate adequately. Therefore, an enhanced DEA method has been proposed for solving the TNEP problem with *n*-1 security criterion consideration in this research. The total investment costs and computational times of the DEA approach are compared to other optimisation techniques on Garver 6-bus system, IEEE 25-bus system, and Brazilian 46-bus system.

2. Transmission network expansion planning problem formulation

In this section, the TNEP is formulated as a mathematical problem. A main goal of solving such problem is typically to fulfill the required planning function in terms of investment and operation restrictions. Normally, the TNEP problem can be mathematically formulated by applying a classical DC power flow model, which is a nonlinear mixed-integer problem with high complexity, especially for large-scale real-world transmission networks. There are several alternatives to DC model such as transportation, hybrid, and disjunctive models. Detailed reviews of the main mathematical models for TNEP problem were found in [13].

2.1 The TNEP problem without security constraints consideration

2.1.1 The objective function

The objective of TNEP problem

2.1.2 Problem constraints

The objective function (1) represents a capital cost of newly installed transmission lines, which has some restrictions. These constraints must be included into mathematical model to ensure that the optimal solution satisfies transmission planning requirements. These constraints are described as follows:

DC power flow node balance constraint

This linear equality constraint represents the conservation of power at each node.

$$g \quad d \quad B \tag{2}$$

where *g*, *d* and *B* are real power generation vector in existing power plants, real load demand vector in all network nodes, and susceptance matrix of existing and added lines in network, respectively. Here   is bus voltage phase angle vector.

Power flow limit on transmission lines constraint

The following inequality constraint is applied to transmission planning in order to limit the power flow for each path.

$$\left| f_{ij} \right| \quad (n_{ij}^{0} \quad n_{ij})\, f_{ij}^{\max}$$

Right-of-way constraint

It is essential to find an accurate TNEP solution, thus planners need to know an exact capacity of newly required circuits. Therefore this constraint must be considered in such planning problem. Mathematically, the constraint defines location and maximum number of circuits, which can be installed in a specified location. It can be represented as following equation.

$$0 \quad n_{ij} \quad n_{ij}^{\max} \tag{6}$$

where n_{ij} and $n_{ij}^{\max}$ represent the total integer number of circuits added to the branch *i-j* and the maximum number of added circuits in the branch *i-j* respectively.

Bus voltage phase angle limit constraint

While the DC power flow model is employed to TNEP problem, bus voltage magnitude is not a factor in this analysis. Therefore, bus voltage phase angle could be included as a TNEP constraint to be increase an accurate solution in technical issue. A calculated phase angle ($_{ij}^{\mathrm{cal}}$) should be less than the predefined maximum phase angle ($_{ij}^{\max}$). Such constraint can be represented as the following mathematical expression.

$$\left| \, _{ij}^{\mathrm{cal}} \right| \quad \left| \, _{ij}^{\max} \right| \tag{7}$$

2.2 The TNEP problem with security constraints consideration

A main purpose of solving the TNEP problem with *n*-1 security criterion consideration is to minimise total expansion cost while satisfying economical, technical, and reliable constraints. In this work, the DC power flow model is adopted to handle the TNEP problem with security constraints consideration as found in [14]. Mathematically, an objective function of such problem can be formulated as follows:

$$\min \quad v \quad \sum_{(i,j)} c_{ij} n_{ij} \tag{8}$$

Subject to

$$n \quad n_{ij} \quad \mathrm{OPC} \tag{9}$$

$$n \quad n_{ij} \quad \mathrm{SCC} \tag{10}$$

where is set of all candidate branches for expansion. OPC represents the planning operational constraints without security as explained in subsection 2.1.2 and can be formulated as following equations (2)-(7). Moreover, SCC represents the security constraints including in TNEP problem. In this work, the TNEP problem is investigated that the system operates with security and satisfied *n*-1 criterion. In this context, the SCC constraints to the problem with *nl* paths to expansion presents the following equations:

$$g^{p} \quad d \quad [B \quad]^{p} \tag{11}$$

$$\left| f_{ij}^{p} \right| \quad (n_{ij}^{0} \quad n_{ij}) f_{ij}^{\max} \qquad (i, j) \quad 1,2,...,nl; \quad \text{and } (i, j) \quad p \tag{12}$$

$$\left| f_{ij}^{p} \right| \quad (n_{ij}^{0} \quad n_{ij} \quad 1) f_{ij}^{\max} \qquad \text{for } (i, j) = p \tag{13}$$

In DC power flow model, each element of the branch power flow in constraints (12) and (13) can be calculated using (14) and (15), respectively:

$$f_{ij}^{p} \quad \frac{(n_{ij}^{0} \quad n_{ij})}{x_{ij}} \quad (\ _{i}^{p} \qquad _{j}^{p}) \qquad (i, j) \quad 1,2,...,nl; \quad \text{and } (i, j) \quad p \tag{14}$$

$$f_{ij}^{p} \quad \frac{(n_{ij}^{0} \quad n_{ij} \quad 1)}{x_{ij}} \quad (\ _{i}^{p} \qquad _{j}^{p}) \qquad (i, j) = p \tag{15}$$

$$g_{i}^{\min} \quad g_{i}^{p} \quad g_{i}^{\max} \tag{16}$$

$$0 \quad n_{ij} \quad n_{ij}^{\max} \tag{17}$$

$$\left| \ _{ij}^{\text{cal}} \right| \quad \left| \ _{ij}^{\max} \right| \tag{18}$$

$$(n_{ij} \quad n_{ij}^{0} \quad 1) \quad 0 \quad \text{and integer for } (i, j) = p \tag{19}$$

$$n_{ij} \quad 0 \quad \text{and integer} \quad (i, j) \quad 1,2,...,nl; \quad \text{and } (i, j) \quad p \tag{20}$$

$$f_{ij}^{p} \text{ and } \ _{\text{j}}^{\text{p}} \quad \text{unbounded} \tag{21}$$

$$(i, j) \qquad \text{and } p \quad 1, 2, ..., nl \tag{22}$$

In this problem formulation, there are *nl* sets of operational variables, a set to each contingency when it is considered all paths $p = (i,j)$.

3. An enhanced differential evolution algorithm method

Regarding a difficult task of DEA control parameters tuning due to complex relationship among problem's parameters has been a drawback of the conventional DEA method as shown in the previous author's work [11], where found the explanation of all basis of DEA optimisation processes. Therefore, further improvement of the conventional DEA method is essentially required before it can be generally adopted for practical use in industry. In this paper, a conventional DEA method has been developed its optimisation procedure. A self-adaptive DEA (SaDEA) technique is proposed and described in this section. The design of SaDEA optimization procedure is to develop two DEA control parameters, mutation factor (*F*) and crossover probability (*CR*), which are self-tuning parameters using probability methodology. This enhanced method is called “Method 2jDE” as found in [15].

As such proposed method, users must define two constant values (T_1 and T_2) that are the indices of control parameters (*F* and *CR*) changing, respectively. The user-defined values T_1 and T_2 are usually selected from within the range [0,1] and they are set as 0.1 in this research for avoiding local optimum trapping. The control parameters *F* and *CR* are updated in their setting bounds when the uniformly distributed random numbers within the range (0,1) are less than T_1 and T_2. The main concept of a self-adaptive DEA optimization process is illustrated in figure 1.

4. Implementation of an enhanced DEA method for TNEP problem with security constraints consideration

An enhanced DEA method is proposed to solve the TNEP problem with *n*-1 security criterion consideration as formulated in previous section. The proposed method can be implemented to handle such problem as following details.

After two constant values (T_1 and T_2) are set by users, then an initial population of SaDEA method is created for next optimisation processes. In the TNEP problem formulation, each individual vector (X_i) contains many integer-valued parameters *n*, where $n_{j,i}$ represents the number of candidate lines in the possible branch *j* of the individual *i*. The problem decision parameter *D* is the number of possible branches for expansion.

$$X_i^{(G)} \quad [n_{1,i}^{(G)},\dots,n_{j,i}^{(G)},\dots,n_{D,i}^{(G)}],\quad i \quad 1,\dots,N_p \tag{23}$$

When an initial population of individuals is initialised successfully, then three significant DEA operators, which are mutation, crossover, and selection as described in [11], create new population of next generation $P^{(G+1)}$ by using current population $P^{(G)}$. The optimisation process is continuously repeated in search of final solution until the maximum number of generations ($G^{\max}$) is reached or other predetermined convergence criterion ( ) is satisfied.

4.1 Fitness function of the TNEP considering security constraints

A fitness function of TNEP problem is applied to search optimal solution, measure performance of candidate solutions, and check for violation of the planning problem constraints. The TNEP fitness function $F(X)$ is a combination of an objective function and two penalty functions and can be formulated according to (24) for each individual. An individual is the best solution if its fitness value $F(X)$ is highest. The penalty functions must be also included in the fitness function in order to represent violations of both planning operational constraints without security (OPC) and the planning security constraints (SCC) of TNEP problem. Regarding the proposed problem, the OPC penalty function (26) investigates all constraints of TNEP problem without security criterion consideration. In addition, the SCC penalty function (27) investigates all security constraints of TNEP problem. The general fitness function of the TNEP problem can be assigned as follows:

$$F(X) = \frac{1}{O(X) + \lambda_1 P_1(X) + \lambda_2 P_2(X)} \tag{24}$$

In (24), $F(X)$ and $O(X)$ represent fitness function and objective function of the TNEP problem, respectively. $P_1(X)$ and $P_2(X)$ are the constraint penalty functions. X denotes the individual vector of decision variables. In this work, λ_1 and λ_2 are penalty weighting factors and set to 0.5, respectively. For this TNEP problem, the objective function and the constraint penalty functions are formulated as follows.

$$O(X) = V(X) = \sum_{(i,j)} c_{ij} n_{ij} \tag{25}$$

$$P_1(X) = \begin{cases} C_1 & \text{if an individual violates the OPC of TEP problem.} \\ 0 & \text{otherwise} \end{cases} \tag{26}$$

$$P_2(X) = \begin{cases} C_2 & \text{if an individual violates the SCC of TEP problem.} \\ 0 & \text{otherwise} \end{cases} \tag{27}$$

where C_1 and C_2 are the constraint constants, which are applied to problem when an individual violates the OPC and SCC of TNEP problem, respectively. In this work, both constants C_1 and C_2 are set as 0.5 for all cases.

4.2 Control parameters setting

The SaDEA optimisation performance depends upon the proper values of control parameters. In this simulation, the setting ranges of SaDEA control parameters used in TNEP problem are as follows: F = [0.5,1], CR

Step 14: Check n-1 security criterion for all constraints (11)-(22);

Step 15: Rank new individuals according to their fitness;

Step 16: Updating F, the F value is updated when a random value $rand_1$ (0,1) T_1;

Step 17: Updating CR, the CR value is updated when random value $rand_2$ (0,1) T_2;

Step 18: Verification of stop criterion, if $F(X)^G$- $F(X)^{G-1}$ > or $G < G^{\max}$, set $G = G + 1$ and return to step 12 for repeating to search the final solution. Otherwise, stop to calculate and go to step 19;

Step 19: Compute and display the final solutions, which are investment cost and convergence curve.

A computer program of the SaDEA method application to TNEP problem with security constraints consideration has been designed and performed as above procedures. The proposed computational program is illustrated in figure 2.

5. Test systems and numerical results

In the simulation, an enhanced DEA procedure is implemented in MATLAB and tested its performance on three electrical transmission systems as shown in [11]. These three test networks are Garver's 6-bus system, IEEE 25-bus system, and the Brazilian 46-bus system and all required data are also available in [13], [16] and [17], respectively. In this work, the proposed algorithm is applied to handle the TNEP problem considering security constraints that are more difficult for solving than the basic TEP problem found in [11]. Moreover, such TNEP problem includes an issue of power generation resizing consideration. The numerical results of proposed SaDEA technique are compared to conventional DEA method, The achieved results of SaDEA method on the Garver 6-bus system can be tabulated in table 1 including the discussion of these results as follows:

For the first test case, total expansion cost of the best solution equals to 180,000 US$ with the following topology: $n_{2\text{-}6} = 2$, $n_{3\text{-}5} = 3$, and $n_{4\text{-}6} = 2$.

A convergence curve of SaDEA method to obtain the best solution is illustrated in figure 3, where the optimal solution was found by SaDEA method at the 152nd iteration.

An average computational time of the proposed method is 64.03 second in this test case.

Table 1: Summary results of Garver 6-bus system

Results of the TNEP with security constraints consideration	The SaDEA method
Best total cost (x10^3 US$)	180
Average total cost (x10^3 US$)	187
Worst total cost (x10^3 US$)	210
% Difference between best and worst	16.67
Standard deviation (x10^3 US$)	11.60
Average CPU time (second)	64.03
Line additions for the best result	$n_{2\text{-}6} = 2$, $n_{3\text{-}5} = 3$, and $n_{4\text{-}6} = 2$

Table 2: Comparisons between real power flow and maximum real power flow at each right-of-way on Garver 6-bus system (Before applying -1 security criterion consideration)

Line path between buses	Power Flow (MW)	Max Power Flow (MW)
2-3	82.1675	100
4-6	157.7034	200
2-6	143.2966	200
3-5	225.8325	400
1-4	16.894	80
1-2	19.9385	100
1-5	14.1675	100
2-4	5.4026	100
5-6	0	0

As results in tables 2 and 3, comparisons between real power flow and maximum real power flow at each right-of-way are presented. Form obtained results in table 2, a transmission path between buses 2-3 is the most critical because it has the lowest gap between the real power flow and the maximum power flow compared to other paths on this system. Therefore, the real power flow and the maximum real power flow at each path are selected to show in table 3, when a line between buses 2-3 is outage. Regarding results in table3, the real power flow are not over the maximum real power flow for each path.

Table 3: Comparisons between real power flow and maximum real power flow at each right-of-way on Garver 6-bus system (After applying -1 security criterion consideration, when a line between buses 2-3 is outage)

Line path between buses	Power Flow (MW)	Max Power Flow (MW)
2-3	0	0
4-6	141.6707	200
2-6	159.3293	200
3-5	308	400
1-4	44.9512	80
1-2	74.0488	100
1-5	68	100
2-4	6.622	100
5-6	0	0

5.2 IEEE 25-bus system

The IEEE 25-bus system is also tested the performance of SaDEA procedure in this work. For the second test system, it has 25 buses, 36 possible branches, and 2750 MW of total demand. The significant electrical system data are available in [16] and [18]. A new bus of this system is bus-25 that is prepared for connecting to bus-5 and/or bus-24. The dotted lines represent new possible line additions and solid lines are the existing lines as shown in [11]. A maximum of four parallel lines is permitted to install in each branch.

The obtained results of SaDEA method on the IEEE 25-bus system can be tabulated in table 4 and the discussion of these results are as follows:

For the second test system, total expansion cost of the best solution equals to 19.131 million US$ with the following topology: $n_{5\text{-}20} = 1$, $n_{5\text{-}25} = 4$, $n_{6\text{-}24} = 1$, $n_{13\text{-}18} = 1$, $n_{13\text{-}20} = 1$, $n_{16\text{-}20} = 1$, and $n_{24\text{-}25} = 1$.

A convergence curve of SaDEA method to obtain the best solution is illustrated in figure 4, where the best solution was found by SaDEA method at the 584th iteration.

An average computational time of the proposed method is 654.52 second in this test case.

Table 4: Summary results of IEEE 25-bus system

Results of the TNEP with security constraints consideration	The SaDEA method
Best total cost (x10^3 US$)	19131
Average total cost (x10^3 US$)	25050
Worst total cost (x10^3 US$)	30020
% Difference between best and worst	56.92
Standard deviation (x10^3 US$)	4060.30
Average CPU time (second)	654.52
Line additions for the best result	$n_{5-20} = 1$, $n_{5-25} = 4$, $n_{6-24} = 1$, $n_{13-18} = 1$, $n_{13-20} = 1$, $n_{16-20} = 1$, and $n_{24-25} = 1$

5.3 Brazilian 46-bus system

The third test network is the Brazilian 46-bus system as found in [11] and [17]. The system comprises 46 buses, 79 circuits, and 6880 MW of total demand. The transmission line, load demand, and generation data including generation resizing range in MW are available in [17]. This system represents a good test to the proposed approach because it is a real-world transmission system. The addition of parallel transmission lines to existing lines is permitted in this case with a limit of four lines for each branch.

Table 5: Summary results of IEEE 46-bus system

Results of the TNEP with security constraints consideration	The SaDEA method
Best total cost (x10^3 US$)	168042
Average total cost (x10^3 US$)	185372
Worst total cost (x10^3 US$)	208870
% Difference between best and worst	24.30
Standard deviation (x10^3 US$)	17152
Average CPU time (second)	1962.43
Line additions for the best result	$n_{2-3} = 2$, $n_{3-46} = 1$, $n_{19-25} = 1$, $n_{20-21} = 1$, $n_{23-24} = 1$, $n_{24-25} = 2$, $n_{26-29} = 3$, $n_{28-30} = 1$, $n_{29-30} = 2$, $n_{31-32} = 1$, and $n_{42-43} = 2$

The obtained results of SaDEA method on the IEEE 46-bus system can be tabulated in table 5 and the discussion of the results are as follows:

For this test case, total expansion cost of the best solution is 168.042 million US$ with following topology: $n_{2-3} = 2$, $n_{3-46} = 1$, $n_{19-25} = 1$, $n_{20-21} = 1$, $n_{23-24} = 1$, $n_{24-25} = 2$, $n_{26-29} = 3$, $n_{28-30} = 1$, $n_{29-30} = 2$, $n_{31-32} = 1$ and $n_{42-43} = 2$.

In this case, the best solution was found by SaDEA method at the 728th iteration and an average CPU time of the proposed method is 1962.43 second.

5.4 Discussion on the results

All obtained results of TNEP problem with security constraints and power generation resizing considerations are summarized in table 6, where the best investment costs of expansion corresponding to the proposed method are compared to other algorithms. As indicated by the results in table 6, the SaDEA and CBGA methods found the optimal solution on Gaver 6-bus system. For IEEE 25-bus system and the Brazilian 46-bus system, the SaDEA method could find the optimal solution as shown the cheapest investment cost.

The achieved numerical results clearly indicate that SaDEA method can be efficiently applied to TNEP problem with *n*-1 security constraint consideration on three test systems. From the results in table 6, SaDEA technique could find the best solution cheaper than other methods in all cases. The proposed algorithm was tested 30 times to find the best result in each case and the suitable setting ranges of SaDEA control parameters were suggested in section 4.3.

Table 6: Results comparison of TNEP problem with security constraints consideration

Methods	Best cost (x10^3 US$)		
	Garver 6-bus system	IEEE 25-bus system	Brazilian 46-bus system
SaDEA	180	19,131	168,042
Chu-Beasley GA (CBGA) [14]	180	-	213,000
Ant Colony Search Algorithm (ACSA) [19]	298	248,943	-
Conventional DEA Method [19]	298	210,818	-

6. Conclusions and further work

In this paper, an enhanced DEA methodology is proposed to deal with the TNEP problem with *n*-1 security criterion consideration. For this study, a single line outage is investigated in such TNEP problem for reliability issue. From obtained results of Garver 6-bus system, IEEE 25-bus system, and the Brazilian 46-bus system, the SaDEA procedure is an acceptable optimization technique and minimizes effectively the total investment cost of TNEP problem with security constraints consideration on realistically transmission systems. As the empirical solutions of these test cases indicate, total investment costs of the SaDEA method are less expensive than other methods on three test networks. The most attractive feature of the proposed algorithm is good computational performance and simple implementation. Regarding a consequence of the successful results, a distribution system planning problem will be investigated as future work.

7. Acknowledgements

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9. Figures

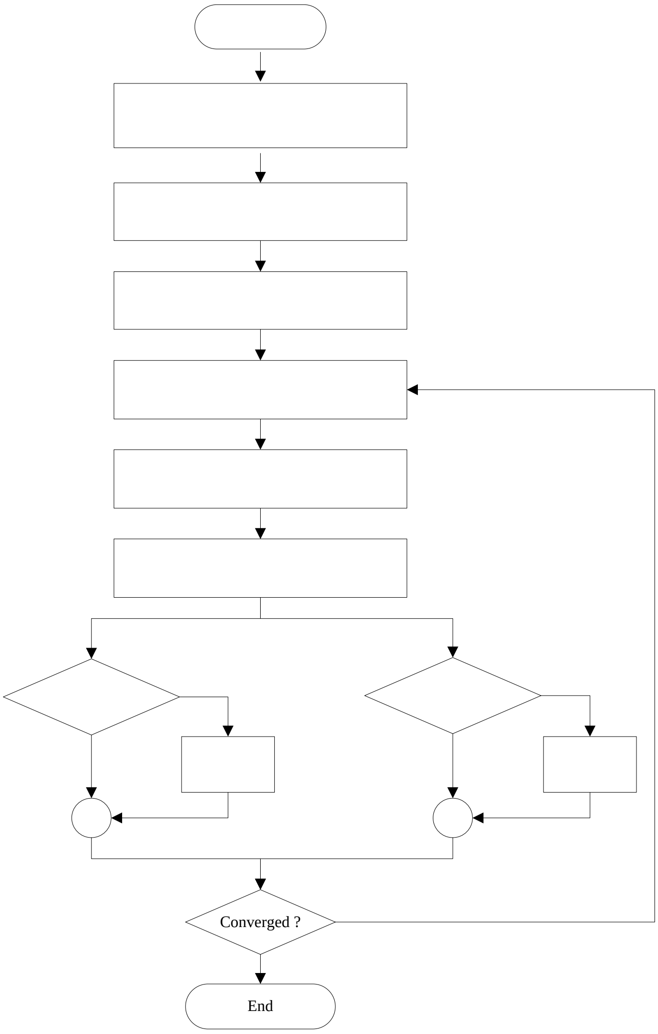

Fig. 1 *The main flowchart of a self-adaptive DEA optimization process*

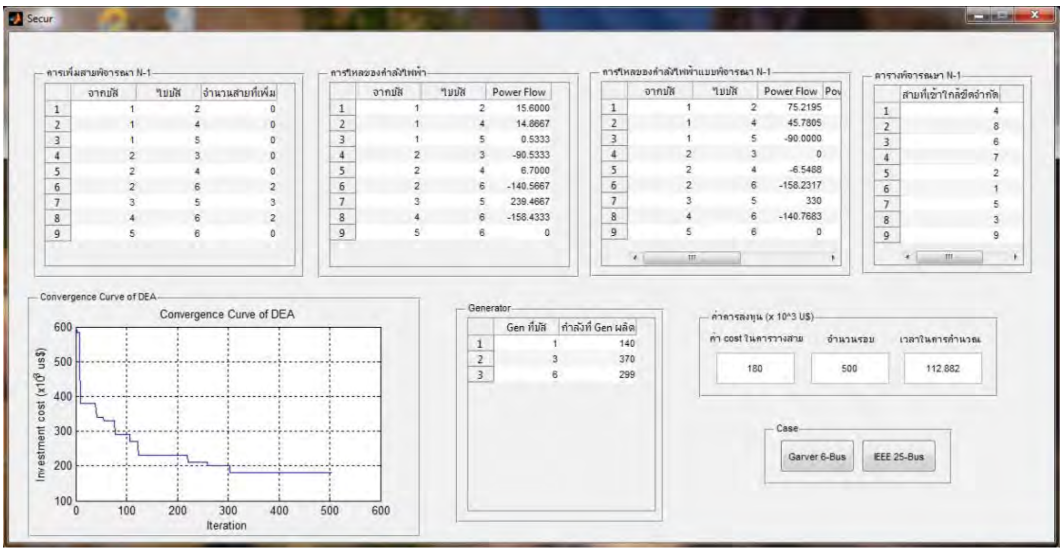

Fig 2 *Example of a SaDEA optimization program for TNEP problem with security constraints consideration*

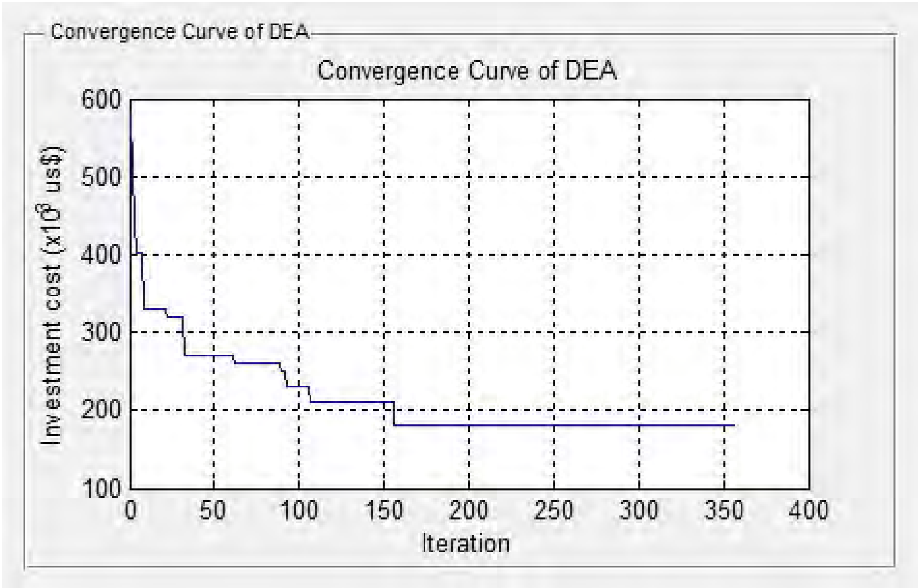

Fig. 3 *A convergence curve of SaDEA method for Garver 6-bus system*

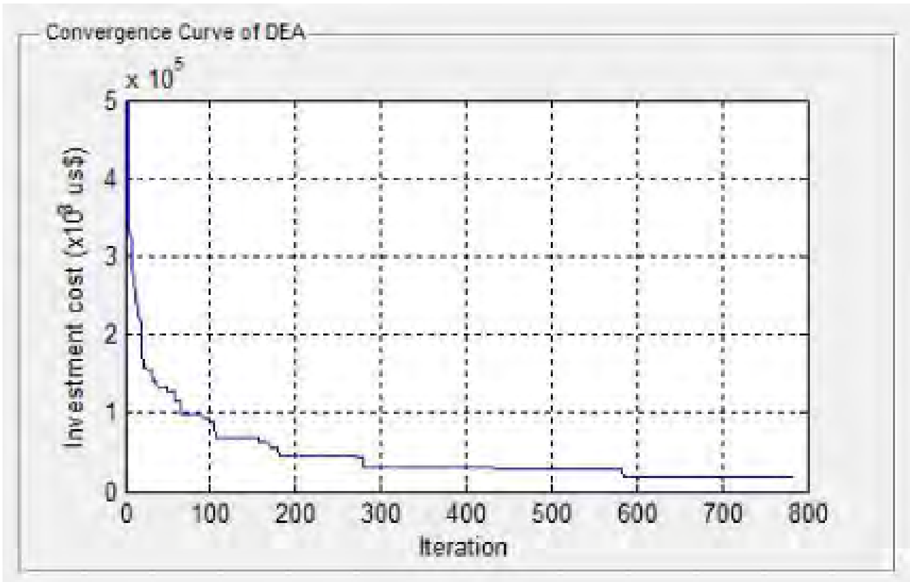

Fig. 4 *A convergence curve of SaDEA method for IEEE 25-bus system*