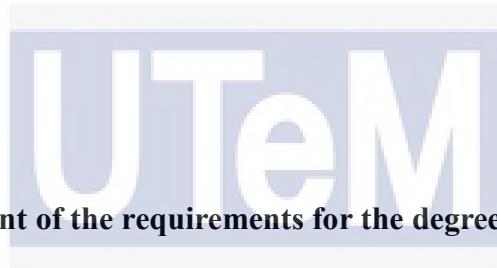


REACTIVE POWER PLANNING USING EVOLUTIONARY PROGRAMMING FOR

IEEE 26-BUS

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A report submitted in partial fulfilment of the requirements for the degree of Bachelor of

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اونیورسٹی تکنیکال ملاک

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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2016

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DECLARATION

I declare that this report entitle “Reactive Power Planning using Evolutionary Programming for IEEE 26-bus” is the result of my own research except as cited in the references. The report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



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To my beloved mother and father



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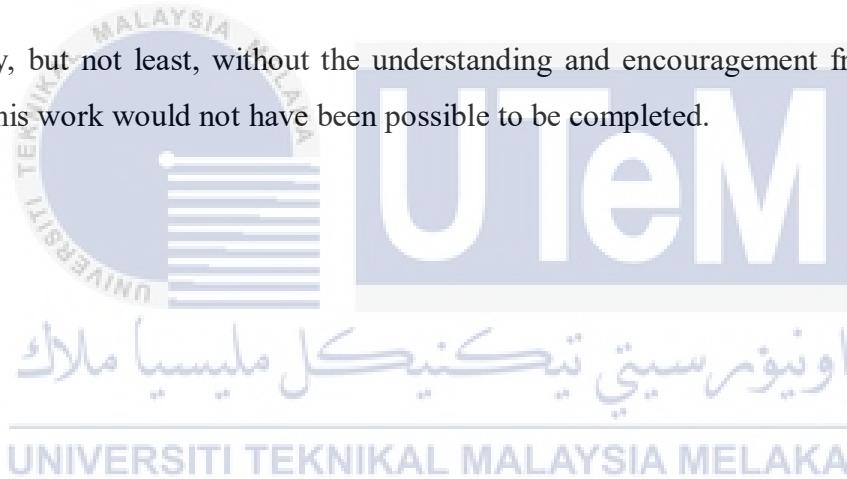
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ABSTRACT

Reactive Power Planning (RPP) is become a vital issue for power system planning and operation in order to avoid voltage instability event which lead to severe blackout incident. The relationship between reactive power reserve and Voltage Stability Margin (VSM) also been studied which found that variation caused changes in network operation. For that reason, most researches intended to enhance voltage stability condition by sustaining the reactive power across power networks. In consequence, this study introduced Evolutionary Programming (EP) technique as a simulation tool in optimizing RPP, on standard IEEE 26 bus system using MATLAB programming. The Maximum Loading Point (MLP) selected as the individual objective function to be optimized with varying on their identified control variables while total system loss minimization is observed during the implementation. From findings, the EP is capable to improve the MLP as well less total loss as referred to results obtained without RPP optimization. Upon completion, this technique also provided the better voltage profile to avoid the unsecured operation condition during any load changes.

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ABSTRAK

Perancangan Kuasa Reaktif (RPP) merupakan isu penting bagi perancangan sistem kuasa dan operasi untuk mengelakkan peristiwa ketidakstabilan voltan yang boleh membawa kepada gangguan bekalan elektrik yang teruk. Hubungan diantara rizab kuasa reaktif dan Margin Kestabilan Voltan (VSM) juga telah dikaji dan didapati akan menyebabkan perubahan dalam operasi rangkaian. Oleh sebab itu, banyak kajian telah dijalankan untuk meningkatkan kestabilan voltan dengan mengekalkan kuasa reaktif pada seluruh rangkaian kuasa. Sehubungan dengan itu, kajian ini memperkenalkan teknik Pengaturcaraan Evolusi (EP) sebagai alat simulasi dalam mengoptimumkan RPP, pada sistem bas IEEE 26 dengan menggunakan pengaturcaraan MATLAB. Titik Bebanan Maksimum (MLP) dipilih sebagai fungsi objektif tunggal yang akan dioptimumkan dengan menggunakan pelbagai pembolehubah kawalan sementara memerhati jumlah kehilangan kuasa yang minima semasa pelaksanaan. Berdasarkan penemuan, EP mampu meningkatkan MLP serta mengurangkan jumlah kerugian yang bertentangan dengan keputusan tanpa pengoptimuman RPP. Selain itu, teknik ini juga memberi profil voltan yang lebih baik untuk mengelakkan keadaan operasi yang bahaya pada sebarang perubahan beban.

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LIST OF ABBREVIATIONS

AC	-	Alternating Current
BFO	-	Bacterial Foraging Optimization
CPF	-	Continuation Power Flow
DE	-	Differential Evaluation
EAs	-	Evolutionary Algorithms
EP	-	Evolutionary Programming
ES	-	Evolutionary Strategies
FACTS	-	Flexible AC Transmission System
GA	-	Genetic Algorithm
GP	-	Genetic Programming
IEEE	-	Institute of Electrical and Electronics Engineers
IP	-	Interior Point
LP	-	Linear Programming
MCGA	-	Mixed Coding of Genetic Algorithm
MINLP	-	Mixed Integer Nonlinear Programming
MLP	-	Maximum Loading Point
NLP	-	Nonlinear Programming
P	-	Active Power

PoC	-	Point of Collapse
PSO	-	Particle Swarm Optimization
Q	-	Reactive Power
Q_{gs}	-	Reactive Power Dispatch
Q_{inj}	-	Compensating Capacitor Placement
RGA	-	Real Coded Genetic Algorithm
RPP	-	Reactive Power Planning
SA	-	Simulated Annealing
SM	-	Stability Margin
TS	-	Tabu Search
VAR	-	Volt-Ampere Reactive
X_{mer}	-	Transformer tap change setting



CHAPTER 1

INTRODUCTION

1.1 Motivation

Most distribution system deals with complicated load behavior as involves with numerous types of end consumers. Reactive power is an essential tool to establish and maintain an AC fluctuating magnetic flux. In almost every section of the system (generation, transmission, distribution and the loads) reactive power is either generated or consumed. The reactive power in the circuit is contributed by the inductive or capacitive reactance. Reactive power is important to control voltage level and subsequently prevent electrical equipment from damage [26] [27] [28]. Reactive power shortage can cause blackout or breakdown event in a system due to the generator and transmission line failure [9].

Reactive Power Planning (RPP) is a nonlinear multi-constraint for large scale uncertainties. There has been huge effect on RPP issue for the security and economy power system [1] [12]. For that reason, researchers in [13] claimed that RPP require the minimization of two objective functions simultaneously. The optimization of RPP problem is completed with continuous and discrete control variable such as generator bus voltages, setting of on-load tap changer of transformers and reactive power output of the compensating devices placed on different bus bars [7].

There are two main categories in solving the optimization problems in RPP which are classified as Conventional method and Heuristic method [1]. Conventional methods-are based on successive linearization which uses the first and second differentiations of objective function and its constraint equations as the search directions, it is suitable for the optimization problems with only one minimum of deterministic quadratic objective function but sometimes result in divergence [1]. Examples of conventional methods are Linear Programming (LP),

Nonlinear Programming (NLP), and Mixed Integer Nonlinear Programming (MINLP) [21]. The Heuristic method is used to overcome Conventional method drawbacks by solving potential for large scale system through their less searching time process [5]. This method comprises of Simulated Annealing (SA), Evolutionary Algorithms (EAs), Differential Evaluation (DE) and Tabu Search (TS) [21] [4]. EA is a process of natural selection and genetics which are used as search algorithms. EA, such as Evolutionary Programming (EP), Real Coded Genetic Algorithm (RGA), Evolutionary Strategies (ES), and Genetic Programming (GP) have been widely used as search and optimization tools in RPP to solve local minimum problems and uncertainties [1].

Several types of EA methods are used to solve the RPP problems over the world since 1960 [9]. The studies involved with control variables such as transformer tap setting T, generator bus voltages Vg and Volt-Ampere Reactive (VAR) source installments Qc [1]. In order to obtain the best solution for RPP objective function identified as the maximum loadability with minimum losses observation during the implementation. The IEEE 26 bus system will be tested in this RPP study utilizing by EP method during any possibility on load increment in the power network.

1.2 Problem Statement

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Mainly, power system network is developed from generating, transmission, and distribution system and deals with the high voltage from 400kV – 11kV with real equipment and components that are extremely dangerous and costly. Moreover, in 1992 a part of Malaysia reported blackout for 48 hours, which affected on both the economics and the consumer part [29]. This may due to the lack amount of real and reactive power demand and low voltage condition that led the entire system to collapse. At the same time, transmission losses also increase due to the low voltage even at peak demand. The flow of reactive power in the transmission lines depend upon the active power loss, voltage profile and voltage security in a power system thus VAR compensation is found as the most significant operational and functional control [7]

Nowadays, power system network becomes more complex and stressed due to the growth in electric consumption. The expansion electricity demand is served continuously by the generation, transmission and reactive power resources. Thus the daily and seasonal load variations reactive resource consumption also changes continually. At that point, RPP is a nonlinear optimization problem for a bulky power system with a lot of uncertainties which must also considered all the constraint condition and the optimization of some control variables such as, transformer tap setting T , generator bus voltages V_g and Volt-Ampere Reactive (VAR) source placement Q_c [1]. In addition, an increment of load demands will reason to insufficient voltage in the system which may lead to voltage collapse and increases thermal effect on transmission line in the system [1]. Thus, RPP plays an important role in order to maintain voltage stability in large scale power system.

The RPP problems are usually solved by using either classical methods or modern heuristic methods. The advantages of classical methods are fast solutions, strong enforcement of binding constraints and convenience of inexpensive efficient packages [21]. However, these tools problems are the disposal of discrete variables and multi-extremum searching. Moreover, ideal optimizations are difficult to achieve due to obstacle such as dimensionality and large mathematical error problems [3]. In addition, Nonlinear Programming (NLP) which is one of the classic methods undergoes slow convergence and can only find one local optimum [21]. Meanwhile, the heuristic methods provided better global searching ability in optimization problems [3]. Even though most algorithm faces problems like local extremum and slow speed in order to accomplish and obtain desired results, but an EP was chosen as an approach mechanism due to its small number of disadvantages as compared to the others classical method [3]. Moreover, a better result could be achieved using this heuristic method [3].

1.3 Objective

1. To develop Evolutionary Programming technique to solve Reactive Power Planning problems with an objective function for maximum loadability or Maximum Loading Point (MLP) on IEEE 26 bus system.

2. To develop Evolutionary Programming technique to solve Reactive Power Planning problems to observe the minimum losses on IEEE 26 bus system produced by the MLP.

1.4 Scope

The scope of this project involved the following:

1. Development of Evolutionary Programming technique to solve Reactive Power Planning problems in power system. All control variables which are reactive power dispatch, Q_{gs} , compensating capacitor placement, Q_{inj} , and transformer tap changing, X_{mer} were considered individually and grouping in order to obtain the maximum loadability or MLP as single objective function. The implementation will be accomplished on standard IEEE 26 bus system using MATLAB software.
2. Development of Evolutionary Programming technique to solve Reactive Power Planning problems in power system. All control variables were considered individually and grouping in order to obtain the minimum losses as the observation value during MLP. The implementation will be accomplished on standard IEEE 26 bus system using MATLAB software.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter will discuss the review of previous researches that is related with this project. The information from the finding is then will be used as guidance and to meet the goal of this research successfully. The related research works will be described by the following subtopic in this chapter 2.

2.1 Reactive Power Planning

The large or insufficient amount of real and reactive power demand and low voltage condition due to different end users act as a factor for the whole system to shut-down. In consequence, reactive power optimization is a constraint, large-scale and nonlinear combinatorial optimization problem in power system network. It is a method to regulate reactive power with a given system parameters and the loads to obtain one or more system optimization objectives through some control variables [2] [3]. In addition, Reactive Power Planning (RPP) is needed to minimize real power loss and to minimize voltage deviation. Thus, the transformer tap setting, generator bus voltage and VAR source replacement are the control variables which necessary to be optimizing in reactive power solution [1].

2.1.1 Load Margin

Voltage stability margin is identified as the amount of additional load in specific pattern of load increase that would cause voltage instability. Failure of components such as generator, transformer, and transmission line usually reduces the voltage stability margin. In consequence, the severe contingencies may cause the voltage instabilities [32].

Furthermore, load margin analysis is defined as one of the principle measurement of voltage stability studies. During load margin evaluation, voltage breakdown point were identified by gradually increasing the load surpass its Maximum Loading Point (MLP), where eventually the system begins to become unstable. Generally, the systems' maximum loading could be determined by Direct Method (DM) and Continuation Power Flow (CPF) method [6]. These techniques involve series of power flow computation for any load increment [6]. In CPF, the MLP value is determined by using the correctorpredictor scheme [6].

Mainly, many of studies on system loadability involves in identifying appropriate techniques to improve the load margin of a system [6]. However, MLP should be kept in range to avoid voltage breakdown by using the proper control action. This analysis is important to occupy increment in system load demand and subsequently promising a secure voltage condition. Several techniques that proposed for load margin enlargement are involved with reconfiguration of distribution system, regulating the generation direction, FACTS devices installation, reactive power planning, and load shedding [6].

For a specific operating point, the tolerable amount of additional load before the incident of voltage collapse is known as the load margin. Figure 2.1 below interprets the situation in a graphical manner.

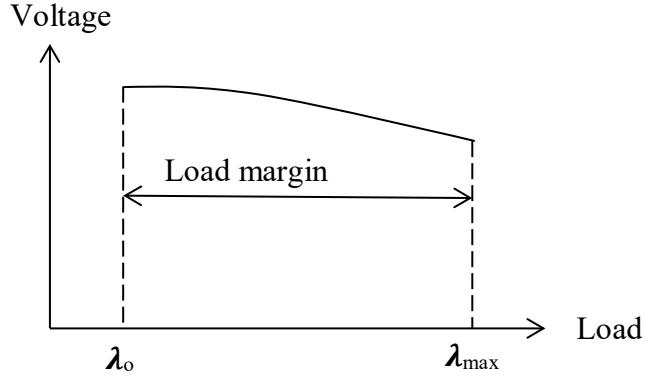


Figure 2.1: Load margin assessment, load vs. voltage

λ_o - The loading at base case

λ_{\max} - The Maximum Loading Point (MLP) value

From the load margin assessment, the critical bus of a system and the maximum load it can provide could be also determined. The bus with the lowest load margin is called as the critical bus; the load margin improvement will be monitored at the critical bus. The proposed EP optimization technique with MLP maximization as the objective function have been used to implement pre and post RPP to conduct comparisons in terms of Maximum Loading Point (MLP) expansion and entire system losses [6]. Graphically, Figure 2.2 below shows the observation of Point A, A' and B.

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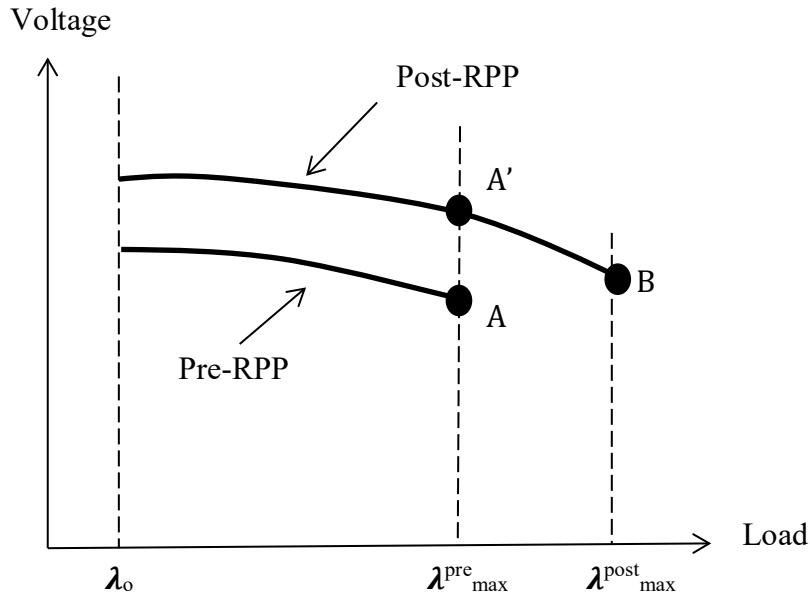


Figure 2.2: Comparison between pre and post RPP implementation.

Point A

- MLP prior to the implementation of the RPP or Pre-RPP

Point B

- MLP obtained as a result of RPP or Post-RPP

The researcher in [10] stated that in order to ensure the system voltage profile is acceptable for system normal and post-contingency conditions, the voltage profile criteria needed to be observed as a practical operation. However, voltage is a poor indicator of proximity to system failure condition when power system is under stressed. Subsequently, the cooperation of voltage stability becomes significant in RPP [10].

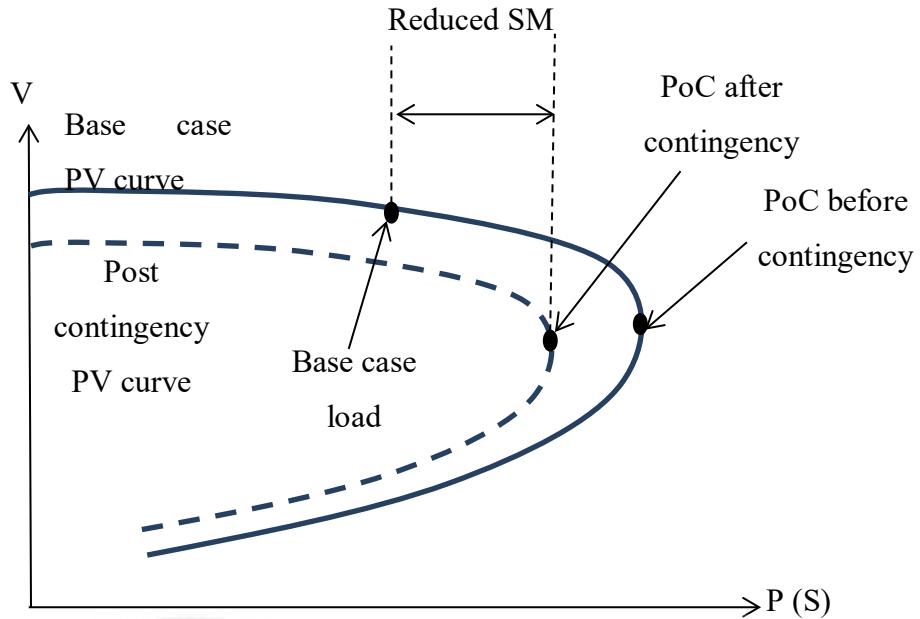


Figure 2.3: PV Curve for Base Case and Contingency

As referred to Figure 2.3, to avoid voltage instability or large scale voltage breakdown, shunt reactive power compensation is used to provide voltage support. In the Figure 2.3, voltage stability is usually identified by a P-V or S-V curve. The knee point of the curve is called the Point of Collapse (PoC), rapid voltage drop causes increment in PoC load which also known as the equilibrium point, where the respective Jacobian becomes singular. Beyond the PoC limit, power flow solution fails to converge, which express the voltage instability and can be associated with a saddle-node bifurcation point. Voltage problems in local area cause instabilities due to the reactive power shortage. Therefore, the objective to improve the static voltage stability margin (SM) defined as the displacement of saddle-node bifurcation point and base case operating point [10].

From thorough literature, several methods have been proposed for voltage stability enhancement in RPP solutions. Those methods were identified as conventional methods, heuristic methods and hybrid methods, which will be described in the following section.

2.2 Conventional Method

Conventional or classical optimization techniques is found as a tool to optimize the RPP problem such as Linear Programming (LP), Nonlinear Programming (NLP), Mixed-Integer Nonlinear Programming (MINLP), and Interior Point (IP) methods have been used in RPP throughout years [2] [21]. The techniques are based on successive linearization which applied the first and second differentiations of objective function and its constraint equations as the search directions [1].

These conventional optimization methods are suitable for quadratic objective function which has only one minimum objective function. However, the formula of RPP problem is hyper quadratic functions, such as linear and quadratic presentation which produce a lot of local minima. As a result, the conventional optimization methods always results in divergence when solving RPP problem due to its only one local minimum [1].

Nonetheless, several classical methods as an alternative approach to solve various optimal reactive power flow problems from many researchers around the world. Thus, nonlinear reactive power optimization problem is also linearized using LP based technique in [21]. The benefits of this technique are fast solution, strong binding constraints enforcement, and low cost efficient packages. Meanwhile, NLP is proposed as a solution to optimum VAR planning problem, but undergoes slow convergence and capable to find only local optimum [21] [7]. Nevertheless, MINLP decomposition method significantly reduces the number of iterations [21]. Generally, these classical method have their own disadvantages which it has limited capability to solve the non-linear and non-convex power system problems with complex constraints [7].

2.3 Heuristic Method

Since years, heuristic optimization algorithms such as genetic algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Evolutionary Programming (EP), and Bacterial Foraging Optimization (BFO) become popular in solving RPP problems [30].

These techniques are adaptable, which solution search and optimization problems could be provided, based on the natural biological genetic processes. Evolutionary algorithms (EA) are able to solve real-world problems, based on the natural selection principle and Charles Darwin rule of ‘survival of the fittest’ [31].

The heuristic method effectively overcame the classical algorithm weaknesses. Even though, these methods may be easily trapped in a local optimum when solving complex multimodal problems and its searching performance depends on the appropriate parameter settings but they have promising global searching ability and process multi-objective optimization problems [30]. However, single algorithm preferred outcome is difficult to be gained due to the numerous weaknesses like local extremum and slow convergence speed [3].

Heuristic algorithms also have been implemented to solve multi-objective reactive power flow problems in order to improve the inaccuracy by conventional techniques. As a reason, EP algorithm is used to overcome RPP problems and reduction of real power losses [3]. Besides that, Mixed Coding of Genetic Algorithm (MCGA) was proposed to minimize the system losses and presented a better result [3]. PSO also have been a solution for RPP problems, while modified PSO method is applied for RPP problems with an improvement in voltage stability margin [3]. DE algorithm is utilized effectively for both network losses minimization and voltage security problems [3].

2.4 Hybrid Method

Hybrid intelligent approaches have been proposed since a few years ago. These methods are created by hybridization of various methods to produce various types of intelligent system architectures [31]. The integration of different algorithms is mainly to overcome their individual weaknesses, by merging attributes and strengths of different approaches [31].

Hybrid methods have been widely used for solving RPP problem such as hybrid Particle Swarm Optimization (PSO), Pseudo-Gradient Guided Particle Swarm Optimization, and Genetic Evolving Ant Direction Particle Swarm Optimization algorithm [22]. Even though, these methods offered better solution than using single methods but it suffers from

longer computational time [22]. The hybrid PSO is applied in order to calculate the amount of shunt reactive power compensation that takes place in each bus. The method is used to minimize losses by determining the most suitable location for reactive power management [15]. A hybrid Genetic Algorithm (GA) is an original GA incorporated with sequential decomposition logic which provided faster search mechanism for generator scheduling [5]. It is also utilized to decide online units of generator and generation scheduling period in order to reduce system cost [5].



CHAPTER 3

METHODOLOGY

3.0 Introduction

In overall, this chapter will discuss on the methodology that have been applied in order to obtain the best solution Reactive Power Planning (RPP) optimization. While, the important control variable that involved to satisfy the selected objective functions are also described. The corresponding individual objective function will be explained as well.

3.1 Objective Functions

This section, all objective function involved in the RPP problem will be discussed. Here, the important procedures and corresponding flow chart are also explained in detail.

The optimal RPP is to optimize the considered objective function in order to ensure steady state performance of a power system which subjected to satisfy equality and inequality constraints [7].

A single objective optimization is a problem when only one objective function is optimized at a time. While, multi-objective optimization involves minimizing or maximizing several objective functions that subjected to a set of constraints [7].

Nonetheless, in this study a single objective function is involved which subjected to follow the equality and inequality constraints at one time. Here, the objective function to Maximize Loading Point (MLP) will be considered.

3.1.1 Maximizing Load Margin

The Maximum Load Margin limit is determined when the load increased beyond its voltage instability. In other words, the maximum amount of load a system can sustain before voltage collapsed. The larger the load margin means more loads can be provided by the system with secured voltage. The load margin could be maximized by increasing the overall load by 0.05 or 5% gradually [36]. While, the minimum voltage of 0.85V was set as the cutoff point to stop increasing the load, because the system is assumed to operate in stress condition when reaching this value.

The system loadability needs restricted procedures to determine safe operating region of a system. This study involves recognizing suitable approaches to improve load margin of a system. During loadability assessment, the load is gradually increased until the system begins to become instable. The point right before the system begins to become unstable is called as the Maximum Loading Point (MLP). MLP should be defined earlier within safety boundary to avoid voltage collapse event. This study is conducted to ensure the system capability to cater increment in load demand while ensuring the stable voltage condition. Among the load margin enhancement techniques were by reconfiguration of distribution system network, controlling the generation path, FACTS devices installation, reactive power scheduling, and load shedding [6]. The load margin range can be defined as the distance from the base case loading point to the MLP value as shown in Figure 3.1.

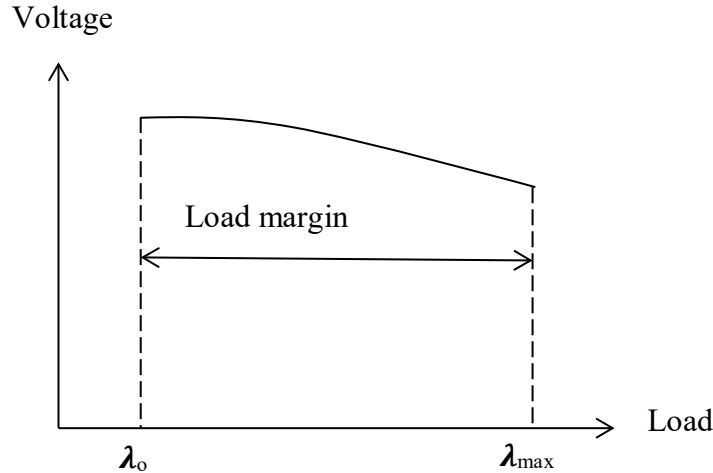


Figure 3.1: Load margin acceptable range load vs. voltage

The load margin is determined by adding 5% load gradually from the total existing load. During this process, the system is assumed to operate under stress condition when reaching the minimum voltage, V_{min} ; that has been set at 0.85p.u as the endpoint [6]. In consequences, Figure 3.2 illustrates the flowchart for MLP calculation.

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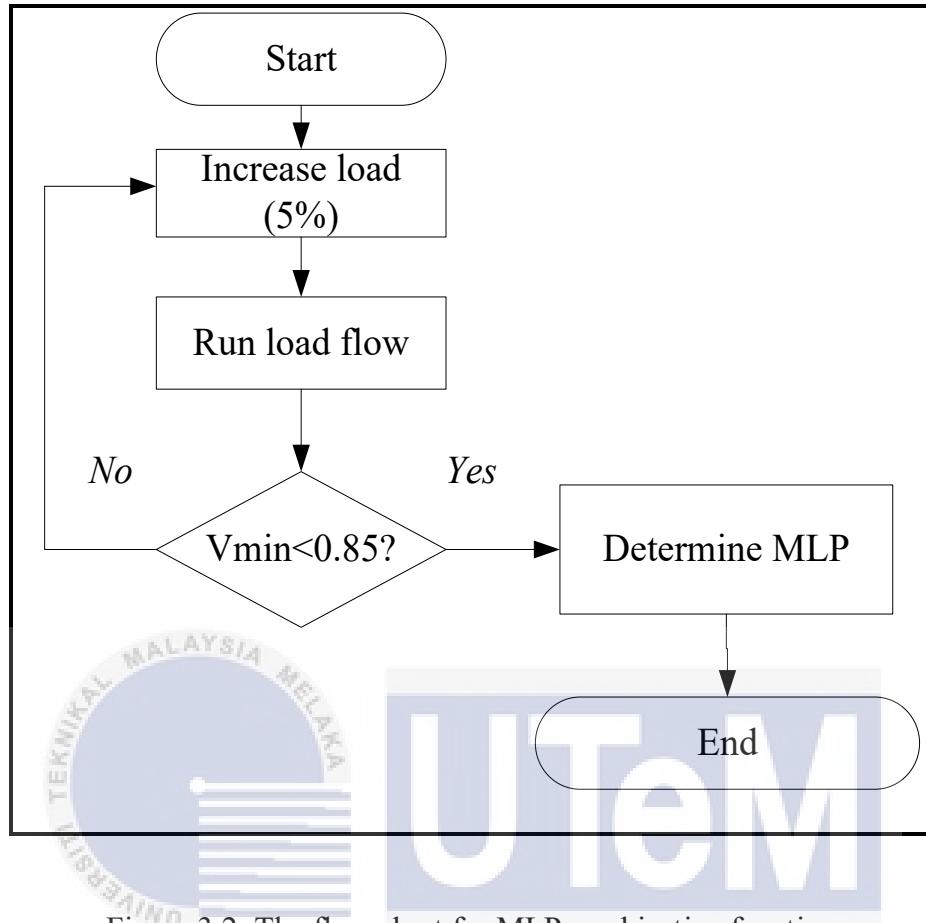


Figure 3.2: The flow chart for MLP as objective function

By conducting the load margin process, the weakest bus of a system with the maximum load that it can stand will also be determined. A bus with lowest load margin is called as critical or weak bus, the load margin enhancement will only monitor at this bus. The MLP improvement comparison is conducted between pre and post RPP implementation by using the proposed EP optimization technique with MLP maximization as the objective function. Based on the Figure 3.3, Point A represents the MLP before RPP implementation, while Point B represents the MLP after applying RPP.

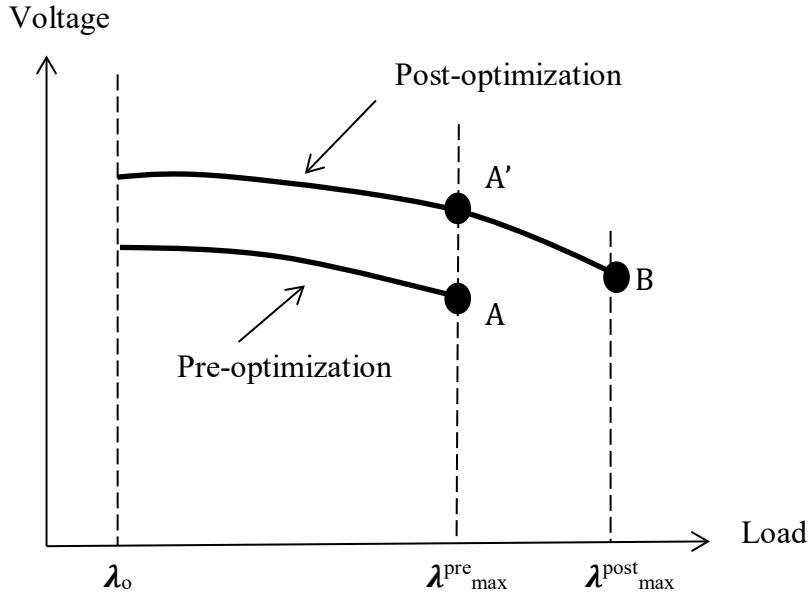


Figure 3.3: General graph for comparison between pre and post RPP implementation

For this part, the weakest bus among the network and the maximum load that it can withstand will be determined. The bus with the smallest margin is identified as the weak or critical bus or named as Case 1. Besides, the other load busses (bus 6 until bus 25) identified as all load busses or named as Case 2. Moreover, two possibilities of load increments will be tested which is when reactive load increment, Q increment and real load increment, P increment increased in order to maximize the MLP respected to the first objective function.

3.2 The Important Control Variables

In order to achieve the best single objective function solution, some variables are optimized under all the constraints with fixed or specified system parameters and loads [3]. There are several control variables are identified to solve RPP problems that considered as generator bus voltages, on-load regulating transformer's transformation ratio, and compensation capacitor [2]. The following is described control variables and constraints that been considered during the power system operation.

3.2.1 Generator Constraints

All the generator voltages and reactive power outputs should be regulated to follow the lower and upper limits as below [7]:

$$V_{Gi}^{\min} \leq V_{Gi} \leq V_{Gi}^{\max}, i = 1, 2, \dots, NG \quad (3.1)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max}, i = 1, 2, \dots, NG \quad (3.2)$$

NG - Number of generators

3.2.2 Load Voltage Constraints

The value of load voltages should be in between the stated restriction below [7],

$$V_{li}^{\min} \leq V_{li} \leq V_{li}^{\max}, i = 1, 2, \dots, NPQ \quad (3.3)$$

3.2.3 Reactive Power Generation Constraints of Capacitor Banks

The permissible values for capacitor bank generation must be within as stated below [7],

$$QC_i^{\min} \leq QC_i \leq QC_i^{\max}, i = 1, 2, \dots, NC \quad (3.4)$$

3.2.4 Transformer Tap Setting Constraints

The bounded as per setting for the transformer On-load tap changers is shown below [7],

$$T_i^{\min} \leq T_i \leq T_i^{\max}, i = 1, 2, \dots, NT \quad (3.5)$$

3.3 Overview on Optimization Techniques

The Reactive Power Planning (RPP) problem is solved by using Evolutionary Programming (EP) mutation strategy. Therefore, this sub-section explains briefly on EP methodology and its behavior.

3.3.1 Evolutionary Programming

Evolutionary Programming (EP) was proposed as a way to achieve artificial intelligence by Fogel et al. in mid-1960. Later, in late 1980's it was practiced in various combinatorial and numerical optimization problems [33]. EP method had successfully applied to various areas of power systems in solving the optimization problem related to unit commitment, optimal reactive power dispatch, RPP and optimal power flow problems. EP is believed has better global optimization result compared to classical optimization technique especially in non-continuous and non-smooth situations [9].

Nonetheless, EP is an artificial intelligence method under Evolutionary Algorithm (EA) search algorithms. The process involved with the initialization, evaluation of fitness, mutation and selection process as explained below.

Step 1: Initialization of population

The initialization process of EP was taken out by selecting initial control variable population randomly. Then the fitness is determined through the Newton Raphson [1]. Random numbers of the generator Qgs, transformer tap changing, Xmer, and capacitor placement, Qinj are the variables to be optimized. Consequently, the random number defined

by using rand function in MATLAB programming, which uniformly distributed in between (0 to 1).

Step 2: Evaluation of the fitness value of each population

The fitness function formulation is essential for the optimization problems. The targeted objective functions on each individual of the population were performed as the fitness function, whereas the best solution to overcome particular constraints with the desired functions is determined. Thus, it will decide the survivals for the next generation. Evolution process is drove by the fitness values of individuals in a certain population.

Step 3: Mutation process

Each parent population is mutated and the respective fitness is gained through Newton Raphson power flow performance. A new combined population is formed from the mutated old generation [1]. Every parent population is mutated as the following equation:

$$\eta'_{i,j} = \eta_{i,j} \exp(\tau' N(0,1) + \tau N_j(0,1)) \quad (3.6)$$

$$L'_{i,j} = L_{i,j} + \eta'_{i,j} (N_j(0,1)) \quad (3.7)$$

$$L'_{oi,j} = L_{oi,j} + \eta'_{i,j} (N_j(0,1)) \quad (3.8)$$

Where:

$$\tau = \sqrt{\frac{1}{\sqrt{2n}}}$$

$$\tau' = \frac{1}{\sqrt{2n}}$$

L_i , and L_{oi} , $\eta_{i,j}$, and $\eta'_{i,j}$	-	i^{th} components of the respective vectors
$N(0,1)$	-	Normal distribution one dimensional random number with mean 0 and 1 .
$N_j(0,1)$	-	New random number for each j value.

Step 4: Selection process

Competition process was conducted as the final selection process, offspring from mutation process were compared with the parents to get an opportunity to be selected in the next generation [1] [12]. This process is applied to choose the fittest individual that will have a better chance to survive.

Step 5: Convergence test

This process is to determine the benchmarks to stop the optimization process. The convergence of maximum and minimum fitness is calculated. If the convergence condition does not meet, the mutation and competition processes will be repeated again. Then, if it converges, the program will verify state variables limits [1].

$$(maximum)_{fitness} - (minimum)_{fitness} \leq 0.0001 \quad (3.9)$$

3.3.2 Development of EP Algorithm for Maximum Loading Point as objective function.

The flow of EP algorithm is displayed in Figure 3.6 has several control variables which are reactive power dispatch, Q_{gs} , compensating capacitor placement, Q_{inj} , and transformer tap change setting, X_{mer} were optimized simultaneously with the equality and inequality

constraints [36]. The simulation will implement on unstressed condition for each Case 1 and Case 2. Based on each possibility of load increment which is reactive load increment, Q increment and real load increment, P increment thus the subsequent procedure is simplified to solve MLP objective function.

Step 1: Generate randomly control variables corresponds to the RPP technique applied. Create Rand functions to produce random numbers which are uniformly distributed in between 0 to 1. Every generated control variables must fulfill its equality and inequality limits [36].

Step 2: Substitute the control variables into their valued bus systems and perform Newton-Raphson load flow method. Establish the load flow solution within the following restriction [36].

- i) Bus voltage violation:

$$0.95p.u \leq V_i \leq 1.05p.u$$

- ii) All generated real power units:

$$P_{gMin} \leq P_g \leq P_{gMax}$$

- iii) All generated reactive power units:

$$Q_{gMin} \leq Q_g \leq Q_{gMax}$$

If any of the restriction is not within the range, go to step 1

Step 3: Determine the fitness value for the objective functions MLP in Section 3.1.1, by using the control variables in Step 1.

Step 4: Store Step 3 outputs or results in program memory.

Step 5: Execute the load flow program and determine the new fitness value for the objective functions MLP in Section 3.1.1 with next control variables generated in Step 1. Repeat the Step 2 to 5 until the maximum population pool reaches 20.

Step 6: Mutate the populations (parents) in Step 5 using the equation in (3.6), (3.7), and (3.8)

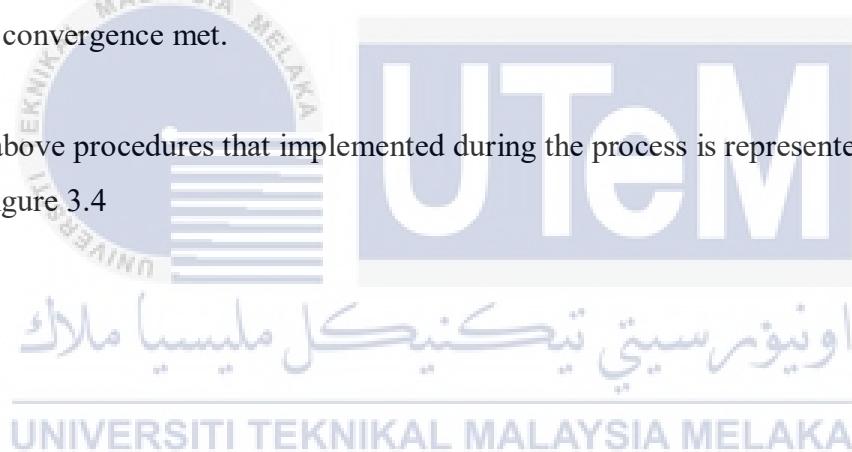
Step 7: Combine the outputs (offspring) produced from the mutation process in Step 6 with the parents, whereas the current total population is 40.

Step 8: Arrange in rank and select the best 20 populations with highest fitness value since the objective function is to obtain the maximum loadability point.

Step 9: Store the result of best 20 populations in program memory.

Step 10: Test the convergence. If met, end the program. Otherwise, repeat Steps 5 to 10 until the convergence met.

The above procedures that implemented during the process is represented with the flow chart as in Figure 3.4



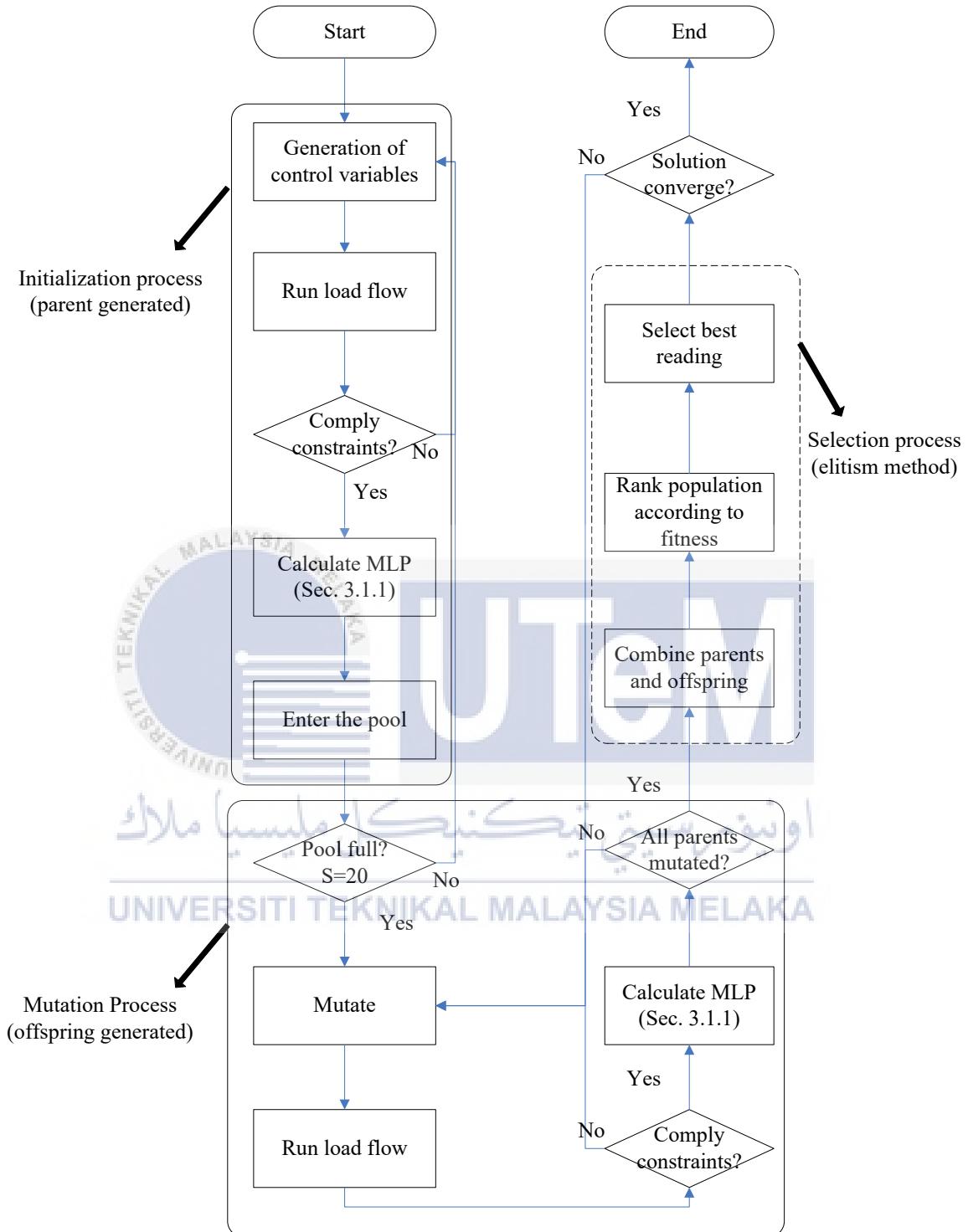


Figure 3.4: Flowchart of EP implementation to maximize MLP for Case 1 and Case 2

3.4 Single Line Diagram

This whole Final Year Project (FYP) will be conducted using Single line diagram of IEEE 26 bus as shown in Figure 3.5.

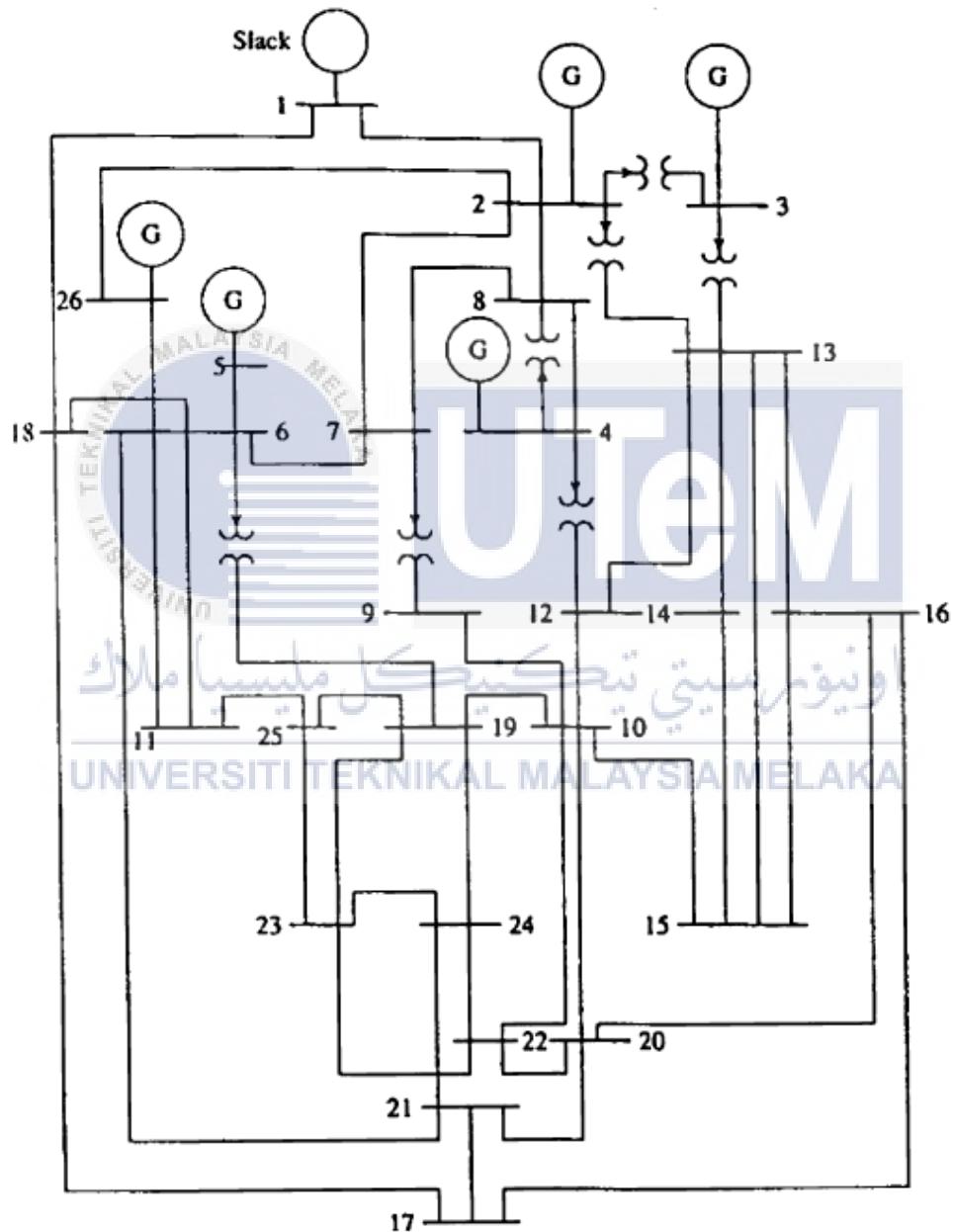


Figure 3.5: Single Line diagram of IEEE 26 Bus.

Based on the above Figure 3.5, the single line diagram consist of total 26 bus system which consist of slack bus (Bus 1), load bus (Bus 6 – Bus 25), and voltage controlled bus (Bus 2, Bus 5 – Bus 26) [37]. According to this research, the P and Q load will be increased at load bus. While, the RPP control variables will be improved at voltage controlled bus [37].

3.5 Overall Research Methodology

Several steps of the process are made according to a sequence to guide and to complete this project within the planned time. The entire steps and procedure to conduct this research have been explained in this chapter aided with flowchart, milestone and Gantt chart.

3.5.1 Flowchart

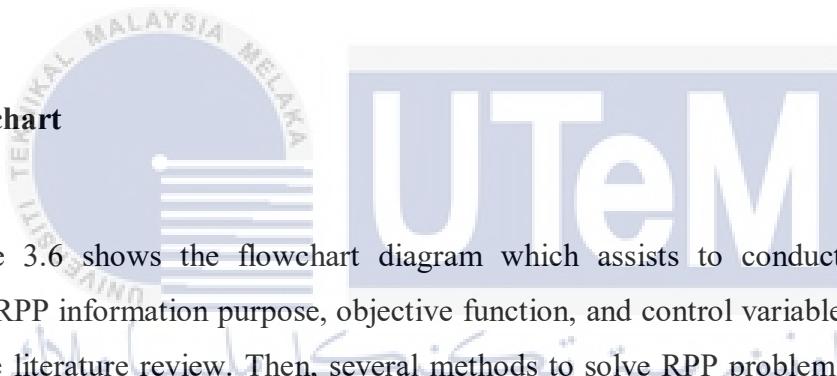


Figure 3.6 shows the flowchart diagram which assists to conduct the activities. Initially, the RPP information purpose, objective function, and control variable were extracted through some literature review. Then, several methods to solve RPP problem were identified by comparing all the previous researches works. Next, the EP technique was developed using MATLAB software on the 26 bus according to the IEEE standard. Subsequently, the complete coding is simulated using MATLAB software. If the result does not satisfied with the objective function, thus the control variable values will be varied and throughout the simulation again until the expected result is obtained. Finally, all the result, analysis and discussion will be prepared for complete full report submission.

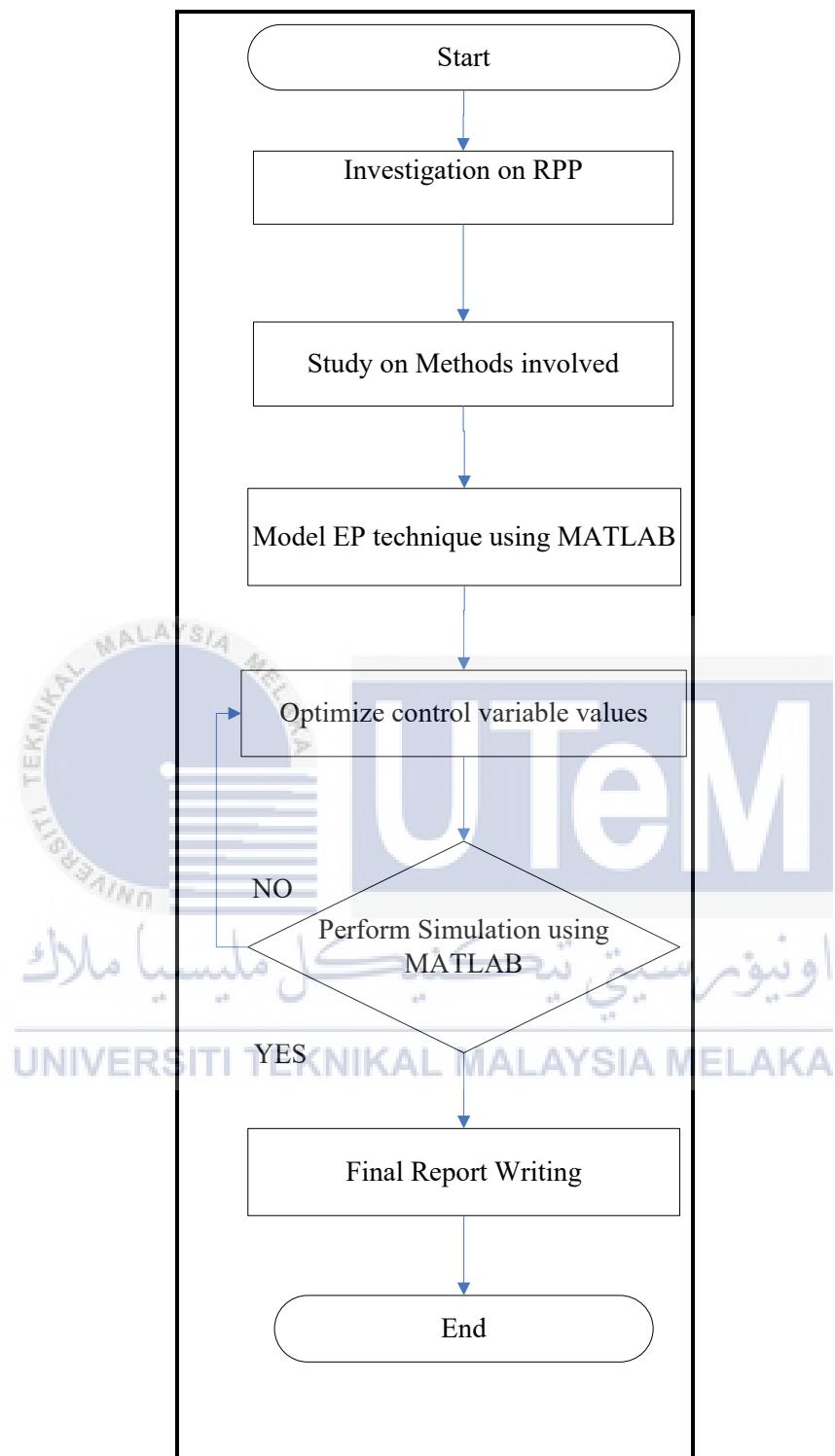


Figure 3.6: Shows the Flowchart of Research Methodology

3.5.2 Milestone

There are 5 milestones were set to ensure this project is keep on track and run smoothly. The first milestone is to study on RPP problems through previous researches. The second milestone is to identify the advantages and disadvantages between classical and heuristic method which applied to overcome RPP problems. The next important milestone is to develop EP algorithm using MATLAB software. The forth milestone is to perform simulation on MATLAB by adjusting selected control variables. The final milestone is to accomplish the thesis and prepare slide presentation.

3.5.3 Gantt Chart

Table 3.1 as in Appendix shows the chart of activities conducted based on the month from start until final completion of this research. The research starts on September 2015. For the first three months, this project focuses more on comprehensive studies of RPP optimization especially on its purpose, objective function, and its control variable. The last two month of the year 2015 will be focused on the implementation between classical and heuristic method used in RPP problem. The time proposed to construct EP technique using MATLAB is approximately three months. Next, three months is required to accomplish MATLAB simulation with the expected result. The report writing and slide preparation is gradually completed within the research process.

CHAPTER 4

RESULT AND DISCUSSION

4.0 Introduction

This chapter will discuss the result obtained using Evolutionary Programming (EP) technique performance in solving Reactive Power Planning (RPP) problems. The simulation was conducted to achieve the objective function through MATLAB software. The discussion focuses on the objective function, which is to obtain higher MLP while observing the minimum total system losses during the implementation on the IEEE 26 bus system by altering the identified RPP control variables, known as reactive power dispatch, Q_{gs} , compensating capacitor placement, Q_{inj} , and transformer tap changing, X_{mer} . The following section will describe in detail about the result obtained from the objective function.

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4.1 Results for Reactive Power Planning

In this study implementation, there are two cases of load increment which are: Case 1 according to the load increase at a single bus which is known as the critical bus and Case 2 refers to the load increment at all buses. The increment of load is assumed at the rate of 5% from base case value as explained in Methodology section 3.1.1. Initially, the critical bus is identified as the bus having the lowest MLP, which only allows the small load growth right before it leads to system collapse. The critical bus was determined when P load and Q load increased respectively. This simulation is completed for 20 running times in order to get the consistent result.

As referred to the graph in Figure 4.1, Point A indicates the MLP before the implementation of RPP or called as pre-optimization. On the other hand, Point B indicates the MLP after the implementation of RPP or called as post-optimization. The interval between Point A and Point B is identified as MLP enhancement. The MLP and the observation of minimum total system losses were recorded for different RPP technique.

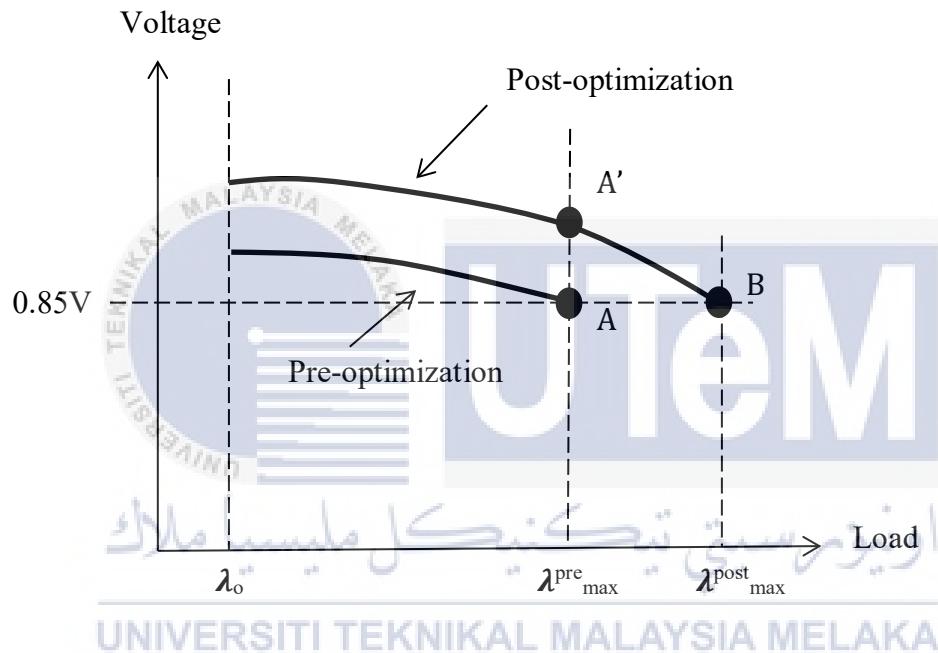


Figure 4.1: Graph to illustrate the Point A (before implementation of RPP) and Point B (after the implementation of RPP).

As mentioned earlier in section 3.1.1, initially the critical bus is identified to be improved by using load margin assessment, which increases the load gradually by 5%. Table 4.1 below shows the outcome after implementation of P increment.

Table 4.1: P load increment before the implementation of RPP (Point A)

Bus_test	MLP (%)	Vm(bus_test) (p.u)	Vmin (p.u)
24	735	0.8500	0.8500
25	755	0.8489	0.8489
17	760	0.8469	0.8469
19	960	0.8473	0.8473
21	1140	0.8491	0.8491
9	1265	0.8472	0.8472
16	1315	0.8498	0.8498
23	1380	0.8494	0.8494
15	1495	0.8499	0.8499
22	1670	0.8496	0.8496
20	1880	0.8497	0.8497
18	2285	0.8911	0.8495
12	2410	0.8614	0.8498
11	2820	0.8497	0.8497
6	2875	0.8747	0.8498
14	4925	0.8499	0.8499
13	7135	0.9162	0.8499

According to the Table 4.1 it can be concluded that load bus 24 has the lowest increment in load, which indicated at 735% when real power at load bus is increased.

Then, the simulation also tested under any Q load increment in order to obtain the critical load bus. In subsequent, the result as in Table 4.2 shows the percentage of increment for all load busses.

Table 4.2: Q load increment before the implementation of RPP (Point A)

Bus_test	MLP (%)	Vm(bus_test) (p.u)	Vmin (p.u)
24	670	0.8496	0.8496
17	760	0.8498	0.8498
9	805	0.8490	0.8490
25	925	0.8495	0.8495
21	940	0.8495	0.8495
23	1305	0.8494	0.8494
16	1375	0.8500	0.8500
15	1425	0.8500	0.8500
22	1540	0.8485	0.8485
20	1560	0.8498	0.8498
19	1915	0.8496	0.8496
11	1955	0.8499	0.8499
12	2165	0.8489	0.8489
18	2295	0.8499	0.8499
6	3565	0.8500	0.8500
14	3965	0.8486	0.8486
13	13230	0.8500	0.8500

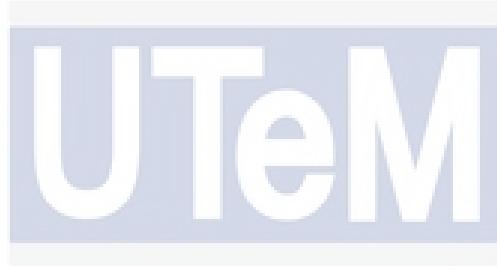
As referred to Table 4.2 above, the lowest MLP is also determined at load bus 24 by increment up to 670% from the base value. Thus, both simulation resulted the weakest load margin is getting from load bus 24.

4.2 Results for Maximum Loading Point as an Objective Function and an observation on Total Losses

Mainly, the objective function is to get the higher MLP with the optimum RPP technique. The simulation was conducted using two types of load increment which is real load, P and reactive load, Q. Consequently, the load was increased only for the critical bus which is the load bus 24. Seven group of RPP technique was implemented in order to identify suitable technique to achieve optimal RPP with the objective function of maximizing loadability while observing the minimum system losses during the implementation. The groups of control variable named, reactive power dispatch, Q_{gs} , compensating capacitor placement, Q_{inj} , and transformer tap changing, X_{mer} identified as RPP technique.

4.2.1 Result for Case 1

- A. For Q load



The bus with the smallest margin which is at bus 24 categorized as Case 1. The maximum load that this critical bus can withstand will be determined by applying the MLP. The best combination of RPP technique acquired via Q increment on critical bus. The simulation is implemented for all RPP techniques which are, (Q_{gs}) , (Q_{inj}) , (X_{mer}) , $(Q_{gs} + Q_{inj})$, $(Q_{gs} + X_{mer})$, $(Q_{inj} + X_{mer})$, and $(Q_{gs} + Q_{inj} + X_{mer})$ which resulted in Table 4.3 at Point A, A' and B as referred to previous Figure 4.1.

Table 4.3: Q load increment during the implementation of RPP (Point A' and B) on Case 1.

Point A' (Post RPP)					Point B (Post RPP)			
RPP techniques	Min voltage (p.u)	Max voltage (p.u)	Losses (MW)	(Fitness) MLP (%)	Min voltage (p.u)	Max voltage (p.u)	Losses (MW)	(Fitness) MLP (%)
Q_{gs}	0.8496	1.0350	24.9936	670	0.8496	1.0350	24.9936	670
Q_{inj}	0.8303	1.0250	27.2710	670	0.8496	1.0350	24.9936	670
X_{mer}	0.8712	1.0350	30.1200	670	0.8492	1.0350	32.9828	725
$Q_{gs} + Q_{inj}$	0.8598	1.0450	24.0688	670	0.8496	1.0350	24.9936	670
$Q_{gs} + X_{mer}$	0.8712	1.0450	26.5660	670	0.8493	1.0450	29.6007	750
$Q_{inj} + X_{mer}$	0.8797	1.0519	25.6337	670	0.8496	1.0493	29.4297	735
$Q_{gs} + Q_{inj} + X_{mer}$	0.8697	1.0450	23.7821	670	0.8498	1.0450	26.3285	770
Point A (base value)					Pre RPP			
					0.8496	1.0350	24.9936	670

* Q_{gs} - Reactive Power Dispatch * Q_{inj} - Capacitor Placement * X_{mer} - Transformer Tap Changing Setting

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Based on the result in Table 4.3 shows that the technique with all control variables which is ($Q_{gs} + Q_{inj} + X_{mer}$) gives the largest MLP with less system losses at Point A' and minimum voltage of 0.8498 p.u at Point B. Moreover it shows that, the minimum voltage at Point B increases from 0.8498 p.u to 0.8697 p.u as in Point A'. It shows that, this RPP technique not only provide the best MLP result, but also gives minimum losses at Point A'. The best result with ($Q_{gs} + Q_{inj} + X_{mer}$) technique is obtained through the optimal control variables parameters as displayed in Appendix C1.

B. For P load

The best combination of RPP technique for Table 4.4 was acquired through P increment on critical bus. The simulation is implemented for all RPP techniques which are, (Q_{gs}) , (Q_{inj}) , (X_{mer}) , $(Q_{gs} + Q_{inj})$, $(Q_{gs} + X_{mer})$, $(Q_{inj} + X_{mer})$, and $(Q_{gs} + Q_{inj} + X_{mer})$ are tabulated in Table 4.4 by referring to the important points as stated in Figure 4.1.

Table 4.4: P load increment during the implementation of RPP (Point A' and B) on Case 1.

Point A' (Post RPP)					Point B (Post RPP)				
RPP techniques	Min voltage (p.u)	Max voltage (p.u)	Losses (MW)	(Fitness) MLP (%)	Min voltage (p.u)	Max voltage (p.u)	Losses (MW)	(Fitness) MLP (%)	
Q_{gs}	0.8500	1.0350	63.1059	735	0.8500	1.0350	63.1059	735	
Q_{inj}	0.8290	1.0250	67.2782	735	0.8500	1.0350	63.1059	735	
X_{mer}	0.8553	1.0350	63.9699	735	0.8499	1.0350	66.8368	755	
$Q_{gs} + Q_{inj}$	0.8609	1.0400	61.2102	735	0.8500	1.0350	63.1059	735	
$Q_{gs} + X_{mer}$	0.8618	1.0450	68.0490	735	0.8498	1.0450	74.5288	780	
$Q_{inj} + X_{mer}$	0.8780	1.0750	72.0334	735	0.8495	1.0750	82.8945	800	
$Q_{gs} + Q_{inj} + X_{mer}$	0.8767	1.0450	60.1090	735	0.8497	1.0450	71.4128	800	
Point A (base value)									
Pre RPP	0.8500	1.0350	63.1059	735					

* Q_{gs} - Reactive Power Dispatch Q_{inj} – Capacitor Placement X_{mer} – Transformer Tap Changing Setting

Based on the result in Table 4.4 shows that the technique with all control variables which is $(Q_{gs} + Q_{inj} + X_{mer})$ gives the largest MLP with less system losses at Point A' and minimum voltage of 0.8497 p.u at Point B. Moreover it shows that, the minimum voltage at Point B increases from 0.8497 p.u to 0.8767 p.u as in Point A'. The $(Q_{inj} + X_{mer})$ technique provide the same MLP as in $(Q_{gs} + Q_{inj} + X_{mer})$ technique, but it has higher system losses. For

that reason, the $(Q_{gs} + Q_{inj} + X_{mer})$ is satisfied the requirement for larger MLP with less total losses dissipated at Point A'. This outcome, $(Q_{gs} + Q_{inj} + X_{mer})$ is obtained through the optimal control variables parameters as displayed in Appendix K1.

4.2.2 Result for Case 2

A. For Q load

During all load busses increment or named Case 2, results as in Table 4.5 are obtained. The best combination of RPP technique for Case 2 acquired via Q increment on all load busses. The simulation is implemented for all RPP techniques which are, (Q_{gs}) , (Q_{inj}) , (X_{mer}) , $(Q_{gs} + Q_{inj})$, $(Q_{gs} + X_{mer})$, $(Q_{inj} + X_{mer})$, and $(Q_{gs} + Q_{inj} + X_{mer})$ are resulted as in Table 4.5 which at important point as referred to Figure 4.1.

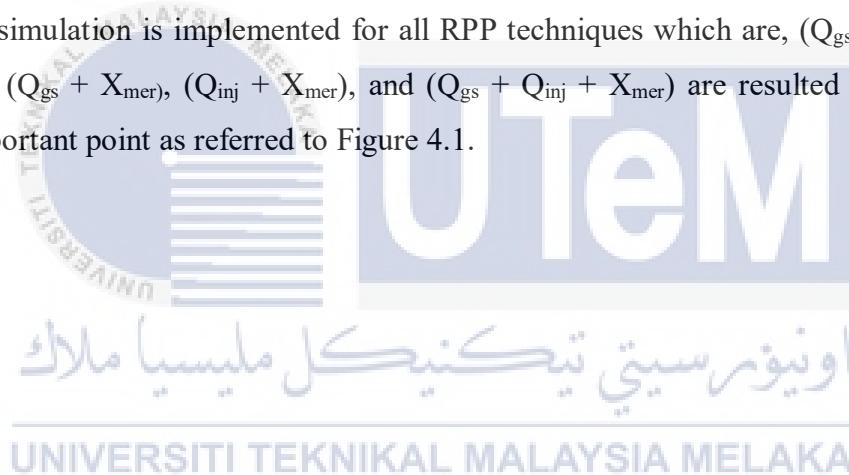


Table 4.5: Q load increment during the implementation of RPP (Point A' and B) on Case 2.

Point A' (Post RPP)					Point B (Post RPP)			
RPP techniques	Min voltage (p.u)	Max voltage (p.u)	Losses (MW)	(Fitness) MLP (%)	Min voltage (p.u)	Max voltage (p.u)	Losses (MW)	(Fitness) MLP (%)
Q_{gs}	0.8482	1.0250	30.6266	245	0.8482	1.0250	30.6266	245
Q_{inj}	0.8562	1.0250	29.5764	245	0.8482	1.0250	30.6266	245
X_{mer}	0.8650	1.0300	39.6500	245	0.8483	1.0300	43.8238	280
$Q_{gs} + Q_{inj}$	0.8551	1.0250	29.7554	245	0.8482	1.0250	30.6266	245
$Q_{gs} + X_{mer}$	0.8715	1.0300	34.7267	245	0.8482	1.0300	40.2770	280
$Q_{inj} + X_{mer}$	0.8720	1.0250	29.1234	245	0.8473	1.0250	33.3770	260
$Q_{gs} + Q_{inj} + X_{mer}$	0.8897	1.0350	26.5115	245	0.8459	1.0299	35.1876	285
Point A (base value)								
Pre RPP	0.8482	1.0250	30.6266	245				

* Q_{gs} - Reactive Power Dispatch Q_{inj} - Capacitor Placement X_{mer} - Transformer Tap Changing Setting

Based on the result in Table 4.5 shows that the technique with all control variables which is ($Q_{gs} + Q_{inj} + X_{mer}$) gives the largest MLP with less system losses at Point A' and minimum voltage of 0.845858 p.u at Point B. Moreover it shows that, the minimum voltage at Point B increases from 0.8459 p.u to 0.8897 p.u as in Point A'. So, it shows that the RPP technique ($Q_{gs} + Q_{inj} + X_{mer}$) fulfilled the objective to maximize MLP with less system losses at Point A'. The best outcome with ($Q_{gs} + Q_{inj} + X_{mer}$) technique is obtained through the optimal control variables parameters as displayed in Appendix C2.

A. For P load

While, the finest combination of RPP technique for Table 4.6 was developed through P increment on all load buses. The simulation is executed for all group of RPP techniques which are, (Q_{gs}) , (Q_{inj}) , (X_{mer}) , $(Q_{gs} + Q_{inj})$, $(Q_{gs} + X_{mer})$, $(Q_{inj} + X_{mer})$, and $(Q_{gs} + Q_{inj} + X_{mer})$ are tabulated in Table 4.6 with the Point A, A' and B as referred to previous Figure 4.1.

Table 4.6: P load increment during the implementation of RPP (Point A' and B) on Case 2.

Point A' (Post RPP)					Point B (Post RPP)				
RPP techniques	Min voltage (p.u)	Max voltage (p.u)	Losses (MW)	(Fitness) MLP (%)	Min voltage (p.u)	Max voltage (p.u)	Losses (MW)	(Fitness) MLP (%)	
Q_{gs}	0.8493	1.0250	138.1795	285	0.8493	1.0250	138.1795	285	
Q_{inj}	0.8534	1.0250	137.1618	285	0.8493	1.0250	138.1795	285	
X_{mer}	0.8603	1.0250	138.1771	285	0.8420	1.0250	164.4882	305	
$Q_{gs} + Q_{inj}$	0.8543	1.0250	137.1310	285	0.8493	1.0250	138.1795	285	
$Q_{gs} + X_{mer}$	0.9024	1.0450	133.5712	285	0.8491	1.0350	219.5989	315	
$Q_{inj} + X_{mer}$	0.8892	1.0250	140.1352	285	0.8476	1.0250	186.0856	320	
$Q_{gs} + Q_{inj} + X_{mer}$	0.9004	1.0550	128.6210	285	0.8475	1.0450	175.7085	320	
Point A (base value)									
Pre RPP	0.8493	1.0250	138.1800	285					

* Q_{gs} - Reactive Power Dispatch Q_{inj} – Capacitor Placement X_{mer} – Transformer Tap Changing Setting

According to the result in Table 4.6 shows that the technique with all control variables which is $(Q_{gs} + Q_{inj} + X_{mer})$ gives the largest MLP with less system losses at Point A' and minimum voltage of 0.8475 p.u at Point B. Moreover it shows that, the minimum voltage at Point B increases from 0.8475 p.u to 0.9004 p.u as in Point A'. Even though, $(Q_{inj} + X_{mer})$

technique has similar MLP as in $(Q_{gs} + Q_{inj} + X_{mer})$ technique, but it has higher system losses. Thus, it shows that the $(Q_{gs} + Q_{inj} + X_{mer})$ technique satisfy the requirement for larger MLP with less system losses at Point A'. This result, $(Q_{gs} + Q_{inj} + X_{mer})$ is obtain through the optimal control variables parameters as in Appendix K2.

4.3 Summary

This section will summarize the best result that had been obtained for Case 1 and Case 2 to achieve the objective function which is to maximize loadability or MLP while observing the minimum system losses during the implementation.

4.3.1 Summary for Case 1

The comparison between P increment and Q increment in term of MLP and system losses on critical bus (Case 1) is simplified as in Table 4.7. The best optimum RPP technique was chosen for Case 1, which $(Q_{gs} + Q_{inj} + X_{mer})$

Table 4.7: Comparison between P load increment and Q load increment in term of MLP and losses on Case 1

	Post RPP		Pre RPP (base value)	
	MLP (%)	Losses (MW)	MLP (%)	Losses (MW)
P increment	800	60.1090	735	63.1059
Q increment	770	23.7821	670	24.9936

According to the Table 4.7 the P increment has a better losses reduction from the base value stated at Pre RPP with the different of 2.9969MW. While, the Q increment has higher MLP percentage increment from the base value stated at Pre RPP section with the different

100%. However, the base value during P increment is already higher than Q increment, with the higher losses provided.

4.3.2 Summary for Case 2

P increment and Q increment in term of MLP and system losses on all load bus (Case 2) is compared and simplified as in Table 4.8. The best optimum RPP technique ($Q_{gs} + Q_{inj} + X_{mer}$) was chosen for Case 2.

Table 4.8: Comparison between P load increment and Q load increment in term of MLP and losses on Case 2

	Post RPP		Pre RPP (base value)	
	MLP (%)	Losses (MW)	MLP (%)	Losses (MW)
P increment	320	128.6210	285	138.1800
Q increment	285	26.5115	245	30.6266

Based on Table 4.8, P increment has greater losses reduction from the base value stated at Pre RPP with the different of 9.559MW. While, the Q increment has higher MLP percentage increment from the base value stated at Pre RPP section with the different of 40%. Anyhow, the base value at P increment is already greater than Q increment, with bigger losses delivered.

For both cases P increment already produce higher margin. It is found that, with the support from the RPP technique, losses at P increment is reducing for Case 1 and Case 2. In contrast, RPP technique helps to enhance more load margin during any reactive or Q growth for both cases.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In overall, this project is introduced an approach to overcome Reactive Power Planning (RPP) problems using heuristic methods named Evolutionary Programming (EP) technique. From previous researcher's works, it is found that the suitable technique to solve RPP problems in an IEEE 26-bus network system are identified as (Q_{gs}) , (Q_{inj}) , (X_{mer}) , $(Q_{gs} + Q_{inj})$, $(Q_{gs} + X_{mer})$, $(Q_{inj} + X_{mer})$, and $(Q_{gs} + Q_{inj} + X_{mer})$. This research is considering the objective function to be maximizing loadability while observing the losses minimization during the implementation in order to find the best solution for RPP issues in power operation system. Thus, with the EP optimization technique, the loadability is expected to improve within the range of secured voltage level. In addition, the system losses also will reduce even though the maximum power is provided by the generators.

According to the cases which were discussed in Chapter 4 are Case 1 which refers to identified critical load bus increment and Case 2 with all load buses increment. Both cases shown the best result was when the $(Q_{gs} + Q_{inj} + X_{mer})$ technique is applied. By comparing those cases with their best technique, Case 1 with reactive load increment (Q increment) shows the finest outcome correspond to the objective function of this research which is to obtain maximum loadability while observing the minimum system losses during the MLP implementation. As a conclusion, this EP heuristic technique is capable for load margin enhancement during critical load bus increment and total load buses increment as well.

5.2 Recommendation

As for the future recommendation, it is suggested to compare this EP algorithm with other heuristic method such as Real Coded Genetic Algorithm (RGA) or Evolutionary Strategies (ES) to verify the best method to solve RPP problems.



REFERENCES

- [1] S.K Nandha Kumar, Dr. P. Renuga “Reactive Power Planning Using Real GA comparison with evolutionary Programming”, *International Journal on Electrical and Power Engineering*, vol. 1, pp. 21-25, 2010.
- [2] Hong-Sheng Su, Pei-Jiong Zhang “Research of Distribution Network Reactive Power Optimization Based on Improved Cloud particle Swarm Optimization BP Neutral Network”, *International Jurnal of Computer and Electrical Engineering*, vol. 5, pp. 164-168, 2013.
- [3] Hongsheng Su, “Cloud Particle Swarm Algorithm Improvement and Application in Reactive Power Optimization”, vol. 11, pp. 468 – 475, 2013
- [4] Tejaswini Sharma, Alka Yadav, Sangeeta Jamhoria, Ritu Chaturvedi, “Comparative Study Of Methods For Optimal Reactive Power Dispatch”, *Electrical and Electronics Engineering*, vol. 3, pp. 53 – 61, 2014.
- [5] Nor Rul Hasma Abdullah, Ismail Musirin, Muhammad Murtadha Othman, “Operating Generator Selection Applied for Reactive Power Dispatched using Evolutionary Programming Technique”, *International Power Engineering and Optimization Conference*, vol. 7, pp. 574– 578, 2013.
- [6] Norziana Aminudin, Titik Khawa Abdul Rahman, Ismail Musirin, Zuhaina Zakaria, “Optimal Reactive Power Planning for Load Margin Improvement using Multi Agent Immune EP”, pp. 1- 8, 2010.
- [7] B.Bhattacharya, Kamal.K.Mandal, N. Chakraborty, L.Ramesh, M.M Beno, “A New Improved Cultural Algorithm Approach for Multiobjective Reactive Power Planning Problem”, *International Conference on Sustainable Energy and Intelligent Systems*, vol 4, pp. 1 – 7, 2013.
- [8] Biplab Bhattacharyya, Vikash Kumar Gupta, S. Das, “Evolutionary Programming for Reactive Power Planning Using FACTS Devices”, *Transactions on Power Systems*, vol. 9, pp. 1 – 6, 2014.
- [9] Nor Rul Hasma Abdullah, Ismail Musirin, Muhammad Murthada, “Constrained reactive Power Control Using Evolutionary Computation Technique for Static

- Security Enhancement”, *International Conference on Computer and Electrical Engineering*, pp. 612 – 616, 2009.
- [10] Du Liang, Cheng Fei, “Discussion and Researching on Dynamic Reactive Power Plainning”, pp. 1 – 4, 2010.
- [11] Zou Yiqin, “Optimal Reactive Power Planning Based on Improved Tabu Search Algorithm”, *International Conference on Electrical and Control Engineering*, pp. 3945 – 3948, 2010.
- [12] S.K Nandha Kumar, Dr. P. Renuga, “Reactive Power Planning using Evolutionary Algorithms”, pp. 255 – 261, 2010.
- [13] S.K Nandha Kumar, Dr. P. Renuga, “FVSI based Reactive Power Planning using Evolutionary Programming”, pp. 265 – 269, 2010.
- [14] M. Rahmani, M. Rashidinejad, E.M. Carreno, R.A Romero “A Combinatorial Approach for Transmission Expansion & Reactive Power Planning”, *Transmission and Distribution Conference and Exposition*, pp. 529 – 536, 2010.
- [15] A.M Ramly, N. Aminudin, I. Musirin, D. Johari, N. Hashim, “Reactive Power Planning for Transmission Loss Minimization”, International Power Engineering and Optimization Conference, vol. 5, pp. 116 – 120, 2011.
- [16] A. Mahmoudabadi, M. Rashidinejad, M. Mohammadian, M. Zeinaddini Maymand, M. Rahmani, H. Khorasani, “An Application of CHA to Concurrent Short-Term Transmission Expansion & Reactive Power Planning”, pp. 1 – 6, 2011.
- [17] Ming Niu, Zhao Xu, “Reactive Power Planning for Transmission Grids with Wind Power Penetration”, pp. 1 – 5, 2012.
- [18] Julio Cesar Lopez, Javier Contreras, Jose I. Munoz, J.R.S Mantovani, “A Multi-Stage Stochastic Non-Linear Model for Reactive Power Planning Under Contingencies”, *Transactions on Power Systems*, vol 28, pp. 1503 – 1514, 2013.
- [19] Julio Cesar Lopez, Javier Contreras, Jose I. Munoz, J.R.S Mantovani, “Optimal Reactive Power Planning Using Risk Analysis”, pp. 1 – 5, 2013.
- [20] Seyed Ali Arefifar, Yasser Abdel-Rady I. Mohamed, “Probabilistic Optimal Reactive Power Planning in Distribution Systems With Renewable Resources in Grid-Connected and Islanded Modes”, *Transactions on Industrial Electronics*, vol. 61, pp. 5830 – 5839, 2014.

- [21] P.R Bijawe, Ashu Verma, Y.V.M.S Prakash, “Reactive power planning with uncertainties in load/generation specifications”, pp. 1 – 5, 2014.
- [22] Y. Amrane, M. Boudour, “Particle Swarm Optimization Based Reactive Power Planning for Voltage Stability Improvement”, pp. 1 – 8, 2014.
- [23] Ashutosh Tiwari, Venkataramana Ajjarapu, “A Computer Package for Multi-Contingency Constrained Reactive Power Planning”, pp. 1 – 5, 2015.
- [24] Zita A. Vale, Carlos Ramos, Marco R. Silva, Joao P. Soares, Bruno Canizes, Tiago Sousa, Hussein M. Khodr, “Reactive Power Compensation by EPSO Technique”, pp. 1512 – 1518, 2010.
- [25] Frano Tomasevic, Kristina Baranasic, Marko Delimar, “Reactive Power Optimization Based on Load Profile Partitioning”, pp. 627 – 632, 2014.
- [26] Leonard L. Grigsby, “Electric Power Generation, Transmission, and Distribution”, CRC Press, (2007).
- [27] A S Pabla, “Electric Power Distribution”, Tata McGraw-Hill, 5th edition, (2004).
- [28] D M Tagare, “Reactive Power Management”, Tata McGraw-Hill, (2004).
- [29] Nor Faridah Abdul Manaf, “Memoir of Tan Sri Ani Arope”, 2013.
- [30] Worawat Nakawiro, Istvan Erlich, and Jose Luis Rueda, “A novel optimization algorithm for optimal reactive power dispatch: A comparative study,” pp. 1555 – 1561, IEEE, 2011.
- [31] Ahmed Mohamed Othman Abd El-Maksoud, “Enhancing the performance of flexible AC transmission system (FACTS) by Computational Intelligence,” Doctoral Dissertation of Electrical Engineering Department Thesis, Aalto University, December 2010.
- [32] Haifeng Liu, “Planning reactive power control for transmission enhancement,” Doctor of Philosophy of Electrical Engineering Thesis, Iowa State University, 2007.
- [33] Ruhul Sarker, Masoud Mohammadian, Xin Yao, “ Evolutionary Optimization”, *Operations Research Management Science*, Kluwer Academic London, 2003.
- [34] M.H Mansor, M. R. Irving, G. A Taylor, “A decomposition/aggregation method for solving electrical power dispatch problems”, IEEE 2012.
- [35] Pirmahamad Jamalbhai Vasovala, Chinmay Y. Jani, Vasim H. Ghanchi, Parth Harshad Kumar Bhavsar, “Economic load dispatch of IEEE-26 bus system with the use of Ant Colony Optimization technique,” *International Journal for Scientific Research & Development*, vol. 2, pp. 1213 – 1217, IEEE 2014.

- [36] Elia Erwani binti Hassan, "Environmentally constraint economic dispatch and reactive power planning for ensuring secure operation in power system," Doctor of Philosophy faculty of Electrical Engineering Thesis, Universiti Teknologi Mara, July 2015.
- [37] Hadi Saadat, "Power System Analysis" Boston , McGraw-Hill, 1999.



APPENDICES

Table 3.1: Gantt chart of Research Methodology

Appendix A1

Q Increment

Critical_Qgs

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	Vmin	Vmax	Tloss	b
197.0449	114.0028	69.0029	69.0601	30.0262	0.8496	1.0350	24.9936	6.7000
54.0007	61.0041	47.0604	107.0112	63.0054	0.8496	1.0350	24.9936	6.7000
141.1080	140.0029	57.0020	127.0082	58.2599	0.8496	1.0350	24.9936	6.7000
255.0008	212.0392	60.0602	89.0088	42.0101	0.8496	1.0350	24.9936	6.7000
214.2110	86.0190	118.0663	181.0135	38.0972	0.8496	1.0350	24.9936	6.7000
72.0313	193.0860	91.0130	91.0023	75.0188	0.8496	1.0350	24.9936	6.7000
280.0029	175.0399	40.0690	108.0038	28.0014	0.8496	1.0350	24.9936	6.7000
48.0377	133.0726	62.0293	226.0275	70.0188	0.8496	1.0350	24.9936	6.7000
155.0478	127.0088	106.0227	153.0215	59.0171	0.8496	1.0350	24.9936	6.7000
249.0213	151.0066	40.0253	72.0281	16.0013	0.8496	1.0350	24.9936	6.7000
229.0267	113.0936	82.0418	166.0017	79.0148	0.8496	1.0350	24.9936	6.7000
264.0314	50.0141	95.1913	213.0786	27.0101	0.8496	1.0350	24.9936	6.7000
180.1989	187.0021	123.0863	95.0024	17.0241	0.8496	1.0350	24.9936	6.7000
188.0925	129.2102	79.0029	195.0628	64.0815	0.8496	1.0350	24.9936	6.7000
82.0104	212.0011	129.0048	202.0011	58.0519	0.8496	1.0350	24.9936	6.7000
305.0510	125.0334	89.0563	69.0087	28.0200	0.8496	1.0350	24.9936	6.7000
310.1023	104.0061	85.0160	152.0208	73.0518	0.8496	1.0350	24.9936	6.7000
230.0450	59.0124	45.0909	103.0020	23.0184	0.8496	1.0350	24.9936	6.7000
313.0066	113.0006	107.0429	87.0028	44.0067	0.8496	1.0350	24.9936	6.7000
81.0184	120.1295	121.1223	198.0099	77.0070	0.8496	1.0350	24.9936	6.7000

Appendix B1

Q Increment

Critical_Qgs_Qinj

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	Qinj	Qinj4	Qinj5	Qinj6
216.0000	214.0000	121.0000	195.0000	50.0000	-11.5335	-11.1130	-6.0040	-7.2171
89.0000	88.0000	47.0000	148.0000	23.0000	-9.5618	-7.8521	-5.9048	-11.0522
287.0000	226.0000	98.0000	40.0000	39.0000	-8.8339	-11.0949	-5.4097	-5.3775
120.0000	171.0000	79.0000	105.0000	19.0000	-5.3009	-11.7086	-8.7326	-9.1917
174.0000	79.0000	87.0000	86.0000	39.0000	-11.5886	-8.8179	-11.2473	-7.8742
159.0000	128.0000	96.0000	189.0000	41.0000	-7.1086	-7.2631	-7.4766	-11.3204
95.0000	70.0000	99.0000	239.0000	49.0000	-6.0912	-11.5640	-7.2927	-11.4230
259.0000	121.0000	96.0000	47.0000	29.0000	-9.3236	-9.3848	-9.8294	-8.8076
266.0000	131.0000	93.0000	201.0000	45.0000	-6.5960	-5.6476	-5.7040	-9.6156
139.0000	116.0000	115.0000	88.0000	78.0000	-5.9703	-10.8378	-10.5996	-9.2639
177.0000	135.0000	129.0000	201.0000	59.0000	-8.1603	-9.2498	-8.3139	-10.2784
162.0000	172.0000	42.0000	46.0000	46.0000	-6.3791	-10.3534	-11.3737	-6.3738
74.0000	60.0000	27.0000	112.0000	25.0000	-7.7930	-9.2659	-8.4546	-5.1839
127.0000	170.0000	66.0000	175.0000	15.0000	-9.8550	-5.9972	-9.7464	-7.5336
223.0000	210.0000	66.0000	111.0000	67.0000	-9.7690	-11.4719	-8.2625	-11.7453
139.0000	141.0000	42.0000	170.0000	69.0000	-5.7465	-9.9261	-6.7420	-10.9019
114.0000	226.0000	114.0000	121.0000	29.0000	-9.7405	-5.7242	-10.5104	-10.1559
325.0000	229.0000	66.0000	218.0000	54.0000	-8.8437	-6.1622	-11.4674	-5.8995
83.0000	104.0000	94.0000	41.0000	36.0000	-8.6879	-8.5083	-11.0578	-9.9763
262.0000	167.0000	28.0000	102.0000	71.0000	-5.0517	-10.2553	-5.0854	-11.0715

Qinj9	Qinj11	Qinj12	Qinj15	Qinj19	Vmin	Vmax	T loss	b
-11.9945	-9.2458	-7.2266	-11.3720	-5.6508	0.8496	1.0350	24.9936	6.7000
-7.3593	-7.8515	-6.7260	-11.3408	-7.1950	0.8496	1.0350	24.9936	6.7000
-9.3180	-8.8971	-6.7182	-6.4042	-10.8640	0.8496	1.0350	24.9936	6.7000
-8.5552	-7.7388	-8.6925	-5.0310	-11.3797	0.8496	1.0350	24.9936	6.7000
-9.2364	-11.6649	-9.8881	-8.3465	-6.0060	0.8496	1.0350	24.9936	6.7000
-9.8633	-9.8732	-10.2126	-11.9474	-10.0398	0.8496	1.0350	24.9936	6.7000
-8.5820	-7.3126	-7.1273	-7.3540	-6.2766	0.8496	1.0350	24.9936	6.7000
-8.6541	-8.6856	-7.4975	-9.5511	-6.6300	0.8496	1.0350	24.9936	6.7000
-9.8124	-7.6048	-11.8859	-7.4379	-7.0980	0.8496	1.0350	24.9936	6.7000
-7.0551	-6.6812	-6.0990	-5.7035	-8.7743	0.8496	1.0350	24.9936	6.7000
-9.7813	-7.0490	-8.5744	-8.9163	-6.0420	0.8496	1.0350	24.9936	6.7000
-9.0283	-10.5589	-8.4390	-7.9004	-5.0798	0.8496	1.0350	24.9936	6.7000
-5.2080	-5.9082	-11.0325	-6.7770	-5.5323	0.8496	1.0350	24.9936	6.7000
-5.9958	-7.9137	-6.8845	-6.9266	-7.8673	0.8496	1.0350	24.9936	6.7000
-11.7715	-7.8216	-11.2068	-10.4793	-5.5895	0.8496	1.0350	24.9936	6.7000
-10.6749	-10.4838	-9.1753	-9.9117	-8.5209	0.8496	1.0350	24.9936	6.7000
-9.2810	-5.5565	-11.6213	-5.1636	-7.6121	0.8496	1.0350	24.9936	6.7000
-8.1462	-8.0608	-7.3817	-6.5582	-7.6566	0.8496	1.0350	24.9936	6.7000
-8.9676	-7.4614	-6.9156	-7.7102	-8.0140	0.8496	1.0350	24.9936	6.7000
-8.9967	-5.5896	-7.5105	-11.4086	-7.2936	0.8496	1.0350	24.9936	6.7000

Appendix C1

Q Increment
 Critical_Qgs_Qinj_Xmer
 Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	txA	txB	txC	txD
130.0594	217.0115	62.0117	107.0467	22.0825	1.0675	1.0790	0.9880	0.9354
202.0000	87.0000	98.0000	139.0000	57.0000	0.9733	0.9826	0.9407	0.9185
225.0000	103.0000	113.0000	177.0000	22.0000	0.9678	1.0485	1.0118	0.9464
265.0000	98.0000	37.0000	199.0000	61.0000	1.0035	0.9503	0.9623	1.0086
276.0000	50.0000	104.0000	213.0000	22.0000	0.9460	0.9893	1.0141	0.9939
221.0000	65.0000	101.0000	112.0000	30.0000	0.9610	0.9433	1.0169	0.9535
202.0000	66.0000	124.0000	148.0000	75.0000	0.9327	0.9884	1.0102	0.9131
265.0000	69.0000	108.0000	125.0000	39.0000	0.9191	0.9173	0.9349	1.0118
255.0000	117.0000	108.0000	142.0000	18.0000	0.9043	0.9819	0.9488	1.0415
264.0000	200.0000	27.0000	61.0000	24.0000	0.9946	0.9599	1.0152	0.9736
188.0000	221.0000	122.0000	102.0000	69.0000	1.0235	1.0444	0.9693	0.9137
96.0000	197.0000	46.0000	130.0000	46.0000	0.9725	0.9453	0.9457	0.9237
245.0000	136.0000	29.0000	229.0000	29.0000	0.9471	1.0422	0.9994	0.9247
111.0000	157.0000	114.0000	121.0000	27.0000	0.9557	1.0372	0.9034	1.0154
275.0000	69.0000	52.0000	227.0000	60.0000	0.9109	1.0357	1.0292	0.9552
254.0000	154.0000	99.0000	183.0000	45.0000	0.9522	0.9313	1.0102	0.9557
213.0000	60.0000	78.0000	67.0000	62.0000	0.9110	0.9019	1.0285	1.0039
60.0000	211.0000	126.0000	230.0000	52.0000	1.0032	0.9416	1.0171	0.9758
76.0000	113.0000	95.0000	142.0000	46.0000	0.9282	0.9203	0.9508	0.9124
117.0000	47.0000	46.0000	143.0000	58.0000	0.9461	1.0389	0.9882	0.9096

txE	txF	txG	Qinj1	Qinj4	Qinj5	Qinj6	Qinj9	Qinj11
0.9897	0.9647	0.9175	-9.9716	-5.1056	-7.2530	-5.0898	-11.4251	-6.3768
0.9595	1.0400	0.9703	-11.1893	-6.0054	-6.7037	-10.5719	-10.9514	-8.0638
0.9010	0.9321	0.9038	-6.0902	-10.4512	-9.7541	-8.2385	-5.6986	-8.1508
1.0388	1.0165	0.9519	-9.6454	-5.2912	-7.3017	-6.2588	-7.9710	-8.8727
1.0086	0.9651	0.9928	-6.3600	-9.7500	-9.9441	-5.5632	-9.2859	-7.2989
0.9182	0.9342	0.9688	-9.8573	-10.5750	-6.2948	-6.8887	-6.5112	-11.6581
0.9133	0.9108	0.9141	-11.5642	-5.0198	-5.3000	-6.7440	-10.6808	-5.0343
1.0258	1.0482	0.9768	-7.7033	-5.4973	-8.9214	-5.4880	-10.2596	-8.9679
0.9709	1.0326	1.0455	-9.6253	-9.9405	-9.7149	-11.2692	-6.4334	-10.4022
1.0476	0.9715	0.9835	-8.9352	-5.8299	-7.2765	-8.5051	-10.0279	-8.6501
1.0247	1.0196	1.0067	-5.7517	-5.8009	-9.1406	-6.1918	-7.1002	-8.5209
0.9961	0.9807	0.9752	-5.7022	-11.0642	-10.9727	-6.5209	-9.8158	-5.9762
0.9754	0.9718	0.9463	-10.7131	-6.0167	-5.6828	-9.2991	-8.7075	-6.4784
0.9683	0.9666	0.9800	-10.4754	-11.9751	-8.9127	-9.6062	-9.2281	-10.8817
0.9350	0.9773	0.9681	-7.2416	-6.1572	-7.0660	-11.2804	-7.8962	-5.0946
1.0328	1.0390	1.0190	-10.0836	-9.5635	-5.3930	-6.6572	-9.6300	-10.7350
1.0020	1.0365	0.9373	-10.1875	-9.2327	-7.8149	-7.3060	-8.6534	-9.0332
0.9522	0.9034	0.9391	-9.3086	-6.6210	-10.7747	-5.9025	-8.1614	-6.9873
1.0421	1.0426	1.0211	-7.2827	-7.4820	-5.5879	-11.0604	-5.7458	-5.5091
1.0162	1.0127	0.9106	-9.6270	-8.9328	-5.1089	-9.3199	-5.9838	-8.1895

Qinj12	Qinj15	Qinj19	Vmin	Vmax	T_loss	b
-11.6431	-7.1407	-5.2867	0.8498	1.0450	26.3285	7.7000
-10.9035	-10.6092	-11.7683	0.8496	1.0350	24.9936	6.7000
-8.8105	-6.3311	-6.5186	0.8496	1.0350	24.9936	6.7000
-7.9612	-7.2344	-5.5231	0.8496	1.0350	24.9936	6.7000
-7.1787	-9.1470	-7.8843	0.8496	1.0350	24.9936	6.7000
-9.4841	-10.2092	-9.1049	0.8496	1.0350	24.9936	6.7000
-5.3157	-8.9314	-5.7122	0.8496	1.0350	24.9936	6.7000
-6.1262	-11.9734	-11.2035	0.8496	1.0350	24.9936	6.7000
-9.9180	-5.3135	-10.1916	0.8496	1.0350	24.9936	6.7000
-7.6561	-10.3656	-9.2083	0.8496	1.0350	24.9936	6.7000
-6.5914	-6.3578	-9.5839	0.8496	1.0350	24.9936	6.7000
-9.6302	-8.1353	-7.5762	0.8496	1.0350	24.9936	6.7000
-8.5224	-7.3264	-10.2798	0.8496	1.0350	24.9936	6.7000
-5.8282	-5.0463	-6.1839	0.8496	1.0350	24.9936	6.7000
-7.3951	-10.8183	-8.9992	0.8496	1.0350	24.9936	6.7000
-7.8639	-9.7596	-7.1453	0.8496	1.0350	24.9936	6.7000
-7.8826	-9.3985	-7.7770	0.8496	1.0350	24.9936	6.7000
-11.9378	-11.1061	-8.7179	0.8496	1.0350	24.9936	6.7000
-11.6430	-8.2241	-6.8990	0.8496	1.0350	24.9936	6.7000
-7.9605	-5.7640	-9.6970	0.8496	1.0350	24.9936	6.7000



Appendix D1

Q Increment

Critical_Qgs_Xmer

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	txA	txB	txC	txD
317.0004	92.0132	39.0569	122.0115	54.0153	0.9866	1.1478	0.9566	1.0164
184.0387	119.0991	56.0096	239.0636	27.0093	0.9666	0.9927	1.0380	0.9954
248.0455	59.0132	33.0203	155.1353	70.0439	1.0531	1.0540	1.0516	0.9156
262.0334	130.0843	125.0108	154.0759	19.0104	1.1560	0.9710	0.9440	0.9888
327.0000	135.0000	60.0000	138.0000	79.0000	1.0211	1.0003	1.0333	1.0473
104.0000	102.0000	35.0000	211.0000	28.0000	1.0428	0.9057	0.9419	0.9577
295.0000	49.0000	77.0000	228.0000	39.0000	0.9288	0.9947	0.9309	0.9352
204.0000	168.0000	125.0000	136.0000	58.0000	0.9435	0.9070	1.0296	1.0307
270.0000	205.0000	29.0000	160.0000	53.0000	0.9569	1.0386	0.9565	0.9285
46.0000	125.0000	72.0000	72.0000	37.0000	1.0395	1.0191	1.0254	0.9509
58.0000	41.0000	78.0000	185.0000	21.0000	0.9939	1.0057	1.0415	0.9628
207.0000	139.0000	68.0000	176.0000	26.0000	0.9881	0.9110	0.9032	1.0215
131.0000	178.0000	75.0000	205.0000	76.0000	1.0359	0.9619	1.0254	1.0125
273.0000	109.0000	80.0000	232.0000	67.0000	1.0310	0.9718	0.9562	0.9422
237.0000	179.0000	123.0000	232.0000	49.0000	1.0053	1.0275	0.9087	0.9584
330.0000	112.0000	67.0000	75.0000	48.0000	0.9779	1.0323	0.9908	0.9563
267.0000	145.0000	110.0000	219.0000	28.0000	0.9860	1.0043	1.0373	1.0193
41.0000	137.0000	85.0000	141.0000	44.0000	0.9380	0.9323	1.0311	0.9102
268.0000	125.0000	116.0000	47.0000	25.0000	0.9880	0.9919	0.9167	0.9801
180.0000	150.0000	100.0000	83.0000	19.0000	0.9758	0.9413	0.9873	0.9881

txE	txF	txG	Vmin	Vmax	T loss	b
0.9252	0.9495	1.0723	0.8493	1.0450	29.6007	7.5000
0.9504	0.9890	1.0797	0.8492	1.0550	25.4194	6.9000
0.9888	0.9493	1.1758	0.8498	1.0450	27.1096	6.7500
1.0704	0.9468	1.0363	0.8497	1.0450	27.2701	6.7500
1.0013	1.0093	1.0266	0.8496	1.0350	24.9936	6.7000
1.0183	0.9392	0.9045	0.8496	1.0350	24.9936	6.7000
1.0463	0.9218	1.0471	0.8496	1.0350	24.9936	6.7000
0.9864	0.9897	0.9393	0.8496	1.0350	24.9936	6.7000
0.9970	0.9999	0.9621	0.8496	1.0350	24.9936	6.7000
0.9479	0.9149	0.9441	0.8496	1.0350	24.9936	6.7000
1.0125	0.9362	0.9078	0.8496	1.0350	24.9936	6.7000
0.9603	1.0430	0.9798	0.8496	1.0350	24.9936	6.7000
1.0279	1.0328	0.9959	0.8496	1.0350	24.9936	6.7000
0.9578	0.9199	0.9490	0.8496	1.0350	24.9936	6.7000
0.9691	0.9832	0.9240	0.8496	1.0350	24.9936	6.7000
0.9313	0.9203	0.9970	0.8496	1.0350	24.9936	6.7000
1.0225	0.9407	1.0305	0.8496	1.0350	24.9936	6.7000
0.9142	0.9725	0.9831	0.8496	1.0350	24.9936	6.7000
1.0241	1.0052	0.9310	0.8496	1.0350	24.9936	6.7000
1.0291	1.0392	0.9918	0.8496	1.0350	24.9936	6.7000

Appendix E1

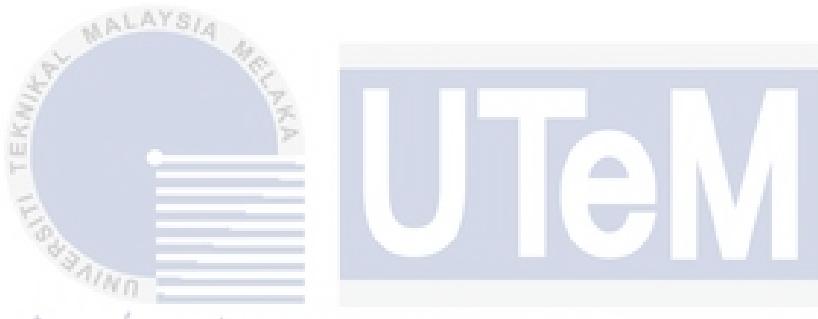
Q Increment

Critical_Qinj_Xmer

Finest parameter (Point B)

txA	txB	txC	txD	txE	txF	txG	Qinj1	Qinj4
1.0792	0.9444	0.9178	1.0098	1.0585	0.9144	0.9873	-6.1016	-5.6667
1.0299	1.0350	1.0396	0.9788	1.0039	0.9449	0.9559	-6.2817	-11.6300
0.9520	1.0455	0.9009	0.9611	0.9678	0.9030	0.9326	-11.0593	-9.2529
1.0484	0.9316	0.9851	0.9517	1.0021	1.0123	1.0408	-11.2341	-11.9390
1.0032	0.9291	0.9683	0.9784	0.9404	1.0204	0.9568	-10.4700	-9.5752
1.0247	0.9771	0.9841	0.9285	0.9740	0.9721	0.9772	-10.3210	-10.0837
1.0056	0.9387	0.9096	0.9075	1.0301	0.9812	0.9729	-10.4851	-10.0900
0.9358	0.9060	0.9203	0.9304	0.9045	0.9934	0.9782	-11.8719	-7.7780
1.0068	0.9738	0.9508	0.9976	0.9765	0.9245	0.9527	-9.6238	-10.3359
0.9088	0.9599	0.9579	0.9778	0.9922	1.0287	0.9072	-7.4541	-5.4195
1.0266	1.0035	1.0449	0.9703	1.0223	0.9645	0.9668	-6.1902	-5.2048
1.0005	0.9562	1.0321	0.9618	0.9392	0.9766	1.0280	-10.6530	-9.0338
1.0493	0.9008	0.9993	0.9455	0.9716	0.9916	1.0455	-5.7792	-6.5791
1.0363	1.0106	0.9327	1.0073	0.9950	0.9854	1.0357	-6.6962	-9.1771
0.9537	1.0058	0.9218	0.9322	0.9059	0.9887	0.9000	-5.2765	-6.7459
0.9631	0.9069	0.9603	0.9180	0.9490	0.9074	0.9423	-6.8696	-5.5117
1.0063	0.9026	0.9277	0.9513	0.9412	0.9022	0.9462	-11.0737	-5.3584
0.9806	1.0316	0.9855	1.0033	1.0309	1.0143	0.9537	-7.7390	-5.0742
0.9773	1.0218	0.9505	0.9037	1.0161	1.0375	0.9568	-5.0791	-5.2513
0.9241	0.9673	0.9567	0.9303	1.0294	0.9233	0.9240	-10.8005	-9.6741

Qinj5	Qinj6	Qinj9	Qinj11	Qinj12	Qinj15	Qinj19	Vmin	Vmax
-9.1644	-9.6733	-6.3585	-9.3004	-5.6622	-11.8962	-5.6830	0.8496	1.0493
-5.1047	-6.0114	-8.0798	-8.2782	-8.5503	-9.1756	-5.7026	0.8496	1.0350
-9.8914	-9.9008	-10.2258	-10.5046	-7.5978	-11.3503	-11.9103	0.8496	1.0350
-7.1467	-11.6635	-11.3193	-8.8442	-6.0544	-8.9633	-6.2474	0.8496	1.0350
-10.9214	-10.8013	-6.1344	-8.2837	-6.7833	-11.4677	-8.7854	0.8496	1.0350
-5.6980	-9.4148	-7.7991	-8.0615	-11.5025	-6.9108	-7.4876	0.8496	1.0350
-7.7265	-8.6137	-8.5981	-8.1579	-11.1190	-9.9255	-9.6717	0.8496	1.0350
-8.4523	-10.9588	-7.4105	-9.9952	-11.1789	-5.2346	-8.9290	0.8496	1.0350
-6.0678	-7.0262	-6.4489	-9.5735	-11.9177	-7.4483	-8.4865	0.8496	1.0350
-8.0746	-5.6705	-10.6581	-9.4523	-6.6390	-6.3507	-5.2692	0.8496	1.0350
-7.3594	-5.4939	-6.2415	-11.4160	-8.7427	-6.4583	-11.9031	0.8496	1.0350
-8.1808	-9.0304	-11.8304	-5.8857	-10.3620	-10.8196	-8.9904	0.8496	1.0350
-6.8834	-6.7272	-10.3889	-5.8062	-5.4019	-6.9074	-5.2288	0.8496	1.0350
-9.0783	-11.0290	-8.0426	-6.5910	-7.1073	-6.9565	-7.2737	0.8496	1.0350
-8.0574	-7.6803	-6.9128	-10.8323	-9.4472	-11.4513	-11.9347	0.8496	1.0350
-6.2916	-11.6168	-7.8355	-6.8525	-5.0191	-11.6741	-10.9635	0.8496	1.0350
-8.4357	-5.7155	-10.8758	-7.2498	-11.4135	-6.5575	-7.7804	0.8496	1.0350
-11.5046	-5.5890	-5.3366	-9.2192	-8.0423	-6.1720	-7.0883	0.8496	1.0350
-8.3043	-11.7572	-10.9276	-9.2638	-6.2157	-7.0397	-5.7047	0.8496	1.0350
-6.1843	-8.7069	-7.5029	-11.6971	-5.1066	-5.4332	-9.4668	0.8496	1.0350



اویورسیٰ یونیکل ملیسا ملاک

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Appendix F1

Q Increment

Critical_Qinj

Finest parameter (Point B)

Qinj1	Qinj4	Qinj5	Qinj6	Qinj9	Qinj11	Qinj12	Qinj15	Qinj19
-10.5326	-10.4692	-8.4946	-10.0182	-9.3470	-9.0940	-11.6509	-6.8520	-10.9221
-9.7001	-5.1686	-9.6707	-5.3705	-5.3027	-8.3447	-6.8695	-9.1918	-5.4535
-11.7269	-6.9562	-9.7009	-10.1956	-6.8399	-5.4955	-9.5616	-10.3983	-10.5091
-9.9061	-10.5828	-6.3169	-8.7024	-6.2373	-7.1365	-6.1858	-5.8743	-7.2896
-8.8516	-11.0096	-10.8032	-11.1681	-9.2549	-11.9847	-9.6228	-8.7238	-8.7859
-6.4926	-6.2022	-7.8998	-8.2056	-9.1975	-10.4068	-5.8832	-7.4278	-7.7025
-5.3468	-10.2834	-9.3850	-8.1824	-11.1188	-9.0473	-9.3318	-11.5573	-10.2485
-11.7092	-9.4233	-5.7855	-7.5010	-5.1358	-8.2046	-7.4855	-6.4501	-8.4792
-11.6739	-10.2109	-9.1604	-9.1359	-7.3224	-9.4001	-6.7048	-7.5337	-10.1996
-5.8911	-10.8130	-5.4039	-9.0951	-9.9349	-9.9078	-6.6387	-5.5096	-8.5072
-5.5815	-8.9382	-7.4546	-7.6421	-11.6554	-5.2530	-10.7231	-8.1739	-11.2470
-10.4255	-8.2415	-5.7842	-10.9569	-7.1968	-5.7884	-11.0908	-6.6205	-10.9995
-8.9222	-5.6679	-6.6623	-10.2998	-6.1110	-5.6344	-7.7331	-10.3653	-11.1045
-8.8966	-6.8028	-10.7656	-10.4587	-9.8844	-10.6886	-7.6985	-10.1623	-6.2326
-7.0968	-10.2964	-7.5567	-11.5126	-10.0301	-10.2858	-5.7264	-6.0308	-7.9428
-10.1548	-8.1718	-9.7954	-8.9799	-6.9475	-6.3230	-7.9822	-9.9401	-10.9282
-5.0958	-11.7413	-5.8418	-7.9656	-9.1527	-6.0550	-7.7116	-11.7182	-7.7544
-10.8000	-11.7235	-8.1759	-5.8992	-5.1755	-8.1629	-6.5516	-11.1968	-7.9802
-11.1872	-6.2815	-9.1691	-5.0983	-7.8770	-11.7044	-9.6642	-11.1832	-6.8809
-7.5146	-10.1544	-7.7630	-9.7839	-9.9283	-8.0961	-5.1370	-7.3160	-7.9702

Appendix G1

Q Increment

Critical_Xmer

Finest parameter (Point B)

txA	txB	txC	txD	txE	txF	txG	Vmin	Vmax
1.1096	1.0817	1.0526	1.0662	0.9293	0.9128	0.9442	0.8492	1.0350
1.0011	1.0224	0.9637	0.9797	1.0279	0.9243	1.0599	0.8491	1.0450
1.0315	0.9310	0.9315	1.0414	1.0000	0.9135	0.9734	0.8496	1.0350
0.9968	0.9460	0.9815	1.0196	1.0017	1.0461	0.9990	0.8496	1.0350
1.0168	0.9025	0.9524	1.0002	0.9874	1.0190	0.9120	0.8496	1.0350
0.9434	0.9043	0.9748	0.9293	1.0446	1.0145	0.9919	0.8496	1.0350
1.0197	0.9423	0.9318	0.9376	0.9320	0.9830	0.9789	0.8496	1.0350
0.9625	0.9362	0.9526	1.0050	0.9733	1.0231	0.9495	0.8496	1.0350
0.9260	1.0285	0.9869	0.9303	1.0013	0.9149	0.9006	0.8496	1.0350
0.9928	0.9697	1.0319	1.0099	0.9884	0.9151	0.9033	0.8496	1.0350
0.9934	1.0051	0.9734	0.9763	1.0170	0.9061	1.0352	0.8496	1.0350
1.0301	1.0290	0.9826	0.9686	1.0275	0.9522	0.9358	0.8496	1.0350
0.9757	0.9946	0.9590	1.0020	0.9195	0.9105	0.9068	0.8496	1.0350
0.9412	0.9357	1.0140	1.0440	0.9249	0.9568	0.9145	0.8496	1.0350
1.0380	0.9479	0.9427	0.9546	0.9749	1.0220	0.9352	0.8496	1.0350
1.0852	1.0390	1.0134	0.9536	0.9925	0.9752	1.0247	0.8496	1.0450
0.9800	0.9942	0.9670	1.0217	0.9217	1.0462	1.0251	0.8496	1.0350
0.9653	0.9237	0.9901	1.0406	0.9162	1.0350	0.9826	0.8496	1.0350
0.9434	0.9103	0.9127	0.9103	0.9615	0.9185	0.9665	0.8496	1.0350
1.0169	1.0073	1.0356	1.0336	0.9501	1.0048	0.9297	0.8496	1.0350

Appendix H1

P Increment

Critical_Qgs

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	Vmin	Vmax	Tloss	b
63.0420	227.0002	82.1507	81.2495	35.0188	0.8500	1.0350	63.1059	7.3500
217.0003	163.0804	48.0515	105.1128	49.0017	0.8500	1.0350	63.1059	7.3500
110.0139	219.0297	87.5221	150.1694	49.0116	0.8500	1.0350	63.1059	7.3500
312.0143	93.0135	129.0543	194.1334	79.0016	0.8500	1.0350	63.1059	7.3500
176.0529	66.0063	60.0478	137.0026	28.1442	0.8500	1.0350	63.1059	7.3500
270.0063	91.0086	50.0012	187.1733	43.0008	0.8500	1.0350	63.1059	7.3500
195.1536	230.0296	122.0607	131.0087	26.0440	0.8500	1.0350	63.1059	7.3500
130.0088	194.0030	106.0314	58.0010	19.0044	0.8500	1.0350	63.1059	7.3500
175.0117	209.1235	105.1403	83.0482	48.0027	0.8500	1.0350	63.1059	7.3500
172.0743	206.0531	108.0013	54.0562	16.1113	0.8500	1.0350	63.1059	7.3500
282.1018	58.0520	125.0179	87.0136	62.0239	0.8500	1.0350	63.1059	7.3500
307.0105	160.0004	58.0299	203.0148	24.0177	0.8500	1.0350	63.1059	7.3500
75.0862	145.0112	46.0305	224.0064	39.0333	0.8500	1.0350	63.1059	7.3500
68.0441	133.0146	34.0179	233.0132	42.0512	0.8500	1.0350	63.1059	7.3500
129.0839	94.0146	97.0740	220.0434	76.0435	0.8500	1.0350	63.1059	7.3500
258.0200	183.0462	29.0140	216.0329	23.0018	0.8500	1.0350	63.1059	7.3500
300.0182	60.0538	92.0028	115.0040	43.0634	0.8500	1.0350	63.1059	7.3500
288.3854	127.2530	98.0196	59.1150	77.1570	0.8500	1.0350	63.1059	7.3500
124.0072	161.1733	101.0159	213.0215	19.0354	0.8500	1.0350	63.1059	7.3500
75.0038	42.0375	86.0013	65.0061	65.0117	0.8500	1.0350	63.1059	7.3500

Appendix II

P Increment

Critical_Qgs_Qinj

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	Qinj1	Qinj4	Qinj5	Qinj6
253.0000	92.0000	122.0000	46.0000	43.0000	-7.7691	-10.1832	-5.9418	-8.2317
233.0000	123.0000	71.0000	71.0000	25.0000	-9.0573	-10.5499	-11.8705	-9.3532
109.0000	96.0000	111.0000	155.0000	74.0000	-10.1090	-11.0911	-8.7303	-11.9470
177.0000	183.0000	31.0000	215.0000	79.0000	-11.8268	-9.6014	-5.2208	-11.0745
312.0000	93.0000	53.0000	152.0000	31.0000	-11.7854	-9.0268	-8.9266	-7.8899
302.0000	152.0000	57.0000	131.0000	75.0000	-7.6370	-8.8962	-9.2628	-9.3433
142.0000	60.0000	102.0000	64.0000	45.0000	-7.6931	-5.0581	-5.4597	-11.7690
132.0000	181.0000	68.0000	222.0000	15.0000	-7.8984	-7.2995	-6.9426	-10.7521
113.0000	148.0000	121.0000	103.0000	70.0000	-10.1114	-9.7091	-8.3445	-6.9058
180.0000	150.0000	108.0000	135.0000	55.0000	-7.5567	-11.8688	-5.9379	-5.6834
281.0000	189.0000	75.0000	60.0000	41.0000	-8.4964	-9.4500	-10.2328	-7.5425
66.0000	126.0000	106.0000	199.0000	71.0000	-9.9137	-9.6810	-6.4820	-11.4768
128.0000	68.0000	53.0000	79.0000	65.0000	-8.9161	-6.6917	-11.8315	-6.5651
308.0000	175.0000	121.0000	230.0000	30.0000	-11.9768	-8.5323	-7.2188	-10.9653
81.0000	185.0000	26.0000	168.0000	60.0000	-5.1711	-8.6461	-6.0301	-6.9752
195.0000	67.0000	70.0000	84.0000	59.0000	-11.6081	-5.8353	-9.6504	-7.3130
136.0000	81.0000	93.0000	53.0000	63.0000	-11.7751	-7.5210	-8.8824	-10.5748
180.0000	167.0000	99.0000	75.0000	71.0000	-5.0432	-9.0390	-10.4125	-8.9004
60.0000	101.0000	100.0000	174.0000	64.0000	-10.0244	-10.4610	-6.7741	-9.6587
310.0000	172.0000	86.0000	203.0000	72.0000	-11.9224	-5.0037	-11.0581	-9.2880

Qinj9	Qinj11	Qinj12	Qinj15	Qinj19	Vmin	Vmax	T loss	b
-9.7591	-9.4343	-7.8086	-10.7333	-9.1685	0.8500	1.0350	63.1059	7.3500
-9.6400	-9.5981	-8.4014	-6.6755	-8.8019	0.8500	1.0350	63.1059	7.3500
-6.0879	-5.0497	-7.0323	-10.8014	-7.5937	0.8500	1.0350	63.1059	7.3500
-6.5202	-6.5169	-7.7986	-7.2291	-10.5341	0.8500	1.0350	63.1059	7.3500
-9.4567	-9.0030	-5.4341	-10.7075	-7.2698	0.8500	1.0350	63.1059	7.3500
-10.1950	-7.7139	-11.4589	-10.9428	-6.0253	0.8500	1.0350	63.1059	7.3500
-7.6575	-5.3221	-6.6814	-11.4157	-9.4376	0.8500	1.0350	63.1059	7.3500
-9.4629	-6.5866	-5.9336	-11.7203	-6.8202	0.8500	1.0350	63.1059	7.3500
-8.4889	-5.8839	-6.3012	-11.0897	-7.5451	0.8500	1.0350	63.1059	7.3500
-6.8880	-11.6939	-6.3268	-7.6660	-8.6780	0.8500	1.0350	63.1059	7.3500
-8.1272	-11.2268	-5.5763	-8.8916	-6.1523	0.8500	1.0350	63.1059	7.3500
-10.9318	-6.8521	-7.9729	-6.5947	-5.8821	0.8500	1.0350	63.1059	7.3500
-10.8524	-9.8024	-6.0764	-5.0170	-9.6116	0.8500	1.0350	63.1059	7.3500
-7.1027	-8.9389	-7.3264	-10.7688	-8.7474	0.8500	1.0350	63.1059	7.3500
-9.8729	-6.4746	-11.4132	-8.5946	-10.7518	0.8500	1.0350	63.1059	7.3500
-9.2874	-10.2433	-9.1042	-5.0525	-8.6528	0.8500	1.0350	63.1059	7.3500
-5.5551	-9.8818	-5.2389	-9.9626	-6.4787	0.8500	1.0350	63.1059	7.3500
-7.9087	-6.3406	-5.7811	-7.8992	-7.7666	0.8500	1.0350	63.1059	7.3500
-9.1475	-6.4688	-8.5692	-9.7776	-8.2909	0.8500	1.0350	63.1059	7.3500
-11.9297	-8.6938	-8.3567	-10.6094	-6.5949	0.8500	1.0350	63.1059	7.3500

Appendix J1

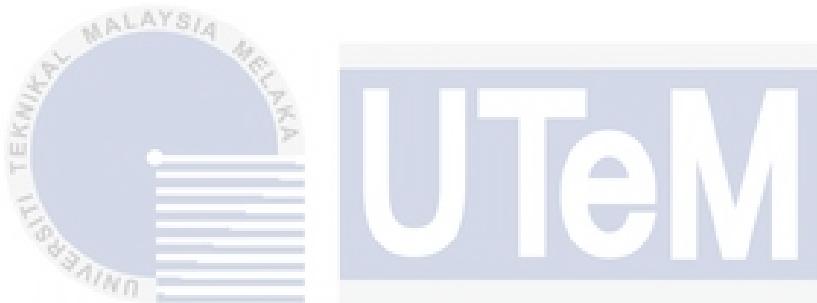
P Increment

Critical_Qgs_Xmer

Finest parameter (Point B)

txA	txB	txC	txD	txE	txF	txG	Qinj1	Qinj4
1.0121	0.9515	1.1959	0.9338	0.9132	0.9526	1.0125	-5.5037	-11.2627
1.0471	1.1129	1.0539	1.0437	0.9551	0.9338	0.9327	-7.3629	-6.5642
0.9396	0.9759	0.9349	0.9573	1.0187	1.0217	1.0123	-5.9939	-8.8111
1.0257	0.9722	0.9596	1.0372	0.9919	0.9550	0.9081	-7.2127	-5.4665
0.9941	1.0143	1.0385	1.0476	0.9086	0.9405	1.0130	-9.7443	-8.6351
0.9103	0.9359	0.9763	0.9250	1.0452	0.9139	0.9724	-10.4615	-7.1500
0.9014	0.9840	0.9899	1.0160	0.9037	0.9819	0.9411	-11.5444	-11.6063
1.0270	0.9090	1.0168	0.9418	0.9226	0.9756	0.9806	-7.6422	-8.6434
0.9321	0.9249	1.0104	1.0439	0.9034	0.9132	0.9212	-8.0868	-9.4224
0.9819	1.0482	0.9149	0.9879	0.9408	0.9836	0.9940	-8.7290	-5.8941
0.9182	0.9394	0.9842	0.9162	0.9729	0.9839	0.9855	-8.3162	-8.0057
0.9483	0.9849	0.9841	1.0484	0.9214	1.0037	0.9889	-7.2998	-6.8705
0.9676	0.9967	1.0358	0.9157	0.9132	0.9023	1.0355	-11.7595	-8.9431
0.9248	1.0475	1.0481	1.0349	1.0266	1.0167	1.0292	-5.9196	-9.8316
0.9170	0.9026	0.9807	0.9979	0.9157	0.9971	1.0315	-7.4985	-8.6421
1.0469	0.9877	0.9012	0.9492	1.0156	1.0233	1.0127	-7.6368	-9.4028
1.0350	0.9629	1.0066	0.9671	0.9577	0.9571	1.0231	-6.2912	-8.0641
1.0005	1.0075	0.9407	1.0002	0.9683	0.9122	0.9010	-5.0756	-9.5669
1.0012	0.9737	0.9850	0.9107	0.9437	0.9274	1.0253	-11.7119	-9.9853
1.0148	0.9749	0.9547	1.0499	0.9791	0.9626	0.9703	-8.1777	-8.7129

Qinj5	Qinj6	Qinj9	Qinj11	Qinj12	Qinj15	Qinj19	Vmin	Vmax
-11.3213	-7.3050	-9.1131	-7.7917	-9.9722	-6.2262	-6.2363	0.8495	1.0750
-5.7466	-11.8576	-10.7074	-9.1205	-9.2832	-9.8495	-9.9915	0.8498	1.0250
-8.5535	-8.4803	-5.8367	-7.8896	-6.1045	-9.4381	-7.1834	0.8500	1.0350
-7.5372	-10.5790	-8.6215	-9.3004	-8.0658	-7.2765	-9.1529	0.8500	1.0350
-10.0462	-9.4150	-10.3899	-6.4538	-5.2363	-8.4198	-9.6587	0.8500	1.0350
-11.8759	-6.9691	-11.9843	-7.8329	-10.5178	-9.5106	-10.7579	0.8500	1.0350
-6.9803	-9.1148	-10.2631	-9.4647	-6.8673	-11.3282	-10.4834	0.8500	1.0350
-10.8591	-5.7334	-10.9929	-5.8305	-8.8165	-10.3557	-8.0796	0.8500	1.0350
-9.6315	-10.0150	-7.0746	-6.0003	-5.4975	-9.1813	-9.8669	0.8500	1.0350
-8.1987	-6.6243	-10.2152	-5.8391	-9.7010	-11.9133	-11.5803	0.8500	1.0350
-9.4465	-8.5135	-8.7044	-9.1348	-6.0837	-8.7050	-9.1692	0.8500	1.0350
-10.7421	-7.0355	-6.2082	-11.1600	-11.2457	-9.4499	-9.6962	0.8500	1.0350
-11.4854	-6.2642	-5.2351	-11.1920	-8.5693	-8.8405	-7.8983	0.8500	1.0350
-9.2169	-9.5381	-5.7693	-11.3216	-11.4623	-6.7015	-10.2343	0.8500	1.0350
-10.8010	-11.7529	-8.3825	-8.1580	-5.6261	-7.2300	-6.6839	0.8500	1.0350
-11.4328	-10.0037	-9.4629	-6.4661	-5.2921	-6.7088	-11.7991	0.8500	1.0350
-9.8460	-7.2369	-10.5405	-7.6606	-10.8548	-10.6972	-5.2466	0.8500	1.0350
-5.8437	-11.1816	-10.6115	-8.0704	-7.2044	-6.6528	-7.8604	0.8500	1.0350
-5.5034	-9.0519	-6.9808	-10.8321	-11.9307	-8.8249	-7.6067	0.8500	1.0350
-6.6318	-8.9968	-6.6785	-8.9405	-8.5925	-9.6153	-7.1997	0.8500	1.0350



اوپر سیئی تکنیکل ملیسیا مالاک

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Appendix K1

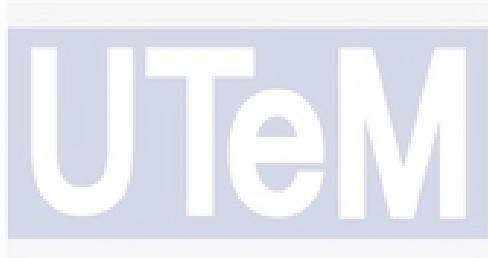
P Increment
 Critical_Qgs_Qinj_Xmer
 Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	txA	txB	txC	txD
293.0245	152.0143	60.0778	67.0029	43.0016	0.9977	1.0108	1.0010	0.9052
295.0305	127.0011	82.0298	128.0081	53.0141	1.0174	1.1676	1.0315	0.9575
83.0977	67.0181	122.0287	229.0056	66.0240	1.0954	1.0135	1.0851	1.0049
161.0000	74.0000	50.0000	152.0000	68.0000	1.0468	1.0302	1.0355	0.9853
249.0000	186.0000	79.0000	201.0000	23.0000	1.0173	0.9646	0.9365	0.9295
128.0000	103.0000	101.0000	67.0000	62.0000	1.0042	0.9155	0.9330	1.0490
170.0000	75.0000	119.0000	134.0000	34.0000	0.9762	0.9943	0.9487	1.0266
84.0000	56.0000	67.0000	186.0000	79.0000	0.9294	0.9512	0.9844	1.0313
269.0000	95.0000	44.0000	163.0000	26.0000	1.0019	0.9303	0.9005	1.0406
275.0000	103.0000	116.0000	217.0000	78.0000	1.0302	0.9687	0.9774	1.0281
211.0000	62.0000	104.0000	113.0000	29.0000	0.9574	0.9996	0.9215	1.0485
239.0000	172.0000	69.0000	101.0000	53.0000	1.0289	0.9432	1.0003	0.9737
68.0000	181.0000	126.0000	97.0000	16.0000	0.9912	1.0018	0.9574	0.9473
132.0000	176.0000	39.0000	231.0000	67.0000	1.0171	0.9857	1.0309	0.9044
225.0000	132.0000	28.0000	100.0000	58.0000	0.9810	0.9494	0.9299	0.9858
94.0000	166.0000	67.0000	108.0000	79.0000	0.9323	0.9580	0.9192	1.0280
311.0000	128.0000	102.0000	231.0000	41.0000	1.0474	0.9212	1.0217	0.9832
270.0000	181.0000	98.0000	159.0000	69.0000	0.9717	1.0474	0.9622	1.0019
137.0000	42.0000	53.0000	227.0000	22.0000	0.9746	1.0386	1.0475	1.0385
169.0000	153.0000	76.0000	149.0000	25.0000	1.0483	1.0324	0.9295	1.0141

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

txE	txF	txG	Qinj1	Qinj4	Qinj5	Qinj6	Qinj9	Qinj11
0.9698	0.9968	0.9815	-8.1292	-6.1835	-10.5060	-10.6322	-5.7130	-4.9602
0.9607	0.9618	0.9719	-11.9170	-9.9392	-5.7008	-10.4023	-11.0831	-11.6412
0.9723	0.9369	0.9655	-5.4304	-8.5775	-6.9705	-8.5929	-9.6945	-7.0577
0.9963	0.9016	0.9141	-5.5536	-5.9059	-8.0486	-8.5103	-7.3634	-11.4955
0.9636	1.0323	0.9512	-5.2574	-8.1250	-6.6838	-5.4746	-11.6205	-7.6425
0.9699	0.9123	1.0500	-5.5863	-7.6156	-11.9176	-8.2649	-10.1020	-10.6397
0.9131	0.9251	1.0283	-9.6232	-9.9543	-6.9528	-9.5455	-5.7396	-11.7685
0.9776	1.0312	1.0304	-10.5879	-10.6345	-11.9909	-5.6422	-11.7511	-9.5573
0.9724	0.9573	1.0499	-7.2584	-11.7336	-9.0521	-5.7184	-11.1169	-5.3050
0.9893	0.9066	1.0481	-7.3545	-8.5325	-7.7028	-10.0855	-5.4856	-6.3123
0.9191	1.0036	0.9662	-10.9565	-7.6749	-9.4505	-11.3065	-6.5331	-6.1538
0.9809	0.9838	0.9707	-6.0499	-10.3015	-10.5762	-7.8511	-10.2993	-11.0909
0.9515	0.9508	1.0056	-7.6135	-6.2396	-10.1659	-7.9278	-8.4699	-8.0011
1.0140	0.9060	0.9973	-5.4997	-7.8790	-6.7339	-10.6233	-9.6452	-9.6912
0.9485	0.9233	0.9690	-10.3468	-5.0956	-10.0338	-8.0242	-5.6638	-6.8839
0.9632	0.9198	0.9994	-11.8912	-5.1177	-10.0180	-6.6641	-7.5757	-9.6900
1.0466	1.0313	0.9249	-7.9406	-8.2891	-11.8029	-11.0853	-8.9559	-7.7344
0.9068	0.9795	0.9463	-5.6611	-9.1870	-6.6527	-6.9910	-9.0202	-6.8992
0.9212	0.9663	0.9277	-6.6951	-5.9924	-11.9071	-10.3526	-6.6500	-11.1001
0.9438	0.9175	0.9685	-5.6069	-11.7687	-11.4818	-7.2166	-5.0807	-7.5672

Qinj12	Qinj15	Qinj19	Vmin	Vmax	T_loss	b
-9.4304	-7.1637	-9.0898	0.8497	1.0450	71.4128	8.0000
-8.4129	-8.2270	-5.2157	0.8489	1.0350	69.5472	7.7500
-7.7356	-11.9731	-7.5274	0.8481	1.0300	67.0203	7.4000
-8.9931	-9.3009	-11.7789	0.8500	1.0350	63.1059	7.3500
-8.0066	-6.2412	-11.8653	0.8500	1.0350	63.1059	7.3500
-5.7253	-11.8351	-9.7578	0.8500	1.0350	63.1059	7.3500
-7.6109	-10.3797	-11.0605	0.8500	1.0350	63.1059	7.3500
-8.1650	-6.2325	-11.0937	0.8500	1.0350	63.1059	7.3500
-9.8498	-9.8082	-5.1104	0.8500	1.0350	63.1059	7.3500
-9.1066	-7.7437	-5.9898	0.8500	1.0350	63.1059	7.3500
-9.4425	-8.0733	-9.6852	0.8500	1.0350	63.1059	7.3500
-8.6216	-6.2589	-10.3400	0.8500	1.0350	63.1059	7.3500
-5.1958	-9.4294	-11.1006	0.8500	1.0350	63.1059	7.3500
-10.2001	-10.7478	-5.9776	0.8500	1.0350	63.1059	7.3500
-5.9943	-8.1013	-7.9507	0.8500	1.0350	63.1059	7.3500
-6.2774	-6.3776	-9.3011	0.8500	1.0350	63.1059	7.3500
-9.5997	-9.6973	-5.7832	0.8500	1.0350	63.1059	7.3500
-8.3478	-10.8550	-9.2475	0.8500	1.0350	63.1059	7.3500
-6.9973	-11.3673	-11.4045	0.8500	1.0350	63.1059	7.3500
-10.0731	-7.1567	-5.7383	0.8500	1.0350	63.1059	7.3500



اوپیورسیٽی یکنیکل ملیسیا ملاک

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Appendix L1

P Increment

Critical_Qgs_Xmer

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	txA	txB	txC	txD
164.0065	74.4790	27.0420	87.0016	22.0504	1.1027	1.0139	1.1344	0.9136
137.0403	82.0298	33.0140	135.0015	60.0142	1.1267	1.1528	0.9981	1.1978
264.0016	164.0160	47.0009	69.0293	28.0019	1.1224	1.1497	1.0293	1.0658
215.0257	157.0038	32.0059	93.0324	53.0946	1.0718	1.1429	1.0750	0.9379
172.0058	89.0429	106.0247	239.0016	27.0287	0.9605	1.0129	1.1080	0.9588
257.0000	166.0000	56.0000	135.0000	64.0000	1.0116	0.9325	1.0229	1.0106
249.0000	129.0000	124.0000	60.0000	17.0000	0.9680	0.9101	1.0318	1.0127
141.0000	196.0000	104.0000	89.0000	43.0000	0.9625	1.0091	1.0227	1.0364
85.0000	96.0000	97.0000	177.0000	49.0000	0.9526	1.0467	0.9990	0.9051
305.1329	161.1060	34.0070	206.1432	49.0018	0.9498	0.9870	0.9994	1.1436
137.0000	59.0000	67.0000	187.0000	67.0000	0.9994	0.9603	0.9735	0.9393
282.0000	203.0000	113.0000	80.0000	35.0000	1.0456	0.9343	0.9330	0.9919
184.0000	164.0000	45.0000	80.0000	64.0000	0.9146	0.9118	0.9506	1.0180
186.0000	84.0000	44.0000	188.0000	79.0000	0.9605	0.9206	1.0279	1.0353
238.0000	154.0000	28.0000	180.0000	52.0000	0.9970	1.0011	0.9261	1.0011
181.0000	93.0000	96.0000	131.0000	67.0000	0.9933	1.0174	0.9432	1.0487
103.0000	176.0000	28.0000	62.0000	36.0000	0.9079	0.9045	0.9249	0.9521
323.0000	113.0000	106.0000	46.0000	28.0000	1.0270	1.0402	0.9919	1.0297
241.0000	194.0000	118.0000	180.0000	74.0000	1.0034	1.0211	1.0469	1.0105
183.0000	205.0000	118.0000	89.0000	54.0000	0.9214	0.9990	0.9365	1.0382

txE	txF	txG	Vmin	Vmax	T loss	b
0.9666	0.9462	1.0702	0.8498	1.0450	74.5288	7.8000
0.9888	0.9074	1.0076	0.8438	1.0400	74.3923	7.6000
0.9347	0.9406	1.0715	0.8494	1.0350	70.4831	7.4500
0.9727	0.9922	0.9640	0.8499	1.0450	67.5777	7.4500
0.9482	0.9964	1.1144	0.8487	1.0750	65.3924	7.4000
0.9847	1.0485	0.9356	0.8500	1.0350	63.1059	7.3500
0.9601	0.9638	0.9057	0.8500	1.0350	63.1059	7.3500
0.9884	1.0131	0.9301	0.8500	1.0350	63.1059	7.3500
1.0476	1.0262	1.0291	0.8500	1.0350	63.1059	7.3500
1.0318	0.9728	0.9408	0.8488	1.0600	65.1319	7.3500
0.9698	0.9471	1.0174	0.8500	1.0350	63.1059	7.3500
1.0366	0.9164	0.9997	0.8500	1.0350	63.1059	7.3500
0.9947	1.0171	0.9827	0.8500	1.0350	63.1059	7.3500
1.0194	0.9768	0.9773	0.8500	1.0350	63.1059	7.3500
0.9234	1.0103	1.0489	0.8500	1.0350	63.1059	7.3500
0.9899	0.9717	0.9265	0.8500	1.0350	63.1059	7.3500
0.9318	1.0193	1.0206	0.8500	1.0350	63.1059	7.3500
1.0114	0.9644	0.9738	0.8500	1.0350	63.1059	7.3500
0.9203	0.9893	0.9521	0.8500	1.0350	63.1059	7.3500
1.0304	1.0484	1.0186	0.8500	1.0350	63.1059	7.3500

Appendix M1

P Increment

Critical_Qinj

Finest parameter (Point B)

Qinj1	Qinj4	Qinj5	Qinj6	Qinj9	Qinj11	Qinj12	Qinj15	Qinj19
-5.7547	-6.5911	-6.9807	-8.8996	-5.3309	-11.5221	-7.8645	-5.2413	-8.1728
-5.4223	-7.9934	-10.4593	-5.0844	-10.0079	-9.9340	-7.3358	-11.0885	-6.2069
-10.1086	-6.3656	-9.8373	-11.9807	-7.7808	-8.6815	-11.3333	-7.0092	-5.3123
-6.7097	-11.5601	-6.9112	-8.7633	-9.9529	-8.9215	-5.6135	-10.1883	-6.7809
-6.5628	-5.8176	-10.6313	-7.0732	-10.0934	-7.3163	-7.9880	-8.4611	-9.0678
-10.5082	-10.3376	-11.7468	-7.6647	-9.6589	-8.8324	-9.5386	-5.2894	-10.4602
-9.5798	-7.0175	-8.6924	-9.2746	-5.8001	-10.1835	-10.9362	-7.9903	-5.1799
-7.6744	-6.0925	-9.5964	-6.6860	-5.7454	-10.3964	-6.6859	-9.1479	-5.3847
-10.7577	-6.0104	-11.2401	-10.8972	-7.0248	-7.1265	-8.0126	-6.3953	-10.4627
-7.1163	-9.0573	-10.6666	-11.5302	-6.7954	-8.5669	-9.3763	-8.5109	-9.0171
-7.0031	-9.0315	-8.2082	-5.2370	-8.9154	-7.5066	-6.4791	-10.8815	-5.7340
-10.1740	-10.2746	-5.9505	-7.0927	-6.9529	-11.9271	-6.8632	-11.8960	-11.6267
-6.9361	-7.2916	-7.9680	-7.8883	-9.9275	-5.0124	-9.3513	-9.6028	-6.1889
-10.9813	-9.5285	-10.5484	-10.6218	-9.1393	-6.1983	-10.5594	-6.3479	-10.2424
-9.9379	-8.0868	-8.9326	-9.5917	-8.2339	-11.9148	-8.9579	-9.5736	-10.6967
-6.3808	-11.6890	-7.3267	-7.3360	-6.3325	-7.0214	-7.7016	-11.9500	-5.4797
-11.4112	-5.6681	-6.8950	-6.7323	-11.3330	-10.7313	-9.8242	-11.8806	-9.1875
-5.7098	-8.6291	-5.0730	-11.6948	-8.1820	-7.1090	-5.2260	-11.8046	-9.5103
-10.3340	-6.0947	-8.6570	-5.6568	-5.6604	-7.6632	-10.1795	-9.5811	-5.4724
-11.2298	-6.8032	-7.0643	-8.4347	-7.6337	-9.7191	-6.6554	-6.9009	-10.8423

Appendix N1

P Increment

Critical_Xmer

Finest parameter (Point B)

txA	txB	txC	txD	txE	txF	txG	Vmin	Vmax
1.1082	1.0738	1.0158	0.9930	0.9896	0.9225	1.0520	0.8499	1.0350
1.1575	1.0433	1.0796	1.1336	0.9117	0.9226	1.0144	0.8495	1.0250
1.0863	1.0445	0.9494	0.9611	0.9159	1.0440	1.1656	0.8491	1.0450
1.1413	1.1405	1.0754	0.9378	0.9990	0.9243	1.0339	0.8490	1.0350
0.9305	0.9564	0.9098	1.0481	0.9774	1.0419	0.9325	0.8500	1.0350
1.0247	1.0124	1.0082	0.9785	1.0368	0.9421	0.9166	0.8500	1.0350
0.9394	0.9940	0.9429	0.9196	1.0140	0.9962	0.9774	0.8500	1.0350
1.0171	1.0046	0.9162	0.9310	1.0400	0.9307	0.9061	0.8500	1.0350
0.9305	0.9855	1.0034	0.9397	0.9651	1.0172	1.0385	0.8500	1.0350
0.9306	0.9580	0.9098	0.9648	1.0035	0.9760	1.0075	0.8500	1.0350
0.9659	0.9836	1.0283	1.0368	0.9527	0.9559	0.9153	0.8500	1.0350
0.9864	0.9120	0.9621	0.9271	1.0493	0.9781	1.0328	0.8500	1.0350
1.1019	1.1121	0.9334	1.0127	0.9625	1.0250	1.0295	0.8494	1.0450
0.9084	0.9107	0.9024	1.0461	1.0102	1.0129	0.9050	0.8500	1.0350
0.9112	0.9086	0.9451	0.9783	0.9843	0.9362	1.0369	0.8500	1.0350
1.0127	0.9784	0.9736	0.9133	0.9376	0.9671	0.9957	0.8500	1.0350
0.9674	0.9365	1.0303	0.9793	1.0371	1.0461	0.9878	0.8500	1.0350
0.9599	1.0046	0.9306	0.9999	0.9665	0.9650	0.9263	0.8500	1.0350
0.9681	0.9580	1.0163	1.0101	0.9645	1.0041	1.0418	0.8500	1.0350
1.0169	1.0073	1.0356	1.0336	0.9501	1.0048	0.9297	0.8500	1.0350

Appendix A2

Q Increment

All_Qgs

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	Vmin	Vmax	Tloss	b
197.0449	114.0028	69.0029	69.0601	30.0262	0.8482	1.0250	30.6266	2.4500
54.0007	61.0041	47.0604	107.0112	63.0054	0.8482	1.0250	30.6266	2.4500
141.1080	140.0029	57.0020	127.0082	58.2599	0.8482	1.0250	30.6266	2.4500
255.0008	212.0392	60.0602	89.0088	42.0101	0.8482	1.0250	30.6266	2.4500
214.2110	86.0190	118.0663	181.0135	38.0972	0.8482	1.0250	30.6266	2.4500
72.0313	193.0860	91.0130	91.0023	75.0188	0.8482	1.0250	30.6266	2.4500
280.0029	175.0399	40.0690	108.0038	28.0014	0.8482	1.0250	30.6266	2.4500
48.0377	133.0726	62.0293	226.0275	70.0188	0.8482	1.0250	30.6266	2.4500
155.0478	127.0088	106.0227	153.0215	59.0171	0.8482	1.0250	30.6266	2.4500
249.0213	151.0066	40.0253	72.0281	16.0013	0.8482	1.0250	30.6266	2.4500
229.0267	113.0936	82.0418	166.0017	79.0148	0.8482	1.0250	30.6266	2.4500
264.0314	50.0141	95.1913	213.0786	27.0101	0.8482	1.0250	30.6266	2.4500
180.1989	187.0021	123.0863	95.0024	17.0241	0.8482	1.0250	30.6266	2.4500
188.0925	129.2102	79.0029	195.0628	64.0815	0.8482	1.0250	30.6266	2.4500
82.0104	212.0011	129.0048	202.0011	58.0519	0.8482	1.0250	30.6266	2.4500
305.0510	125.0334	89.0563	69.0087	28.0200	0.8482	1.0250	30.6266	2.4500
310.1023	104.0061	85.0160	152.0208	73.0518	0.8482	1.0250	30.6266	2.4500
230.0450	59.0124	45.0909	103.0020	23.0184	0.8482	1.0250	30.6266	2.4500
313.0066	113.0006	107.0429	87.0028	44.0067	0.8482	1.0250	30.6266	2.4500
81.0184	120.1295	121.1223	198.0099	77.0070	0.8482	1.0250	30.6266	2.4500

Appendix B2

Q Increment

All_Qgs_Qinj

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	Qinj1	Qinj4	Qinj5	Qinj6
75.0000	194.0000	111.0000	41.0000	38.0000	-7.8329	-5.3916	-10.4953	-6.3092
64.0000	187.0000	79.0000	124.0000	50.0000	-9.9142	-11.3346	-7.5910	-8.1060
93.0000	132.0000	55.0000	163.0000	57.0000	-8.8402	-6.4196	-7.4406	-6.4279
275.0000	56.0000	107.0000	46.0000	57.0000	-11.8471	-6.9006	-7.1285	-8.8524
197.0000	52.0000	35.0000	224.0000	18.0000	-8.4782	-11.8359	-5.6927	-8.2261
279.0000	140.0000	128.0000	184.0000	53.0000	-5.9648	-5.0372	-10.7024	-6.8946
147.0000	40.0000	128.0000	70.0000	55.0000	-5.4800	-8.2660	-6.3551	-10.6583
78.0000	194.0000	74.0000	223.0000	39.0000	-7.3353	-7.2523	-11.2745	-10.0552
243.0000	196.0000	72.0000	59.0000	67.0000	-8.4190	-5.5302	-7.8194	-6.9414
44.0000	226.0000	92.0000	118.0000	19.0000	-5.1653	-9.2401	-9.7492	-8.8083
224.0000	45.0000	130.0000	183.0000	68.0000	-8.1088	-6.9778	-11.4110	-9.6953
237.0000	221.0000	80.0000	103.0000	46.0000	-11.2035	-8.1203	-8.5503	-6.1279
41.0000	46.0000	110.0000	209.0000	46.0000	-11.5537	-11.3123	-9.1699	-9.2904
293.0000	72.0000	67.0000	147.0000	66.0000	-5.3807	-9.7118	-10.6823	-7.0407
246.0000	114.0000	116.0000	110.0000	30.0000	-8.1378	-6.0888	-7.6646	-10.1006
320.0000	149.0000	104.0000	225.0000	28.0000	-8.6722	-6.8965	-9.3750	-8.6251
61.0000	120.0000	100.0000	44.0000	49.0000	-8.9082	-5.9329	-11.7055	-7.4475
230.0000	192.0000	73.0000	183.0000	56.0000	-8.0635	-9.0434	-10.4271	-11.0162
112.0000	44.0000	113.0000	64.0000	40.0000	-6.2265	-7.7079	-9.9858	-10.8697
167.0000	198.0000	106.0000	73.0000	71.0000	-11.9291	-8.6010	-11.1900	-9.1162

Qinj9	Qinj11	Qinj12	Qinj15	Qinj19	Vmin	Vmax	T loss	b
-9.1163	-7.4874	-6.2117	-10.2135	-7.8075	0.8482	1.0250	30.6266	2.4500
-5.6630	-8.2299	-8.8627	-11.1272	-9.0409	0.8482	1.0250	30.6266	2.4500
-6.0683	-7.0872	-10.8950	-9.8057	-5.3074	0.8482	1.0250	30.6266	2.4500
-5.9759	-9.0951	-9.1278	-9.0573	-9.4520	0.8482	1.0250	30.6266	2.4500
-11.7357	-6.7517	-10.0308	-10.5913	-10.7516	0.8482	1.0250	30.6266	2.4500
-11.1929	-8.2186	-10.4806	-11.4258	-5.1951	0.8482	1.0250	30.6266	2.4500
-9.1991	-8.1527	-9.1095	-8.8270	-10.9173	0.8482	1.0250	30.6266	2.4500
-6.3093	-9.7073	-5.8981	-9.8559	-5.7461	0.8482	1.0250	30.6266	2.4500
-7.9578	-5.6667	-9.6811	-11.7138	-10.7075	0.8482	1.0250	30.6266	2.4500
-5.7813	-10.6136	-10.7064	-11.3289	-5.5459	0.8482	1.0250	30.6266	2.4500
-9.4065	-6.6074	-10.0733	-7.9182	-7.8298	0.8482	1.0250	30.6266	2.4500
-8.3493	-11.8132	-6.9149	-8.3953	-10.1174	0.8482	1.0250	30.6266	2.4500
-10.4494	-5.0820	-7.3213	-7.2853	-7.8233	0.8482	1.0250	30.6266	2.4500
-8.0860	-6.6356	-11.8571	-7.4693	-11.5768	0.8482	1.0250	30.6266	2.4500
-10.2752	-10.8949	-11.1978	-10.8410	-6.7865	0.8482	1.0250	30.6266	2.4500
-7.0757	-9.4601	-7.4569	-6.3397	-5.5086	0.8482	1.0250	30.6266	2.4500
-9.6808	-9.4692	-9.4664	-10.8258	-5.3921	0.8482	1.0250	30.6266	2.4500
-6.9479	-6.4656	-6.8133	-8.8063	-5.3546	0.8482	1.0250	30.6266	2.4500
-10.1178	-11.9766	-9.9393	-5.2951	-10.8501	0.8482	1.0250	30.6266	2.4500
-6.0833	-6.3990	-7.8487	-10.2409	-10.7791	0.8482	1.0250	30.6266	2.4500

Appendix C2

Q Increment
 All_Qgs_Qinj_Xmer
 Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	txA	txB	txC	txD
53.0198	163.0635	53.0758	193.0056	16.0167	1.0449	0.9764	0.9286	0.9589
289.0116	42.0672	72.0194	176.0389	33.0179	1.0016	1.0237	0.9885	1.0764
128.0389	226.0102	129.0016	185.0378	42.0209	1.1267	0.9453	0.9898	0.9831
316.1653	123.0357	113.0701	195.0020	23.0000	1.0222	0.9562	1.0342	1.1583
184.0268	110.0062	39.0621	92.0028	26.0640	1.0665	1.1055	1.0656	1.1378
291.1069	202.0103	32.1046	170.0089	53.0263	1.0580	1.1632	0.9508	0.9772
117.0494	180.1092	105.0065	189.0185	26.0028	0.9485	0.9909	1.1532	0.9641
309.0005	184.0308	48.0058	67.0735	22.0713	1.0484	1.0732	0.9310	1.1214
208.0440	151.0456	96.1372	138.0312	22.0303	1.1351	0.9578	1.0493	1.0616
142.0063	115.0464	97.0062	67.0129	53.2601	0.9623	1.0958	1.0608	0.9600
248.0000	178.0000	63.0000	156.0000	61.0000	1.0281	1.0421	0.9445	1.0355
249.0000	83.0000	79.0000	193.0000	26.0000	0.9054	1.0351	1.0406	1.0123
104.0000	131.0000	74.0000	66.0000	25.0000	0.9164	0.9313	0.9379	0.9902
241.0300	177.0637	93.0194	59.0087	55.0163	1.0096	0.9703	1.1421	0.9274
104.0000	108.0000	76.0000	59.0000	63.0000	1.0395	1.0464	1.0129	0.9314
164.0000	82.0000	63.0000	189.0000	45.0000	0.9411	0.9465	1.0000	0.9792
102.0003	158.0007	91.0319	162.0098	33.0044	1.1590	1.1933	1.0677	0.9806
129.0000	196.0000	60.0000	193.0000	42.0000	0.9177	0.9504	1.0083	1.0419
59.0000	167.0000	68.0000	171.0000	70.0000	0.9305	0.9953	0.9963	1.0122
254.0000	207.0000	87.0000	146.0000	27.0000	0.9509	1.0200	0.9762	0.9357

txE	txF	txG	Qinj1	Qinj4	Qinj5	Qinj6	Qinj9	Qinj11
0.9798	0.9932	1.0204	-7.9879	-7.6306	-9.4699	-7.6210	-5.6692	-11.5806
0.9579	0.9120	1.0583	-7.9123	-11.7277	-9.9556	-6.2600	-11.3301	-5.2436
1.0036	0.9586	1.0477	-5.6043	-9.0003	-8.7996	-9.2720	-7.1859	-7.8995
0.9518	0.9115	1.0603	-11.3491	-8.8484	-9.3170	-9.5534	-5.5353	-6.0409
0.9176	0.9089	1.0924	-7.0940	-6.2264	-7.3966	-5.7861	-8.7907	-11.8774
1.0297	0.9925	1.0362	-10.0670	-5.6006	-7.1504	-7.4053	-5.3204	-5.6127
0.9490	1.0592	0.9473	-10.4523	-10.1864	-5.6308	-11.2191	-10.4280	-10.1039
1.0343	0.9461	1.0451	-9.0143	-11.3856	-5.3764	-6.9095	-5.8069	-9.0955
0.9752	0.9572	0.9497	-5.3966	-10.8678	-6.6629	-8.9796	-9.5658	-9.3364
1.0317	0.9586	0.9652	-5.7228	-11.0730	-6.1741	-9.3717	-10.4911	-6.1479
0.9805	0.9577	1.0340	-10.9947	-8.2503	-10.9609	-7.2314	-7.4270	-10.6584
0.9672	0.9399	0.9824	-10.3021	-7.2328	-7.2347	-10.3046	-8.4298	-8.8031
1.0137	0.9935	0.9902	-5.6455	-5.4140	-10.6094	-11.2674	-9.7660	-11.3445
0.9293	1.1326	1.0036	-5.5363	-6.9000	-10.9777	-7.1235	-6.7773	-6.3440
0.9957	0.9256	1.0444	-6.9385	-11.4465	-9.8486	-5.1687	-8.8563	-11.6090
0.9837	0.9345	0.9978	-7.1390	-10.5225	-9.5017	-8.4395	-8.7575	-11.8475
1.0265	0.9540	0.9787	-10.0580	-7.1936	-5.7448	-5.0490	-7.4242	-5.4542
0.9857	0.9980	0.9527	-11.8244	-7.1669	-5.6022	-10.5740	-9.5251	-10.3201
1.0385	0.9750	1.0020	-11.0772	-7.2878	-7.8423	-7.0021	-8.4266	-9.6626
1.0133	1.0419	1.0191	-8.4187	-7.4278	-9.6930	-9.0309	-9.2935	-6.7548

Qinj12	Qinj15	Qinj19	Vmin	Vmax	T_loss	b
-11.7715	-8.2978	-8.4833	0.8459	1.0299	35.1876	2.8500
-9.3099	-11.6084	-11.6851	0.8481	1.0250	36.3685	2.7000
-11.1390	-5.0324	-10.9286	0.8474	1.0250	31.2572	2.6000
-8.7861	-5.5679	-6.2326	0.8475	1.0250	39.3224	2.5500
-5.1465	-5.9643	-6.5688	0.8496	1.0250	42.9834	2.5500
-5.4244	-10.1434	-6.7142	0.8458	1.0300	32.9204	2.5500
-8.1778	-8.8410	-5.2711	0.8487	1.0750	32.3413	2.5000
-10.6576	-8.0261	-6.6518	0.8443	1.0250	39.2567	2.5000
-9.3042	-11.9001	-6.1314	0.8481	1.0250	34.3262	2.5000
-5.1469	-10.4555	-7.2165	0.8494	1.0250	29.7822	2.5000
-11.4791	-5.2857	-10.9201	0.8482	1.0250	30.6266	2.4500
-10.2772	-6.5654	-8.4475	0.8482	1.0250	30.6266	2.4500
-8.4423	-10.8145	-9.4149	0.8482	1.0250	30.6266	2.4500
-6.2083	-10.9171	-8.5061	0.8430	1.0550	36.1282	2.4500
-5.5512	-10.1994	-7.0675	0.8482	1.0250	30.6266	2.4500
-7.0826	-7.6731	-9.3960	0.8482	1.0250	30.6266	2.4500
-11.3345	-11.3076	-6.3023	0.8469	1.0300	32.6956	2.4500
-9.7727	-9.0262	-5.4634	0.8482	1.0250	30.6266	2.4500
-11.3269	-5.1943	-11.6484	0.8482	1.0250	30.6266	2.4500
-9.3742	-8.5220	-9.0950	0.8482	1.0250	30.6266	2.4500



Appendix D2

Q Increment

All_Qgs_Xmer

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	txA	txB	txC	txD
107.0009	52.3399	28.0026	143.0127	37.0709	1.1631	1.1689	0.9502	1.0865
176.0193	69.0084	71.0243	177.0090	34.1102	1.1342	0.9445	1.0871	0.9588
155.0211	106.1012	71.0225	146.0030	18.0219	1.0955	1.0734	1.0292	1.0059
255.0009	49.0021	127.0020	194.0029	35.0115	1.0964	1.1598	1.0838	1.0088
59.0284	181.0682	77.0556	211.0644	50.0324	0.9425	1.0288	1.0104	0.9245
199.0096	70.0012	123.0028	157.0282	43.0010	1.1650	1.1479	0.9125	1.1318
196.1018	94.0167	46.0983	159.0471	35.0028	1.1927	1.0458	1.0058	0.9549
52.0093	164.0359	88.0115	53.0013	24.0941	1.0638	1.1141	1.0440	0.9183
254.0617	212.1281	54.0549	222.0260	55.0183	1.1620	1.1544	0.9926	0.9603
158.0115	216.1122	124.0413	59.0267	55.0367	1.0181	0.9605	0.9452	1.0370
271.1649	76.2635	76.0115	129.0890	57.0171	1.0244	1.1394	1.0471	0.9385
286.0000	75.0000	41.0000	229.0000	21.0000	1.0285	0.9254	1.0190	1.0312
306.0000	197.0000	65.0000	95.0000	73.0000	1.0161	1.0271	0.9880	1.0364
163.0000	61.0000	71.0000	105.0000	61.0000	0.9616	1.0245	1.0465	1.0474
314.0280	215.0208	104.0057	74.0273	39.0450	1.0145	1.0534	1.0790	1.0692
296.0054	88.0139	64.0022	49.0262	52.0726	1.1558	1.0480	0.9436	1.1448
51.0000	42.0000	47.0000	112.0000	19.0000	0.9868	1.0196	0.9834	1.0401
190.0000	163.0000	114.0000	169.0000	58.0000	0.9374	0.9893	1.0207	1.0118
134.0030	159.0044	44.0083	92.0006	28.0492	0.9907	1.0290	0.9055	1.1383
250.0000	96.0000	90.0000	59.0000	53.0000	0.9772	0.9466	1.0334	1.0203

txE	txF	txG	Vmin	Vmax	T_loss	b
0.9807	0.9173	1.0859	0.8482	1.0300	40.2770	2.8000
0.9425	1.0405	0.9032	0.8484	1.0250	36.4373	2.7500
0.9176	1.0611	0.9664	0.8488	1.0250	35.1165	2.7000
0.9686	0.9053	1.0691	0.8487	1.0250	36.8804	2.7000
1.0260	1.0293	1.0652	0.8472	1.0250	29.2915	2.5500
0.9336	1.0720	1.0983	0.8476	1.0400	42.7398	2.5500
0.9540	1.0938	1.0426	0.8490	1.0350	31.3806	2.5500
1.0598	0.9603	1.0359	0.8458	1.0250	30.7589	2.5500
1.0318	1.0102	1.0483	0.8483	1.0300	29.9474	2.5000
0.9756	1.0792	1.0088	0.8481	1.0250	31.2761	2.5000
0.9889	0.9631	1.1531	0.8495	1.0250	30.9122	2.5000
0.9621	0.9699	1.0378	0.8482	1.0250	30.6266	2.4500
0.9024	1.0302	0.9578	0.8482	1.0250	30.6266	2.4500
1.0391	1.0382	0.9012	0.8482	1.0250	30.6266	2.4500
0.9769	0.9793	0.9677	0.8497	1.0250	31.3838	2.4500
1.0551	1.0306	0.9706	0.8482	1.0500	34.0676	2.4500
0.9109	0.9037	1.0405	0.8482	1.0250	30.6266	2.4500
0.9977	1.0349	0.9103	0.8482	1.0250	30.6266	2.4500
1.1591	0.9925	1.0984	0.8472	1.1000	37.7559	2.4500
0.9546	0.9262	1.0202	0.8482	1.0250	30.6266	2.4500

Appendix E2

Q Increment

All_Qinj_Xmer

Finest parameter (Point B)

txA	txB	txC	txD	txE	txF	txG	Qinj1	Qinj4
1.1202	0.9475	1.0546	1.0002	0.9839	0.9505	0.9579	-10.8099	-6.0736
1.0062	1.0878	0.9799	1.0239	0.9108	1.0452	1.1491	-11.5884	-6.6535
1.1329	1.1857	0.9810	0.9414	0.9732	1.0475	1.1222	-8.2862	-5.1167
1.1502	0.9362	0.9578	1.1576	0.9087	0.9580	1.1285	-8.7156	-9.5107
0.9247	0.9571	1.0415	0.9656	1.0177	1.0404	0.9711	-9.1647	-7.6225
0.9871	0.9322	0.9272	0.9905	1.0498	0.9399	0.9344	-7.0845	-5.0700
0.9322	1.0267	1.0202	0.9234	1.0092	0.9937	1.0025	-7.8327	-9.6855
1.0259	1.0211	1.0428	1.0452	0.9153	1.0068	0.9753	-9.0875	-10.6627
1.0570	1.0698	0.9351	1.1582	1.0687	0.9703	0.9885	-7.4358	-9.9407
0.9963	0.9144	0.9554	1.0122	1.0309	0.9095	1.0395	-11.9800	-11.4348
0.9921	0.9130	0.9967	0.9703	1.0081	0.9754	0.9198	-8.9370	-5.2386
0.9346	1.0080	1.0205	1.0259	0.9888	1.0206	0.9292	-6.0780	-8.1044
0.9192	0.9862	0.9774	1.0314	0.9276	1.0330	0.9641	-10.6995	-7.5450
0.9605	0.9172	0.9834	1.0051	0.9803	1.0202	0.9654	-9.7227	-8.6871
0.9540	1.0160	0.9559	0.9659	0.9133	0.9802	0.9922	-6.9451	-7.4032
1.0400	1.0123	1.0139	1.0261	0.9165	0.9872	1.0004	-10.0294	-11.5188
0.9600	1.0055	1.0272	1.0303	0.9510	0.9361	0.9284	-9.7860	-8.3446
0.9671	0.9904	1.0278	1.0019	1.0443	0.9385	0.9624	-5.0307	-8.2672
0.9288	1.0186	0.9349	0.9164	1.0121	1.0493	0.9491	-6.2328	-7.6800
0.9018	0.9196	1.0188	0.9025	0.9026	0.9628	0.9621	-9.4583	-6.2602

Qinj5	Qinj6	Qinj9	Qinj11	Qinj12	Qinj15	Qinj19	Vmin	Vmax
-11.1126	-5.7288	-6.3793	-8.0579	-7.1228	-10.6021	-11.5664	0.8473	1.0250
-5.6257	-11.4609	-11.2947	-6.3477	-6.3311	-7.0274	-5.8231	0.8472	1.0250
-7.6552	-5.9482	-5.9338	-6.5684	-9.0427	-6.4456	-6.2367	0.8485	1.0300
-7.7875	-5.5743	-5.9349	-11.3318	-8.1102	-7.6763	-8.9626	0.8489	1.0250
-6.6846	-9.7384	-10.9724	-8.8226	-6.1669	-10.2089	-10.0925	0.8482	1.0250
-11.4210	-8.7478	-11.3097	-7.0171	-10.9548	-5.9771	-10.4843	0.8482	1.0250
-10.8349	-9.0008	-6.3352	-6.0825	-8.5071	-7.2311	-7.8722	0.8482	1.0250
-8.3871	-5.4203	-11.0101	-9.1549	-10.5499	-7.4168	-6.4516	0.8482	1.0250
-6.0703	-5.7583	-7.3311	-8.0193	-8.2194	-7.3162	-9.6723	0.8466	1.0500
-8.5573	-5.6224	-10.3198	-9.1950	-10.6328	-11.1130	-10.7412	0.8482	1.0250
-7.4276	-5.7635	-9.1562	-7.0506	-6.7202	-6.4417	-6.3991	0.8482	1.0250
-5.0648	-5.8319	-10.0823	-8.1174	-6.9640	-9.3331	-5.4994	0.8482	1.0250
-10.9253	-5.7183	-9.2593	-10.0563	-10.4790	-9.8614	-10.9715	0.8482	1.0250
-5.2851	-11.9616	-5.6984	-6.4688	-6.3663	-11.1003	-5.2491	0.8482	1.0250
-5.4724	-9.0735	-6.9553	-7.8430	-10.2385	-6.2010	-5.4171	0.8482	1.0250
-11.7016	-5.3748	-6.4145	-6.2221	-6.6903	-8.4541	-8.3074	0.8482	1.0250
-6.5608	-7.6120	-7.3894	-10.7524	-7.0612	-7.1419	-10.9705	0.8482	1.0250
-10.1996	-6.6444	-5.3487	-8.6500	-6.4629	-11.5283	-8.9513	0.8482	1.0250
-10.3447	-5.5731	-6.5377	-7.7569	-5.8532	-11.3390	-9.9993	0.8482	1.0250
-6.8989	-8.1044	-10.6046	-5.9543	-9.8770	-5.1804	-10.2273	0.8482	1.0250



Appendix F2

Q Increment

All_Qinj

Finest parameter (Point B)

Qinj1	Qinj4	Qinj5	Qinj6	Qinj9	Qinj11	Qinj12	Qinj15	Qinj19
-11.2576	-6.6256	-10.5289	-11.5612	-9.7345	-6.3534	-9.9874	-5.1110	-10.8544
-11.4408	-9.8254	-6.6914	-9.8522	-9.9518	-8.7996	-8.7427	-11.4182	-9.3402
-10.5285	-5.5732	-6.8080	-7.2941	-8.2677	-5.7730	-5.6601	-5.3284	-8.0026
-9.5539	-11.8604	-5.4572	-9.5922	-8.7895	-9.7957	-6.8290	-9.9038	-7.4731
-9.8367	-8.2923	-11.7560	-5.7162	-8.7787	-11.1283	-10.6417	-8.1572	-6.6149
-10.4328	-5.1383	-7.0649	-5.5455	-10.3208	-9.2304	-9.1592	-10.6719	-9.6250
-11.6565	-6.0587	-7.7070	-10.8981	-6.0322	-9.8783	-11.15651	-8.0430	-7.3475
-6.7020	-9.8190	-7.8171	-10.5183	-6.9916	-6.5954	-10.2647	-11.3757	-7.1133
-5.6940	-11.9031	-11.4052	-7.7695	-7.1149	-9.3591	-11.3545	-6.0519	-10.2753
-11.5895	-11.2831	-10.2818	-7.1928	-6.6210	-10.2998	-11.8442	-8.1332	-7.6779
-5.0368	-10.9062	-10.9431	-11.3727	-11.8767	-5.4715	-11.9928	-10.2440	-7.5923
-5.5215	-7.6394	-7.4209	-5.4416	-6.3613	-10.8338	-6.5774	-6.2033	-6.1460
-7.8130	-8.3915	-10.3772	-8.4408	-5.6506	-5.5794	-9.9950	-11.3505	-5.1449
-10.9413	-5.1965	-6.8017	-9.5135	-8.0388	-8.4183	-7.1894	-6.0081	-9.7509
-7.5354	-8.2190	-6.7852	-7.1625	-11.9974	-8.0811	-11.6890	-6.6378	-7.8259
-8.2652	-9.2614	-10.6780	-8.7098	-10.9502	-8.3893	-11.4318	-6.5838	-5.1751
-7.9663	-5.5505	-10.6143	-5.1804	-9.3805	-11.2656	-10.3855	-6.9698	-6.3006
-8.3041	-7.0428	-5.6717	-9.1581	-9.8326	-9.7425	-10.6769	-9.2400	-6.2737
-8.4288	-8.6134	-7.2043	-9.8890	-8.7344	-5.5405	-5.0136	-6.5039	-9.2193
-10.9242	-10.6715	-6.6910	-11.9584	-11.1257	-8.2147	-7.2401	-5.9273	-9.9575

Appendix G2

Q Increment

All_Xmer

Finest parameter (Point B)

txA	txB	txC	txD	txE	txF	txG	Vmin	Vmax
1.1622	1.0931	1.1482	0.9753	0.9403	0.9411	0.9965	0.8483	1.0300
1.1837	1.0807	0.9258	1.0734	1.0851	0.9752	0.9072	0.8476	1.0300
1.0691	1.1154	0.9563	0.9165	0.9251	1.1485	1.1141	0.8485	1.0450
1.0949	1.0259	0.9215	0.9490	1.0486	0.9161	1.1523	0.8481	1.0336
0.9305	1.1469	1.1317	0.9523	0.9968	1.0014	0.9490	0.8493	1.0550
0.9857	0.9122	0.9401	1.1015	1.1054	0.9154	1.0247	0.8483	1.0400
1.1640	0.9327	1.0198	0.9534	1.0552	0.9403	1.0614	0.8483	1.0250
1.1454	0.9975	0.9276	0.9582	1.1027	0.9790	1.0380	0.8484	1.0300
1.1635	1.1661	0.9211	0.9924	1.0158	1.0413	1.0926	0.8473	1.0300
1.0687	1.0903	0.9504	1.0032	1.1793	0.9045	0.9363	0.8499	1.0250
1.0845	1.0528	0.9350	0.9660	1.1074	0.9682	1.0552	0.8466	1.0250
1.1246	0.9352	0.9598	1.1394	1.0759	0.9500	1.0955	0.8471	1.0500
1.0361	0.9960	1.0850	0.9978	0.9677	1.0609	0.9273	0.8475	1.0250
1.0308	0.9628	0.9398	0.9041	1.0330	1.0346	1.0254	0.8482	1.0250
0.9392	1.0291	0.9104	0.9799	1.0343	0.9833	1.0308	0.8482	1.0250
0.9924	0.9217	0.9167	0.9221	1.0446	0.9736	0.9945	0.8482	1.0250
0.9663	1.1675	0.9309	1.0599	1.0519	0.9832	1.0548	0.8479	1.0250
0.9698	1.0061	0.9778	1.1091	1.0308	0.9599	0.9423	0.8470	1.0250
1.0353	0.9735	0.9397	1.0033	1.0258	1.0461	1.0311	0.8482	1.0250
0.9780	0.9550	1.0385	1.0050	1.0486	1.0453	0.9139	0.8482	1.0250

T_loss	b
43.8238	2.8000
39.1904	2.7000
35.1469	2.6500
36.1068	2.6500
30.3053	2.6000
37.0695	2.6000
31.0435	2.5500
36.6391	2.5500
35.5138	2.5500
39.3642	2.5500
35.6649	2.5000
34.6654	2.5000
30.6645	2.5000
30.6266	2.4500
30.6266	2.4500
30.6266	2.4500
35.4223	2.4500
33.3210	2.4500
30.6266	2.4500
30.6266	2.4500

Appendix H2

P Increment

All_Qgs

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	Vmin	Vmax	Tloss	b
182.0066	80.0013	54.0027	51.0002	16.0366	0.8493	1.0250	138.1795	2.8500
273.1132	185.0096	80.0060	131.1269	40.0054	0.8493	1.0250	138.1795	2.8500
276.0445	156.0774	124.0016	197.0357	18.0050	0.8493	1.0250	138.1795	2.8500
329.1566	116.0090	109.0042	208.0297	59.0520	0.8493	1.0250	138.1795	2.8500
156.0900	201.0128	39.0349	171.0081	75.0538	0.8493	1.0250	138.1795	2.8500
243.0054	114.0711	117.0041	193.0697	21.0617	0.8493	1.0250	138.1795	2.8500
310.0012	78.0151	77.0484	128.0030	30.0137	0.8493	1.0250	138.1795	2.8500
169.1197	203.0069	66.0147	158.0368	67.0006	0.8493	1.0250	138.1795	2.8500
226.0210	167.0416	33.1430	111.0336	74.0406	0.8493	1.0250	138.1795	2.8500
244.0359	146.0106	67.0025	43.0233	50.0177	0.8493	1.0250	138.1795	2.8500
182.0389	175.0479	113.0408	89.0272	73.0200	0.8493	1.0250	138.1795	2.8500
314.0068	207.0326	82.1524	78.0019	48.3144	0.8493	1.0250	138.1795	2.8500
322.0426	173.2541	108.0007	75.0122	54.0820	0.8493	1.0250	138.1795	2.8500
148.0192	116.0108	70.0056	194.0372	31.0148	0.8493	1.0250	138.1795	2.8500
273.0660	220.0889	68.0361	106.0004	71.0151	0.8493	1.0250	138.1795	2.8500
312.0039	75.0192	30.0378	166.1557	43.0900	0.8493	1.0250	138.1795	2.8500
222.0261	189.0262	48.0371	57.0270	63.0023	0.8493	1.0250	138.1795	2.8500
306.1903	165.0466	37.1009	180.0967	74.0606	0.8493	1.0250	138.1795	2.8500
117.0259	64.3301	122.0222	113.0328	28.0047	0.8493	1.0250	138.1795	2.8500
79.0402	80.0498	48.0334	226.0848	44.0234	0.8493	1.0250	138.1795	2.8500

Appendix I2

P Increment

All_Qgs_Qinj

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	Qinj1	Qinj4	Qinj5	Qinj6
245.0000	112.0000	73.0000	232.0000	31.0000	-9.2648	-9.8527	-10.9647	-5.0840
220.0000	105.0000	80.0000	90.0000	19.0000	-9.8871	-9.8781	-7.0888	-11.5133
72.0000	196.0000	68.0000	225.0000	57.0000	-6.7375	-5.0730	-7.3220	-10.1138
264.0000	91.0000	95.0000	85.0000	50.0000	-11.3319	-11.0701	-9.6473	-10.7247
302.0000	63.0000	102.0000	97.0000	26.0000	-5.3949	-7.6140	-10.9195	-11.0217
167.0000	142.0000	97.0000	155.0000	23.0000	-11.3420	-7.1196	-9.5714	-5.7293
222.0000	142.0000	37.0000	67.0000	44.0000	-11.9711	-8.3534	-6.3530	-9.5558
133.0000	50.0000	82.0000	47.0000	46.0000	-11.2206	-7.2961	-6.9214	-7.4936
73.0000	199.0000	89.0000	187.0000	24.0000	-6.5351	-6.4277	-6.9980	-8.3577
305.0000	162.0000	36.0000	140.0000	43.0000	-11.4612	-9.5882	-8.4237	-8.2555
268.0000	73.0000	115.0000	82.0000	27.0000	-11.8323	-8.7436	-9.5818	-9.3928
58.0000	135.0000	62.0000	52.0000	25.0000	-9.3535	-7.1300	-10.2457	-11.3181
203.0000	126.0000	42.0000	79.0000	45.0000	-6.7534	-6.4996	-6.9901	-9.0855
216.0000	216.0000	57.0000	238.0000	49.0000	-11.9491	-5.1087	-5.9871	-10.7212
307.0000	203.0000	51.0000	127.0000	50.0000	-8.8302	-6.3343	-11.7463	-8.3586
185.0000	78.0000	125.0000	176.0000	46.0000	-7.9205	-9.7037	-6.8637	-7.7548
323.0000	156.0000	64.0000	180.0000	27.0000	-7.6446	-11.8277	-10.0618	-10.0618
97.0000	74.0000	57.0000	141.0000	61.0000	-11.6424	-10.5245	-5.8166	-7.5301
74.0000	149.0000	110.0000	69.0000	36.0000	-5.3696	-7.7918	-5.3891	-11.4359
62.0000	77.0000	124.0000	202.0000	23.0000	-11.7632	-9.2210	-9.7362	-6.6989

Qinj9	Qinj11	Qinj12	Qinj15	Qinj19	Vmin	Vmax	T_loss	b
-6.8211	-6.9098	-5.7648	-11.7377	-11.4237	0.8493	1.0250	138.1795	2.8500
-10.9459	-10.7354	-11.7666	-6.7793	-8.0381	0.8493	1.0250	138.1795	2.8500
-11.6122	-10.3397	-7.2645	-11.3248	-11.2924	0.8493	1.0250	138.1795	2.8500
-10.2080	-10.3339	-10.2655	-6.7355	-6.1347	0.8493	1.0250	138.1795	2.8500
-11.8880	-7.7446	-9.6875	-5.0801	-6.0564	0.8493	1.0250	138.1795	2.8500
-6.6420	-10.8316	-9.2959	-11.2831	-5.6085	0.8493	1.0250	138.1795	2.8500
-11.2836	-7.9613	-11.2448	-8.0329	-10.9298	0.8493	1.0250	138.1795	2.8500
-11.6539	-11.9073	-6.3369	-5.0524	-6.9998	0.8493	1.0250	138.1795	2.8500
-11.3160	-8.0293	-11.1789	-9.7921	-9.5093	0.8493	1.0250	138.1795	2.8500
-9.5439	-9.5119	-7.4645	-5.7406	-10.4639	0.8493	1.0250	138.1795	2.8500
-10.8471	-8.4167	-6.1609	-11.2805	-5.4824	0.8493	1.0250	138.1795	2.8500
-5.3380	-6.2832	-5.5480	-11.7604	-11.7240	0.8493	1.0250	138.1795	2.8500
-6.7041	-8.5613	-9.4056	-10.2874	-8.6436	0.8493	1.0250	138.1795	2.8500
-9.1188	-10.7967	-6.3560	-11.8840	-8.8195	0.8493	1.0250	138.1795	2.8500
-9.3459	-8.7140	-10.9740	-5.0360	-8.4469	0.8493	1.0250	138.1795	2.8500
-6.7954	-8.3372	-7.9520	-7.7972	-6.6595	0.8493	1.0250	138.1795	2.8500
-5.4998	-9.5079	-7.7997	-9.3390	-8.7486	0.8493	1.0250	138.1795	2.8500
-8.0686	-11.4279	-9.1649	-5.0011	-6.1458	0.8493	1.0250	138.1795	2.8500
-9.4120	-8.0485	-7.0596	-9.3022	-6.0440	0.8493	1.0250	138.1795	2.8500
-11.5439	-8.7320	-5.0614	-11.7932	-11.1612	0.8493	1.0250	138.1795	2.8500

Appendix J2

P Increment

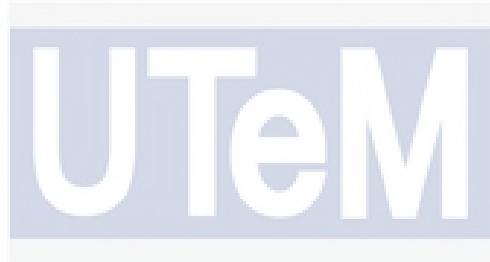
All_Qinj_Xmer

Finest parameter (Point B)

txA	txB	txC	txD	txE	txF	txG	Qinj1	Qinj4
1.0474	1.0630	1.0201	1.0564	0.9074	0.9580	0.9075	-6.7446	-6.3920
1.0092	0.9413	0.9744	1.0376	1.0530	0.9201	1.0221	-6.5644	-11.5977
1.0066	0.9418	1.0920	0.9728	0.9356	1.0266	1.0322	-11.2143	-10.5090
0.9786	1.0477	0.9290	0.9119	0.9794	0.9074	0.9065	-9.3244	-6.0505
1.0435	0.9305	1.0021	0.9540	0.9774	1.0443	1.0313	-5.1210	-5.0537
1.1436	1.1021	1.0543	1.0606	1.0030	0.9196	1.0677	-9.1484	-11.9132
0.9808	0.9519	0.9527	1.0474	0.9514	0.9041	0.9220	-10.4892	-9.7089
1.0106	0.9112	0.9369	0.9209	0.9063	1.0295	1.0196	-11.5348	-11.9186
0.9374	1.0301	0.9287	0.9722	1.0246	0.9417	0.9336	-10.1224	-7.9374
0.9907	0.9926	0.9158	1.1139	1.1222	0.9667	0.9566	-5.7865	-6.6565
0.9222	1.1442	1.0019	0.9546	0.9586	1.0388	1.1089	-9.6783	-8.0430
1.0312	1.0157	0.9171	0.9679	0.9148	0.9122	0.9055	-7.1579	-6.8849
0.9664	1.0097	1.0194	0.9163	0.9920	0.9528	0.9069	-10.1719	-9.7929
0.9822	1.0371	1.0312	0.9867	0.9333	0.9862	1.0306	-8.8062	-6.9754
1.0358	0.9922	1.0437	0.9107	0.9356	0.9078	0.9699	-7.9169	-6.1795
1.0143	0.9046	0.9865	0.9397	0.9524	0.9236	0.9177	-6.8050	-11.4262
0.9159	0.9990	1.0486	0.9641	0.9254	0.9973	0.9297	-6.6447	-7.9077
0.9987	1.0265	0.9527	0.9798	0.9338	0.9427	1.0320	-6.4283	-7.1461
1.0290	0.9541	1.0241	0.9297	0.9890	1.0033	1.0069	-10.7483	-9.6747
0.9683	0.9680	0.9109	0.9928	0.9507	0.9157	0.9724	-11.0163	-8.1047

Qinj5	Qinj6	Qinj9	Qinj11	Qinj12	Qinj15	Qinj19	Vmin	Vmax
-10.4951	-5.6703	-8.0160	-7.2805	-9.7923	-11.9685	-5.8360	0.8476	1.0250
-5.8123	-10.3794	-7.9799	-8.7530	-7.3049	-9.4746	-6.1043	0.8482	1.0250
-11.3087	-6.3870	-9.2120	-6.2516	-5.2836	-6.3818	-8.7357	0.8495	1.0450
-6.3043	-10.5214	-5.5686	-11.4172	-6.5915	-5.0184	-10.8424	0.8493	1.0250
-8.0620	-6.0648	-5.3229	-5.0288	-9.5902	-8.2859	-6.1682	0.8493	1.0250
-6.1078	-8.5249	-9.1916	-5.9196	-9.0653	-7.7672	-6.1330	0.8472	1.0250
-9.8610	-9.0820	-7.8300	-9.6272	-8.2488	-9.0863	-10.7321	0.8493	1.0250
-11.6508	-9.9006	-5.2713	-9.3993	-7.2440	-6.5990	-7.4564	0.8493	1.0250
-5.4274	-7.4863	-7.7167	-9.5386	-9.0736	-5.5116	-11.1107	0.8493	1.0250
-11.6791	-7.8584	-8.4889	-7.2792	-11.8314	-6.5297	-11.5703	0.8441	1.0500
-9.0996	-11.1584	-11.9065	-6.6681	-5.6729	-7.0954	-11.6369	0.8416	1.0250
-7.0666	-9.0375	-8.7980	-10.6533	-7.5826	-7.1430	-11.3995	0.8493	1.0250
-5.8400	-7.6974	-8.5115	-9.3506	-10.1371	-11.2250	-5.3201	0.8493	1.0250
-10.3658	-7.7704	-8.6745	-6.6965	-5.5427	-6.4253	-8.4602	0.8493	1.0250
-10.5515	-8.4142	-11.4206	-9.6201	-5.4119	-11.9056	-10.6100	0.8493	1.0250
-6.9885	-6.4942	-5.0519	-8.7082	-6.8420	-10.5040	-5.9829	0.8493	1.0250
-5.4771	-11.3339	-5.5784	-10.1633	-5.2067	-7.4341	-11.9521	0.8493	1.0250
-5.7220	-7.0849	-5.2535	-9.6039	-10.7278	-8.1579	-8.1179	0.8493	1.0250
-8.9291	-6.7804	-10.4967	-5.2919	-6.7408	-5.2257	-11.7318	0.8493	1.0250
-8.2043	-11.4796	-11.1911	-6.8496	-9.1391	-8.6448	-11.7992	0.8493	1.0250

T_loss	b
186.0856	3.2000
145.5270	2.9000
143.6187	2.9000
138.1795	2.8500
138.1795	2.8500
145.1192	2.8500
138.1795	2.8500
138.1795	2.8500
138.1795	2.8500
143.0947	2.8500
139.7512	2.8500
138.1795	2.8500
138.1795	2.8500
138.1795	2.8500
138.1795	2.8500
138.1795	2.8500
138.1795	2.8500
138.1795	2.8500
138.1795	2.8500
138.1795	2.8500
138.1795	2.8500



اوپیورسیتی تکنیکال ملیسیا ملاک

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Appendix K2

P Increment
 All_Qgs_Qinj_Xmer
 Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	txA	txB	txC	txD
133.0583	197.0679	45.0060	219.0784	20.0054	0.9414	1.0084	1.0485	0.9207
111.0707	226.0015	97.0351	94.0177	60.0151	1.0929	1.0473	0.9830	0.9624
64.1346	193.0126	30.0254	45.0447	26.1565	0.9547	0.9589	1.0853	0.9599
70.0420	42.0111	91.0228	130.0521	59.0237	0.9980	1.0588	1.0247	1.1285
330.0046	80.0133	120.0031	67.0134	17.0178	1.0279	1.0123	1.0144	1.1524
147.0000	108.0000	54.0000	48.0000	60.0000	1.0302	0.9184	0.9506	0.9276
135.0000	224.0000	122.0000	79.0000	29.0000	0.9931	0.9161	0.9419	1.0223
326.0000	205.0000	86.0000	185.0000	32.0000	0.9883	0.9786	1.0423	0.9074
267.0000	99.0000	47.0000	121.0000	62.0000	1.0396	0.9385	0.9252	0.9914
241.0000	131.0000	100.0000	197.0000	36.0000	0.9911	0.9547	0.9216	0.9776
120.0000	136.0000	111.0000	139.0000	22.0000	0.9037	0.9342	1.0369	1.0420
61.0161	109.0484	40.0002	92.1180	66.0214	1.0442	1.1237	1.0709	0.9694
329.0000	139.0000	65.0000	181.0000	73.0000	0.9029	1.0201	1.0305	1.0228
161.0000	56.0000	105.0000	162.0000	62.0000	0.9720	0.9328	0.9820	0.9456
278.0000	190.0000	47.0000	51.0000	75.0000	1.0133	1.0315	0.9880	0.9546
237.0000	42.0000	40.0000	66.0000	50.0000	0.9301	0.9437	1.0413	0.9199
204.0000	122.0000	31.0000	129.0000	37.0000	1.0062	0.9316	1.0194	0.9664
142.0000	109.0000	48.0000	155.0000	20.0000	0.9860	1.0251	0.9009	1.0226
304.0000	66.0000	106.0000	138.0000	29.0000	0.9714	0.9965	0.9723	0.9168
118.0000	62.0000	37.0000	111.0000	26.0000	1.0377	1.0390	0.9472	0.9775

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

txE	txF	txG	Qinj1	Qinj4	Qinj5	Qinj6	Qinj9	Qinj11
0.9395	1.0006	0.9418	-9.5899	-11.0898	-10.3099	-11.8436	-11.0217	-6.8979
0.9691	0.9794	1.0585	-7.3353	-5.3513	-4.8986	-9.4112	-7.1873	-8.4089
0.9405	1.0415	1.0023	-8.5053	-8.0172	-7.7244	-11.8420	-7.8028	-8.0266
0.9241	0.9597	1.0785	-5.1364	-5.0346	-6.3161	-6.2874	-10.8988	-9.3289
0.9540	0.9282	1.0166	-7.6504	-8.2279	-7.8723	-8.1673	-6.1717	-9.4636
1.0370	0.9745	0.9660	-11.8111	-8.4912	-10.3140	-5.2973	-9.0972	-6.6036
0.9692	0.9226	0.9403	-7.0606	-7.1845	-6.1966	-5.4842	-5.7927	-10.0093
1.0283	0.9133	1.0441	-6.6484	-9.3968	-7.2473	-6.2907	-6.2068	-6.7721
0.9913	0.9938	1.0034	-9.7533	-9.7698	-7.7555	-5.6032	-5.2185	-9.5711
1.0054	1.0235	1.0120	-7.1177	-8.7114	-7.7852	-6.8023	-8.8480	-7.6609
0.9146	1.0383	0.9649	-7.2172	-10.9843	-9.3437	-6.0446	-11.4449	-5.9695
0.9901	0.9636	1.0606	-6.8278	-10.9007	-8.2016	-5.2820	-10.6286	-6.0651
0.9181	1.0179	0.9801	-5.4314	-6.2934	-5.4972	-8.7113	-9.6650	-6.1838
1.0190	1.0490	1.0174	-11.7415	-7.9800	-7.0990	-11.7268	-10.6530	-11.9638
1.0368	1.0485	1.0065	-7.5209	-8.5189	-9.4742	-9.0399	-10.0980	-5.4770
0.9997	1.0172	0.9110	-11.4399	-8.9126	-8.7887	-10.2225	-6.8490	-11.4856
1.0341	1.0431	0.9747	-6.9936	-7.9320	-9.5263	-9.9577	-10.1004	-7.5829
1.0079	0.9966	0.9269	-11.4667	-10.8054	-5.3498	-9.7547	-8.2145	-8.5491
0.9767	0.9940	0.9413	-6.2821	-10.4745	-8.0791	-9.6039	-6.6310	-7.3167
1.0432	1.0414	1.0398	-5.7371	-9.4071	-8.6820	-10.9096	-10.9527	-11.3745

Qinj12	Qinj15	Qinj19	Vmin	Vmax	T_loss	b
-7.1761	-10.9305	-8.8668	0.8475	1.0450	175.7085	3.2000
-6.1613	-8.9597	-9.3083	0.8487	1.0250	153.3531	3.0000
-6.5179	-11.3550	-7.1836	0.8452	1.0550	142.9549	2.9000
-10.4501	-11.1860	-5.5173	0.8457	1.0250	152.4275	2.9000
-10.9385	-5.9005	-5.2309	0.8494	1.0250	152.3884	2.9000
-10.6231	-9.4045	-10.5511	0.8493	1.0250	138.1795	2.8500
-9.0376	-11.3457	-5.7711	0.8493	1.0250	138.1795	2.8500
-11.9335	-9.9266	-9.0821	0.8493	1.0250	138.1795	2.8500
-5.5950	-7.6069	-8.1394	0.8493	1.0250	138.1795	2.8500
-10.8318	-5.4089	-8.6063	0.8493	1.0250	138.1795	2.8500
-10.1764	-8.1799	-7.0693	0.8493	1.0250	138.1795	2.8500
-6.0281	-7.7133	-5.6475	0.8492	1.0250	141.4889	2.8500
-8.8501	-5.0611	-10.6728	0.8493	1.0250	138.1795	2.8500
-7.9974	-6.3999	-11.2986	0.8493	1.0250	138.1795	2.8500
-9.3091	-9.7454	-5.4699	0.8493	1.0250	138.1795	2.8500
-10.4946	-11.7660	-5.2527	0.8493	1.0250	138.1795	2.8500
-11.4635	-10.7629	-11.2445	0.8493	1.0250	138.1795	2.8500
-9.8759	-11.7017	-5.9498	0.8493	1.0250	138.1795	2.8500
-8.6415	-9.8574	-8.5283	0.8493	1.0250	138.1795	2.8500
-5.7873	-7.1906	-5.6835	0.8493	1.0250	138.1795	2.8500



Appendix L2

P Increment

All_Qgs_Xmer

Finest parameter (Point B)

Qg2	Qg3	Qg4	Qg5	Qg26	txA	txB	txC	txD
52.0173	160.0391	110.0549	174.0009	23.0002	0.9239	1.1009	1.0624	1.0014
203.0026	178.0006	112.1004	115.0061	58.0045	0.9942	1.1305	0.9330	0.9867
111.0115	216.0146	81.1943	230.0211	65.0417	0.9879	0.9753	0.9536	1.0221
217.0171	132.0057	82.0475	117.2610	44.0643	1.1564	0.9738	1.0200	1.0321
102.0015	114.0009	39.0506	209.0413	40.0407	1.0482	0.9312	0.9304	1.0365
77.1072	46.0138	41.0052	129.0078	70.0526	1.0235	1.0182	0.9361	1.0180
59.0293	63.0199	41.0414	127.0086	68.0012	1.1182	1.0474	0.9786	0.9797
255.0000	117.0000	93.0000	100.0000	46.0000	0.9036	1.0322	0.9226	1.0130
324.0000	204.0000	123.0000	51.0000	54.0000	0.9367	0.9314	1.0025	1.0158
58.0388	209.0112	83.0082	60.0001	26.0061	1.0648	1.1781	1.0327	1.1735
197.0000	200.0000	101.0000	161.0000	40.0000	0.9492	0.9587	1.0106	1.0249
125.0000	70.0000	76.0000	64.0000	22.0000	0.9405	0.9350	1.0360	0.9757
175.0000	146.0000	66.0000	134.0000	34.0000	0.9882	1.0121	0.9234	1.0247
308.0000	78.0000	76.0000	172.0000	56.0000	0.9831	1.0384	1.0287	0.9979
143.0000	204.0000	57.0000	217.0000	58.0000	0.9310	1.0428	1.0157	0.9296
326.0000	135.0000	87.0000	107.0000	78.0000	1.0021	0.9720	0.9043	0.9497
93.0000	150.0000	41.0000	130.0000	52.0000	0.9891	0.9238	0.9127	0.9878
113.0000	64.0000	124.0000	126.0000	48.0000	1.0178	1.0276	0.9845	1.0458
118.0000	167.0000	86.0000	153.0000	37.0000	1.0037	1.0196	1.0035	1.0434
319.0009	117.0362	62.0844	149.0233	32.0602	1.0703	0.9798	1.1811	0.9927

txE	txF	txG	Vmin	Vmax	T_loss	b
0.9188	0.9105	1.0294	0.8491	1.0350	219.5989	3.1500
0.9425	0.9779	1.1842	0.8448	1.0250	186.5053	3.1000
1.0116	0.9395	1.1131	0.8476	1.0250	165.2060	3.1000
1.0380	0.9040	1.0529	0.8485	1.0250	157.7822	3.0000
1.0087	1.0056	0.9699	0.8492	1.0319	147.0412	2.9500
0.9613	1.0360	1.1391	0.8486	1.0250	143.3040	2.9000
0.9750	1.0441	1.1246	0.8468	1.0250	137.5337	2.8500
0.9414	1.0196	0.9654	0.8493	1.0250	138.1795	2.8500
0.9179	1.0048	0.9508	0.8493	1.0250	138.1795	2.8500
0.9435	0.9643	1.0360	0.8473	1.0250	150.1752	2.8500
0.9529	0.9322	0.9291	0.8493	1.0250	138.1795	2.8500
0.9489	0.9820	0.9205	0.8493	1.0250	138.1795	2.8500
0.9584	0.9528	0.9842	0.8493	1.0250	138.1795	2.8500
0.9286	0.9356	1.0376	0.8493	1.0250	138.1795	2.8500
0.9983	0.9195	1.0222	0.8493	1.0250	138.1795	2.8500
0.9647	0.9017	1.0475	0.8493	1.0250	138.1795	2.8500
1.0251	0.9802	0.9005	0.8493	1.0250	138.1795	2.8500
1.0182	0.9006	1.0185	0.8493	1.0250	138.1795	2.8500
1.0113	1.0051	0.9222	0.8493	1.0250	138.1795	2.8500
0.9358	1.0012	1.1566	0.8489	1.0450	149.1035	2.8500

Appendix M2

P Increment

All_Qinj

Finest parameter (Point B)

Qinj1	Qinj4	Qinj5	Qinj6	Qinj9	Qinj11	Qinj12	Qinj15	Qinj19
-8.3763	-11.5757	-7.4708	-7.2815	-10.2368	-11.3869	-6.3818	-7.9030	-5.7050
-6.8089	-8.5128	-7.8351	-6.9566	-5.5397	-10.0679	-7.0883	-5.6783	-11.9887
-6.7218	-11.9235	-11.0820	-10.1517	-10.5997	-8.2914	-7.1864	-5.1072	-7.0075
-7.0215	-6.4330	-7.2252	-9.7424	-5.9633	-9.3850	-10.9262	-8.2884	-8.5265
-5.0245	-9.8649	-10.8441	-6.6920	-11.3985	-11.8759	-11.0865	-6.5477	-5.1432
-7.2104	-6.5775	-10.7697	-11.2343	-11.9554	-6.8203	-11.0694	-6.9650	-9.6092
-9.6833	-6.5754	-8.8678	-11.3371	-9.9426	-8.1683	-9.3789	-10.5396	-6.2507
-8.7045	-10.1901	-10.3619	-9.3564	-8.1603	-5.5849	-10.4740	-7.6389	-5.4444
-8.7708	-9.0296	-8.7222	-5.5518	-6.3047	-5.2067	-7.3991	-11.4606	-5.6588
-8.6841	-11.0476	-7.3325	-10.9047	-9.6132	-9.1189	-11.0082	-7.7514	-8.2258
-10.4208	-5.2306	-9.4408	-11.6399	-10.6382	-7.6337	-10.8972	-9.0280	-5.7771
-10.3980	-5.7800	-6.8997	-10.2715	-11.7494	-8.0273	-11.2767	-7.7187	-5.2791
-9.5162	-11.4782	-7.9541	-5.5384	-6.6695	-8.2628	-8.0499	-10.1227	-6.9658
-8.4170	-9.2031	-10.6666	-7.0276	-10.0061	-8.0293	-7.1411	-9.4885	-8.4306
-5.7202	-6.4094	-8.0075	-5.6398	-10.8081	-8.3741	-10.8025	-11.2327	-9.6698
-10.8477	-8.5608	-9.0262	-11.9901	-6.2556	-8.6038	-11.9967	-10.1815	-11.6083
-11.8926	-6.3055	-11.7811	-5.2885	-7.9816	-7.1567	-6.5384	-9.3563	-9.6933
-7.6466	-6.6748	-9.9026	-9.9682	-11.4544	-8.5646	-5.4139	-5.6945	-6.4339
-8.2088	-10.6216	-10.2442	-11.3127	-9.5550	-11.6724	-10.0994	-5.6211	-7.2567
-9.9077	-9.6644	-8.7739	-9.8867	-9.6657	-6.2469	-5.8961	-11.9936	-6.1978

Appendix N2

P Increment

All_Xmer

Finest parameter (Point B)

txA	txB	txC	txD	txE	txF	txG	Vmin	Vmax
0.9408	1.1811	1.0116	1.0459	0.9695	0.9681	0.9778	0.8420	1.0250
1.0712	1.1131	1.0215	1.0084	1.0614	0.9050	0.9427	0.8499	1.0250
0.9130	1.1650	1.0796	0.9359	1.0170	0.9817	1.0101	0.8455	1.0350
1.0829	1.1864	0.9358	1.0435	1.0145	0.9944	1.0136	0.8444	1.0250
1.0067	1.1681	0.9839	1.0416	1.0444	0.9306	1.0706	0.8482	1.0250
0.9865	1.1217	1.1073	0.9159	0.9802	1.0492	0.9775	0.8489	1.0350
1.1491	1.0814	1.0267	1.0987	0.9311	1.0101	1.0345	0.8425	1.0250
1.0159	0.9481	1.0511	0.9403	1.0394	0.9900	1.0228	0.8472	1.0250
1.0795	1.0739	0.9358	0.9841	0.9862	1.0472	1.1060	0.8466	1.0250
1.0053	1.0493	0.9153	1.0338	0.9947	0.9714	0.9036	0.8493	1.0250
0.9492	0.9212	1.0382	0.9965	0.9272	0.9561	0.9813	0.8493	1.0250
0.9794	1.0396	0.9611	0.9712	1.0425	0.9243	0.9623	0.8493	1.0250
1.1601	0.9988	1.0468	1.0208	0.9545	1.0253	0.9874	0.8490	1.0250
1.1982	0.9612	1.0638	0.9639	1.0320	0.9758	1.0469	0.8451	1.0250
0.9275	0.9565	0.9820	1.0423	0.9810	1.0484	0.9193	0.8493	1.0250
0.9966	0.9614	1.0331	0.9985	0.9540	0.9084	1.0412	0.8493	1.0250
0.9771	0.9956	1.0125	0.9262	0.9990	0.9763	1.0500	0.8493	1.0250
0.9094	1.0244	1.0099	1.0433	1.0088	0.9546	0.9547	0.8493	1.0250
0.9089	0.9933	1.0470	0.9633	1.0398	0.9395	1.0410	0.8493	1.0250
1.0184	0.9907	1.0152	1.0484	0.9191	1.0000	1.0476	0.8493	1.0250

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