RISK BASED SECURITY ASSESSMENT OF POWER SYSTEMS USING STATISTICAL COMPUTATIONAL INTELLIGENT TECHNIQUES

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PENILAIAN KESELAMATAN BERASASKAN RISIKO MENGGUNAKAN TEKNIK BERSTATISTIK DAN KEPINTARAN PENGKOMPUTERAN

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DISERTASI YANG DIKEMUKAKAN UNTUK MEMENUHI SEBAHAGIAN DARIPADA SYARAT MEMPEROLEH IJAZAH DOKTOR FALSAFAH

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DECLARATION

I hereby declare that the work in this thesis is my own except for quotations and summaries which have been duly acknowledged.

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RISK BASED SECURITY ASSESSMENT OF POWER SYSTEMS USING STATISTICAL COMPUTATIONAL INTELLIGENT TECHNIQUES

ABSTRACT

Power system operation is currently becoming more complex due to financial and environmental constraints that limit the expansion of transmission networks. Thus, power transmission networks become heavily loaded and a great importance has to be given to power system security assessment. Traditionally, power system security is assessed using deterministic approach in which power system operation is deemed to be secure if it operates within the pre-defined security margin. However, in the current competitive environment, there is a drawback with the deterministic approach because it does not reflect the stochastic or probabilistic nature of the system in terms of load profiles, component availability, failures and other uncertainties. To incorporate probabilistic or stochastic techniques, power system security assessment based on the concept of risk is required. Risk assessment is an approach that quantitatively captures the factors that determine security level, namely likelihood and the severity of events. The objective of this research is to develop a comprehensive and fast risk based security assessment in power systems which consider risk based static security assessment (RBSSA) that includes risk of low voltage (LV) and line overload (LO), and risk based voltage collapse assessment (RBVCA). The probability of transmission line outage is modeled using the Poisson distribution function. The non-sequential Monte Carlo simulation is also implemented and the result is compared with the Poisson distribution function so as to investigate its effectiveness in calculating the probability of contingency. To consider the effect of weather on the likelihood of outage, an improved failure rate model using the data pooling method is proposed. The outage history data obtained for six years period is used in the data pooling procedure. Severity function is another important attribute in risk assessment and therefore three types of severity function are considered in the implementation of RBSSA. For RBVCA, a new severity function utilizing a voltage collapse prediction index is considered. To reduce the number of power flow simulation that needs to be performed, transmission line outage screening using risk factor is proposed. In order to develop fast and accurate RBSSA and RBVCA methods, two computational intelligent techniques based on support vector machine (SVM) and generalized regression neural network (GRNN) are used because of their robustness and fast training time. A feature extraction technique based on the principle component analysis is applied for the purpose of reducing the SVM and GRNN training times. The proposed techniques for RBSSA and RBVCA are implemented on the IEEE 24 bus test system and the 87 bus practical power system. Simulations are carried out using the Power System Analysis Toolbox and the development of the computational intelligent techniques are implemented in the MATLAB version 7 environment. Results showed that the GRNN give better risk prediction performance compared to SVM because it provides the lowest mean average error, mean square error and root mean square error (RMSE). For low voltage RBSSA, line overload RBSSA and RBVCA, the accuracy obtained using GRNN model in terms of RMSE are 0.019, 0.018 and 0.026, respectively.

PENILAIAN KESELAMATAN BERASASKAN RISIKO MENGGUNAKAN TEKNIK BERSTATISTIK DAN KEPINTARAN PENGKOMPUTERAN

ABSTRAK

Operasian sistem kuasa pada masa kini telah menjadi lebih kompleks disebabkan kekangan sekitaran dan kewangan yang menyekat pengembangan rangkaian penghantaran. Oleh demikian, rangkaian penghantaran kuasa terbeban berat dan perhatian harus diberikan terhadap penilaian keselamatan sistem kuasa. Secara tradisi, penilaian keselamatan sistem kuasa dinilai menggunakan pendekatan deterministik yang mana operasian sistem kuasa dianggap selamat jika beroperasi dalam jidar keselamatan yang ditetapkan. Namun, dalam persekitaran kompetitif pada masa kini, terdapat kelemahan dengan pendekatan deterministik kerana ianya tidak menunjukkan sifat stokastik atau berkebarangkalian sistem dalam sebutan profil beban, ketersediaan komponen, kegagalan dan ketidaktentuan yang lain. Untuk menggabungkan teknik berkebarangkalian atau stokastik, penilaian keselamatan sistem kuasa berasaskan risiko adalah diperlukan. Penilaian risiko merupakan satu pendekatan kuantitatif yang mengambil kira faktor yang menentukan tahap keselamatan, iaitu, besar kemungkinan dan keparahan peristiwa. Objektif penyelidikan ini adalah untuk membangunkan penilaian keselamatan berasaskan risiko dalam sistem kuasa yang menyeluruh dan cepat dengan menimbangkan penilaian keselamatan statik berasaskan risiko (PKSBR) yang meliputi risiko voltan rendah dan talian berlebihan beban, dan penilaian keruntuhan voltan berasaskan risiko (PKVBR). Kebarangkalian putusan talian penghantaran dimodel dengan menggunakan fungsi agihan Poisson. Simulasi Monte Carlo tanpa berjujukan turut dilakukan dan hasilnya dibandingkan dengan fungsi agihan Poisson untuk meninjau keberkesanannya dalam pengiraan kebarangkalian kemungkinan. Untuk menimbangkan kesan cuaca terhadap besar kemungkinan putusan bekalan kuasa, satu pembaikan model kadaran kegagalan menggunakan kaedah penyatuan data dicadangkan. Data perihal putusan bekalan kuasa untuk tempoh enam tahun digunakan dalam prosidur penyatuan data. Fungsi keparahan merupakan atribut penting dalam penilaian risiko dan oleh itu tiga jenis fungsi keparahan dipertimbangkan dalam pelaksanaan PKSBR. Untuk PKVBR, fungsi keparahan baru menggunakan indeks ramalan keruntuhan voltan dipertimbangkan. Untuk mengurangkan jumlah simulasi aliran kuasa yang perlu dilakukan, penapisan putusan talian menggunakan faktor risiko penghantaran dicadangkan. Dalam pembangunan kaedah PKSBR dan PKVBR yang cepat dan tepat, dua teknik kepintaran pengkomputeran berdasarkan mesin penyokong vektor (MPV) dan rangkaian neural regresi umum (RNRU) digunakan. Sebuah teknik penyarian sifat berdasarkan analisis komponen prinsip digunakan untuk mengurangkan masa latihan MPV dan RNRU. Teknik-teknik yang dicadangkan untuk PKSBR dan PKVBR dilaksanakan ke atas sistem ujian IEEE 24 bas dan sistem kuasa praktikal 87 bas. Simulasi dilakukan dengan menggunakan Power System Analysis Toolbox dan pembangunan teknik kepintaran pengkomputeran dilaksanakan dalam persekitaran versi MATLAB 7. Keputusan menunjukkan bahawa RNRU memberikan prestasi ramalan risiko yang lebih baik berbanding dengan MPV kerana ia menghasilkan ralat yang terendah dari segi ralat min mutlak, ralat min persegi dan ralat punca kuasa dua (RPKD). Untuk PKSBR voltan rendah, PKSBR talian berlebihan beban dan PKVBR, kejituan yang diperolehi dari model RNRU dalam sebutan RPKD adalah masing-masing 0.019, 0.018, dan 0.026.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
c	Critical
GRNN	Generalized Regression Neural Network
LO	Line overload
LV	Low Voltage
MAE	Mean Absolute Error
MSE	Mean Square Error
nc	Non critical
PCA	Principle Component Analysis
PI	Performance Index
PSAT	Power System Analysis Toolbox
RBSA	Risk Based Security Assessment
RBSSA	Risk Based Static Security Assessment
RBVCA	Risk Based Voltage Collapse Assessment
RMSE	Root Mean Square Error
SVM	Support Vector Machine
VCPI	Voltage Collapse Prediction Index
VC	Voltage Collapse

LIST OF SYMBOLS

λ	Failure rate
P	Pool number
n	Number of failure
T	Sample size
l	Total length of transmission line
$\Pr(E_i)$	Probability of transmission line outage
C	Regularization parameter for SVM
σ	Parameter that controls the width of the RBF kernel
y_{LV}	Real risk index of low voltage
$f(x)_{LV}$	Predicted risk index of low voltage
y_{LO}	Real risk index of line overload
$f(x)_{LO}$	Predicted risk index of line overload
y_{VC}	Real risk index of voltage collapse
$f(x)_{VC}$	Predicted risk index of voltage collapse
$\bar{x}_j$	Mean value of a data set
φ_j	Variance of a data set
eig	Eigenvalue
u	Eigenvector

CHAPTER I

INTRODUCTION

1.1 RESEARCH BACKGROUND

The unprecedented changes in the world's technology have also changed customer's expectation towards availability in the electricity supplies. Few seconds of interruption may cause millions of profit loss due to the increased level of dependency on electricity supply in our daily activities. Economic impacts due to supply interruptions are not restricted to loss of revenue by the utility or loss of energy utilization by the customer but it includes indirect costs imposed on society and the environment (Billinton & Li 1994; Milanovic & Gupta 2006). These factors have increased the demand for more accurate and up to date information in power system operation.

Nowadays, power system operation becomes more complex than earlier due to the financial and environmental constraints that limit the expansion of transmission network. Therefore, the existing transmission networks need to be fully utilized and always required to transmit power at capacities closed to their limits in order to provide greater profit at a lower cost without compromising the security of the power system. A heavily loaded power system has substantially different response to disturbances from that of a lightly loaded system. This scenario has resulted in a more highly stressed and unpredictable operating conditions, more vulnerable power network and an increased need to monitor the security level of the transmission system (Ni et al. 2003a). In power system operation, security and reliability have the same implication. For example, an operating system whose security level is low is said to be unreliable and vice versa. Power systems have evolved over decades and their primary concern has been on providing a reliable and economic supply of electrical energy to their customers (Haroonabadi & Haghifam 2008). Power system security refers to the degree of risk in its ability to survive imminent contingencies without interruption of customer service (Kundur et al. 2004). Among the factors that can affect security of power systems is system operating condition and probability of contingency (Kirschen et al. 2004; Bi et al. 2008; Xiao et al. 2009; Halilcevic et al. 2009).

In a power system, any contingency resulting in line overload, low voltage or voltage collapse may occur for a number of reasons at any time. To limit the consequences of such events, power system operators usually maintain a deterministic security margin that takes into account only a limited set of contingency. A typical set of contingency consists of a list of contingency with severe impact, while the other possible contingencies are neglected. Although the effect of less severe contingency can be compromised but it may endanger the power system if the occurrence rate is higher. Several recent major blackouts reported in Denmark, Sweden, Italy and United Kingdom have shown that deterministic security margin does not always prevent customer outage and system collapse (Kirschen & Jayaweera 2007). In a power system that consists of thousands of components, it is impossible to completely eliminate the occurrence of contingency. Therefore, the use of probabilistic methods that take into account of the actual real-time conditions in combination with past knowledge, are extremely important in the current uncertain power system environment.

In order to alleviate the stressed condition, operations engineer have to make quick complex decision on whether an action is necessary, and if so which action to take and to what extent. This scenario has forced power utilities to adopt an online based power system security assessment in order to continuously assess the power system condition (Di Santo et al. 2004;Ni et al. 2003a, 2003b). Such a real time security analysis leads to sensible improvement in power system security. However, large computational effort is required in terms of the number of power flow solutions.

1.2 PROBLEM STATEMENT

Power system security assessment is a main concern in planning and operating electric power systems. It generally involves evaluating the power system's ability to deal with various contingencies, and proposing ways to counter its weaknesses when necessary. In power system operation and planning, security assessment needs to be performed to assist system operators in maintaining system security level within an acceptable range. The occurrence of faults, failures and equipment malfunction are unpredictable and unavoidable. Due to this uncertainty, deterministic approach that has been used for many years is no longer applicable (McCalley et al. 1999, 2004; Wan et al. 2000; Di Santo et al. 2004;

Kirschen & Jayaweera 2007) because it provides only a limited perspective on the actual level of security of a power system. In the traditional deterministic security assessment practice, power system has to be operated within significant security margin considering only the most credible contingencies (Wan et al. 2000; Ning et al. 2006; Kirschen & Jayaweera 2007). These traditional methods find the deterministic security margin based on the performance of the most severe credible contingencies. An operating condition is said to be insecure if it violates any of the pre-defined voltage or thermal limits. This approach is conceptually simple and easy to implement but it has significant drawbacks due to the fact that it gives highly conservative decisions (Dai 2001) and the effects of less severe operating conditions are neglected (Ning et al. 2006). Furthermore, the deterministic approach does not provide information on the current operating condition and the extent of security violation (Wan et al. 2000) but only provides binary information as to whether the current operating condition is secure or insecure (Mohammadi & Gharehpetian 2008). To allow power system to operate closer to its limits, a more refined and realistic security assessment method is required at the planning and operating stage.

Risk based security assessment (RBSA) is a probabilistic technique that evaluates the power system's ability to deal with various contingencies. The risk index computed from RBSA technique quantitatively measures the degree of risk of a given operating condition and can be used to assess the system security level as a function of existing or near-future network conditions. RBSA is considered as a refined security assessment method that takes into account the probabilistic nature of many uncertain variables and the extent of security violations. In RBSA, the probability of security violation is an essential element and it considers the probability of contingencies that cause security violation in a power system. To obtain the probability of contingencies, a Poisson probability model utilizing fixed parameters that characterizes the occurrence of transmission line outage is usually assumed (Wan et al. 2000; Ni et al. 2003a; Chen et al. 2006). There are many factors that affect the likelihood of transmission line outage, such as weather condition (Xiao et al. 2006; Bollen 2000), equipment aging (Bollen 2000) and vegetation related failure (Radmer et al. 2002). Based on the recent studies in Canada, it was estimated that most of the failure occurred during bad weather condition (Kirschen & Jayaweera 2007). Therefore, in this study an improved probability model considering the effect of weather in the occurrence of contingency is considered.

The main stages in RBSA process involve selection of power system state, calculation of state probability and determination of risk index value. The process of computing the risk index value is a straightforward process using the two commonly used methods for system state selection in a power system, namely, state enumeration and Monte Carlo simulation (Li, 2005). In state enumeration, a system state is selected based on the enumerated contingency list while the Monte Carlo simulation uses a random event generator that works by sampling a system state which can be categorized into sequential and non-sequential sampling. The computational burden of Monte Carlo simulation does not depend on system size or complexity. Thus, the Monte Carlo simulation method is used for probability estimation of security violation.

In a large power system that is complex and highly interconnected, security assessment has become computation intensive since it involves exhaustive power flow simulations due to the long list of possible transmission line outages. Therefore, to quickly identify those critical contingencies which may cause security violation so as to reduce the number of transmission line outages that need to be analyzed by full AC power flow, contingency screening should be implemented. Previously, contingency screening based on the severity towards security violation calculated by using performance index is implemented (Jasmon & Lee 1993; Arya et al. 2001; Chauhan 2005; Singh & Srivastava 2007). However, this method is deterministic in nature, since the probability of contingency is not taken into account and therefore, may unnecessarily restrict system operation.

Another important attribute in RBSA is the severity of security violation. There are three types of severity functions, namely, discrete, continuous and percentage of violation severity function that can be adopted for the assessment of risk of low voltage and line overload (Ni et al. 2003a). The selection of severity function in RBSA is an important issue since it represents the extent of security violation. Therefore, it is essential to investigate the effect of severity function so as to select the best impact indicator to security violation. In voltage collapse, the extent of violation is usually represented by percentage of loading margin which can be determined using the forecasted load and loadability obtained from continuation power flow (Ni et al. 2003a; Ni et al. 2003b). A good severity function should reflect the consequence of contingency and loading condition, simple, reflect relative severity between different problems and measure the extent of violation (Ni et al. 2003a). Based on these criterions a new severity function for voltage collapse considering voltage collapse prediction index (VCPI) is developed.

The existing online RBSA methods are developed by using the outputs of post-contingency power flow simulations which require extensive computational burden (Ni et al. 2003a, 2003b; Arya et al. 2006; Chen at al. 2006; Berrizi et al. 2008). For that reason, a faster and accurate method for RBSA using artificial intelligent techniques need to be developed in order to overcome the drawbacks of the existing tools. In recent years, various enhancements in solving power system related problems can be achieved with the advent of artificial intelligence (AI). The application of AI has shown great promise in power system engineering due to its ability to synthesize complex mapping accurately and rapidly. AI consists of several branches, namely expert system, artificial neural network, Genetic algorithm, fuzzy logic and hybrid system (Mellit & Kalogirou 2008).

1.3 RESEARCH OBJECTIVES AND SCOPE OF WORKS

This research focused on developing new methods and approaches to solve problems in the RBSA of power systems. The objectives of this research can be summarized as follows:

(i) To develop an improved failure rate model based on the weather condition for the estimation the probability of contingency.

(ii) To investigate the effectiveness of Monte Carlo simulation against the analytical method based on the Poisson distribution function in estimation of contingency probability.

(iii) To develop a critical transmission line outage list with respect to low voltage, line overload and voltage collapse by using a newly developed method based on risk factor.

(iv) To develop a fast and accurate method for the assessment of RBSA using support vector machine and generalized regression neural network.

Initial research work begins with modeling of uncertainty considered in the study. For the purpose of this study, only probability of transmission line outage in the order of ‘N-1’ is considered. To reduce the number of transmission line outages that need to be analyzed, a contingency screening by using the newly developed technique based on risk factor is performed so as to select the critical transmission line outages. Risk factor of a line outage is defined as a product of its probability factor and the severity factor associated with security violation. The probability of critical transmission line outage is assumed to follow the Poisson distribution characteristic and hence, the Poisson distribution function is used to perform the computation of contingency. In order to utilize the Poisson distribution function, the failure rate of each transmission line has been known. Another method for calculating the probability of contingency using the Monte Carlo method is also considered and compared with the Poisson distribution function. The non-sequential Monte Carlo simulation is employed in this study because it does not involve chronological time dependent event. One of the factors that affect the likelihood of transmission outage is weather condition. Therefore, in order to reflect the effect of weather in the computation of contingency probability, failure rate estimation incorporating weather condition is also considered. The data pooling method is proposed for failure rate estimation related to weather utilizing real historical outage data.

The study of RBSA is divided into two categories, namely, RBSSA which evaluates the risk of low voltage and line overload, and RBVCA which involves the assessment of risk of voltage collapse. The implementation of RBSSA begins with modeling of severity function for both low voltage and line overload. The three types of severity functions considered are discrete, continuous and percentage of violation severity functions. The severity of each line outage with respect to load condition is evaluated using discrete, continuous and percentage of violation severity function which utilizes information attained from the post-contingency power flow. To assess the severity of a contingency, post-contingency power flow simulations are performed using the Power System Analysis Toolbox (Milano 2007). The risk of line outage with respect to low voltage and line overload is computed by multiplying the probability of line outage with its severity associated with low voltage and line overload respectively. The risk index of an operating point associated with low voltage and line overload is computed by summing all risks of line outage with respect to low voltage and line overload correspondingly.

The most commonly used severity function in RBVCA is the percentage of load margin determined using the forecasted load and loadability (Ni et al. 2003a). In this case, a new severity function for RBVCA is proposed by using the voltage collapse prediction index (VCPI) (Balamourougan et al. 2004). VCPI has values which varies between zero to one and can be determined by using information obtained from power flow analysis. The status of voltage instability in a power system can be determined by using the VCPI in which zero index value represents a secure operating point while a unity index value represents an insecure operating point. The risk of line outage with respect to voltage collapse is defined as the product of probability of contingency and its severity function value (Ni et al. 2003b).

To achieve fast and accurate RBSA, AI techniques based on support vector machine (SVM) and generalized regression neural network (GRNN) are implemented, and their performances are evaluated and compared based on the mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE). SVM and GRNN are proposed in this study because of their robustness and fast training time as compared to the conventional multi layer perceptron artificial neural network model. The performance of SVM and GRNN are compared in terms of MAE, MSE and RMSE so as to choose the best AI techniques in predicting the risk index for low voltage, line overload and voltage collapse respectively. Feature extraction based on the principle component analysis is employed so as to reduce the number of input features.

CHAPTER II

LITERATURE REVIEW

2.1 POWER SYSTEM SECURITY DEFINITION

In today's competitive market environment with different business interests, power system is heavily utilized. The increasing competitiveness in the power system's environment has created new challenges to the power system security assessment. The major blackouts that occurred recently reported that large proportion of these incidents is caused by events that were deemed not credible (Kirschen et al. 2004). The ability of a power system to withstand sudden disturbances such as electric short circuits or non-anticipated loss of system components is referred as power system security (Kundur et al. 2004). Power system security relates to the robustness of a power system to contingencies such that no physical constraints are violated in the post-contingencies and the system must survive the transition state. When a power system has an insufficient degree of security, it becomes exposed to severe and, in some cases, may cause catastrophic system wide collapse (Morison et al. 2004).

Nowadays, various power system failures around the world are due to inadequate security margin. The security of a power system can be assessed by simulating potential contingencies, such as faults or loss of facilities, and determine if the disturbances will result in any adverse impacts that could cause unsafe conditions, customer interruptions, or equipment damage (Wang & Morison 2006). The analysis of power system security is divided into two categories, namely, static and dynamic security assessment. Static security assessment involves steady-state analysis of post-disturbance system conditions to verify that no equipment ratings and voltage constraints are violated (Weerasooriya et al. 1992). Dynamic security assessment includes examining rotor angle, voltage and frequency stabilities (Wang & Morison 2006). Security of a power system network could be violated due to numerous contingencies that could lead to problems like low bus voltage, line overload and voltage collapse. The order of contingency is normally written as '*N-k*' where '*k*' represents the number of elements being taken out of service. Loss of a single element in a power system such as a transmission line outage is denoted by '*N-1*' event. The number of possible contingencies in 'N-k' events is given as $\dfrac{N!}{k!(N-k)!}$ (Chen & McCalley 2005). For a simple power system network consisting of 50 elements, there are 50 '*N-1*' contingencies, 1225 '*N-2*' contingencies, 19600 '*N-3'* contingencies and 230300 '*N-4'* contingencies. The number of possible combination of contingency increases as the order increases.

2.2 POWER SYSTEM SECURITY ASSESSMENT

Recent trend in power system operation has forced the utility to fully utilize their resources. The increase in long distance transmission usage, results in heavy transmission loading, depressed bus voltage magnitude and close proximity to voltage instability. To prevent such problems from occurring, construction of a new generation of network or expansion of the current transmission network is required. Unfortunately, the initial investment cost associated with these options is not always affordable. Due to this limitation, monitoring the status of a power system under load changes and maintaining an adequate security margin becomes a task of critical importance. This condition has raised the need of an effective tool for security assessment in large-scale interconnected system. Previously, in power system operation and planning, a power system security assessment was performed using deterministic method. However, due to its significant drawbacks, a probabilistic security assessment approach is proposed.

2.2.1 Deterministic Approach

In the past, power system security assessment using deterministic approach has been widely recognized. In the deterministic approach, the security criterion is usually defined by a set of credible contingencies. Deterministic approach makes the assumption that all events in the contingency list have equal frequency and it occurs in the order of 'N-1' contingency (McCalley et al. 1999). Under the deterministic criterion, power system should be operated within the pre-defined deterministic security margin. Based on the security margin developed using the deterministic approach, power system should be able to continue operating normally if any one of these credible contingencies were to occur (Kirschen & Jayaweera 2007). The operating state of a power system is deemed to be insecure if it violates the constraint of the pre-defined set of contingencies.

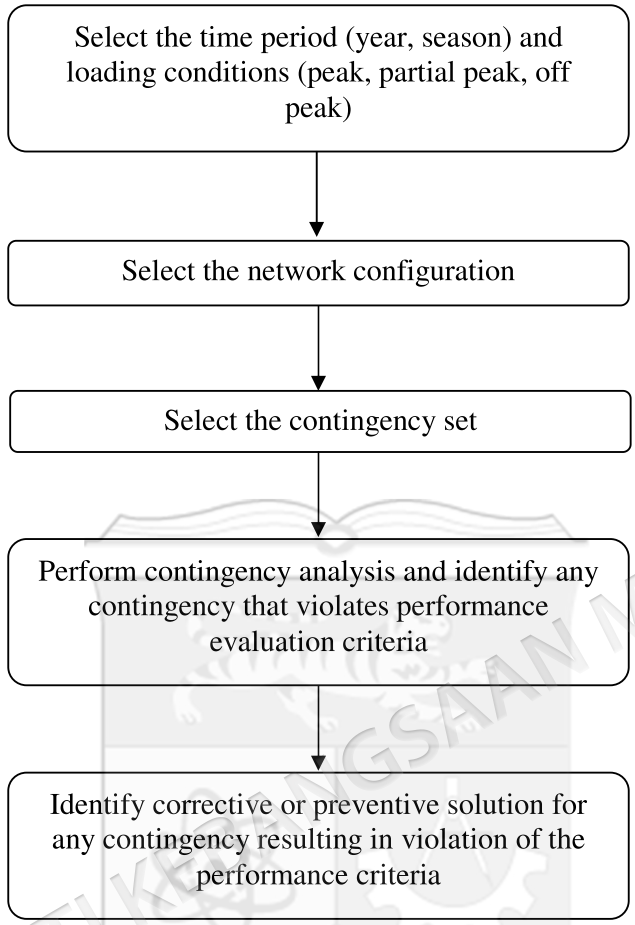

Figure 2.1 Power system security assessment based on the deterministic approach

The deterministic security margin is developed based on the credibility and severity. Credibility signifies that each network configuration, outage event and operating conditions should be reasonably likely to occur. Severity of an outage event represents that operating condition on which a decision is made that result in severe system performance. Basically, security assessment using deterministic approach is performed by considering the procedure as shown in Figure 2.1.

Deterministic approach is conceptually appealing and easy to implement but it has significant drawbacks. Limiting the contingency set to *'N-1'* credible contingencies, using simple and conservative performance requirement was acceptable in the earlier power system structure in which the occurrence of stressed operating condition was infrequent. Using this approach, power system becomes overbuilt from the planning perspective since power system is operated with a large security margin. Hence, it is difficult to integrate security into the economic decision making process.

2.2.2 Probabilistic Approach

An ambiguous distinction between secure and nonsecure operating state has resulted from the partition of set of all contingencies into credible and noncredible subsets. Therefore, in order to study the effect of other possible contingencies, there is a need to account for the probabilistic nature of power system conditions and events (Kundur et al. 2003). Using probabilistic security assessment method, the contingency set is usually created by state enumeration rather than by pre-selecting a limited number of contingencies (McCalley et al. 2004). Enlarging the number of contingencies analysis in security assessment of power system results in heavy computational burden, however with today's computing and analysis resources this is no longer impossible.

The framework of probabilistic security assessment considering steady state and dynamic security takes into account the uncertainty in the occurrence of contingency, power injections at load buses and load model (Wang et al. 2005). A dominant contingency set which includes contingency with prominent influence on system insecurity is considered in Wang et al. (2005), while other contingencies with little contribution to system insecurity and rare failures rate are neglected. A probabilistic steady security assessment using the Monte Carlo method is presented by Agreira et. al (2006). Contingency selection based on fast filtering and ranking method is adopted in order to limit the number of simulation. Apart from the probability of transmission line and generator outage, the impact of contingencies in line overloads, voltage limit violation and voltage stability problem are also taken into account (Agreira et. al 2006).

In order to account for the probabilistic nature of uncertain variables and their impact in power system operation, a probabilistic security assessment based on the concept of risk is required. Risk based security assessment (RBSA) has been extensively discussed in a comprehensive series of papers (McCalley et al. 1997; Dai et al. 2001; Fu et al. 2002; Ni et al. 2003a; Mili & Qiu 2004; Ning et al. 2006; Kirschen & Jayaweera 2007; Feng et al. 2008). Risk based approach develops operating limits based on a composite measure computed from risk contribution from all contingencies. The probability and impact of undesirable events are considered in the calculation of the risk index developed using probabilistic security assessment method. The risk index provides a more complete overview of the condition of a given operating point.

2.3 RISK BASED SECURITY ASSESSMENT

Risk assessment has become a challenge and an essential commitment in the power utility industry. The stochastic behavior of power systems is the root origin to the risk assessment. Risk and reliability have the same implications in which an operating system whose risk level is high is said to be unreliable and vice versa. Risk based technique has given a paradigm shift towards security assessment. Risk based assessment is a quantitative validation that takes into account the impact associated with the interruption and the likelihood of contingency. In this approach, a risk index developed quantitatively capture the probability of occurrence of each possible contingency and the impact of the event.

2.3.1 Definition of Risk

In RBSA approach, the developed risk level quantitatively captures the probability of occurrence of each possible contingency that causes security violation and the impact of the event. A probabilistic feature of RBSA is that it is able to reflect the uncertainties faced in a power system environment. There are two important attributes that determine the risk index, namely, event likelihood and severity of event. The risk index of a given operating condition is the sum of all risk of contingency which is defined as the product of the probability of contingency that leads to security violation and the severity of the security violation. Risk index of a given operating condition can be written as follows (Ni et al. 2003a);

$$Risk = \sum_{i} \left(\Pr(E_i) \times Sev(E_i) \right) \tag{2.1}$$

where E_i represents the contingency state, $\Pr(E_i)$ is the probability of the occurrence of a contingency and $Sev(E_i)$ signifies the severity of a contingency in a given loading condition.

The probability of contingency identifies the likelihood of an event. The Poisson probability model is usually used to approximate the probability of transmission line outage. The severity function is adopted to uniformly quantify the severity of network performance towards security violation.

2.3.2 Architecture of Risk Based Security Assessment

The architecture of RBSA proposed in this study is shown in Figure 2.2. In this study, the implementation of RBSA includes risk of low voltage, line overload and voltage collapse.

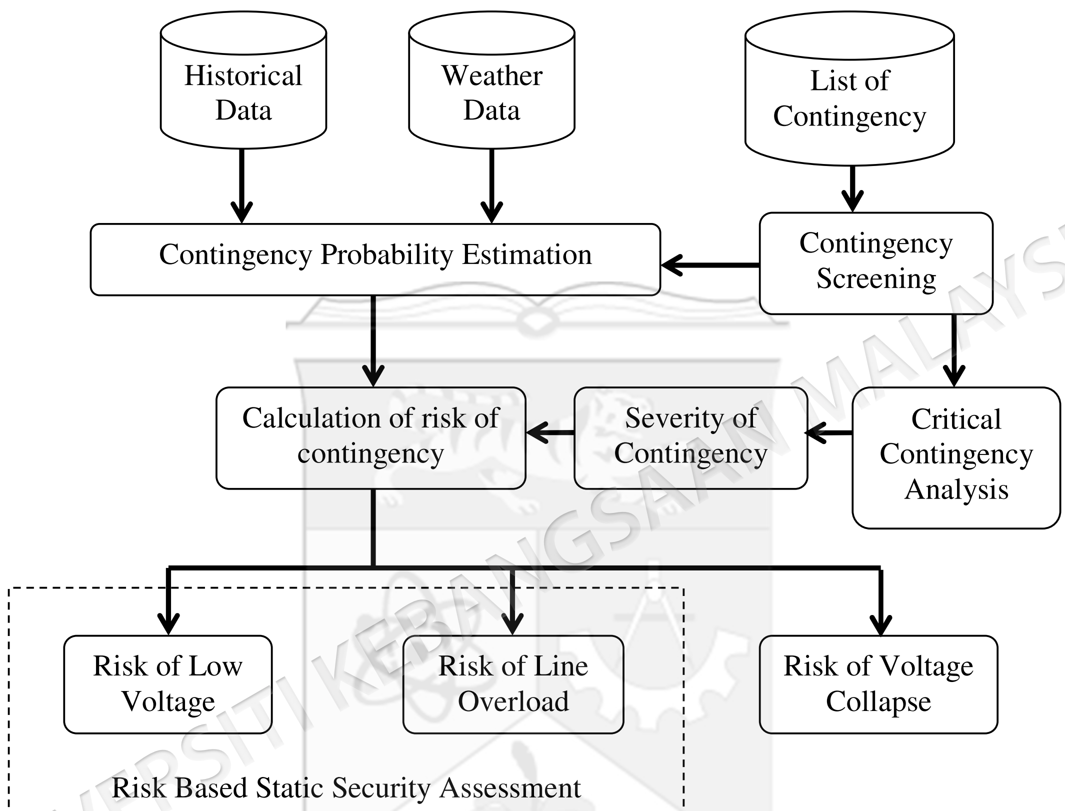

Figure 2.2 Architecture of RBSA

Contingency screening is performed to quickly identify those critical contingencies which may cause security violation so as to reduce the number of contingencies that need to be analyzed by full AC power flow. In critical contingency analysis stage, a full AC power flow is then performed in order to evaluate the severity of security violation. Contingency probability estimation is an important attribute in RBSA in which it is usually estimated using fixed failure rate values computed based on the historical outage data (Ni et al. 2003a). Failure rate is the average number of failure per-unit time. Normally, this probability estimation method does not address the effect of weather. Therefore an improved failure rate model considering the effect of weather is proposed in this research work and the probability of each contingency in the contingency list is estimated.

The severity of a contingency is calculated based on the type of security violations which are low voltage, line overload and voltage collapse. Severity function is adopted to uniformly quantify the severity of network performance for low voltage, line overload and voltage collapse. The calculation of risk of contingency is then performed by multiplying the probability and severity of contingency. The risk index of a given operating condition is obtained by summing all risk of contingencies listed in the critical contingency list (Xiao 2007).

2.3.3 Risk of Low Voltage

A power system operating at the lower voltage would require excessively high current to produce the power (Tiranuchit & Thomas 1988). In a power network, the magnitude of bus voltage should be maintained within ±5% of its nominal value. The bus voltage is considered to operate in low voltage if the magnitude is less than 0.95 p.u. Fig. 2.3 illustrates the range of voltage limits in a power system.

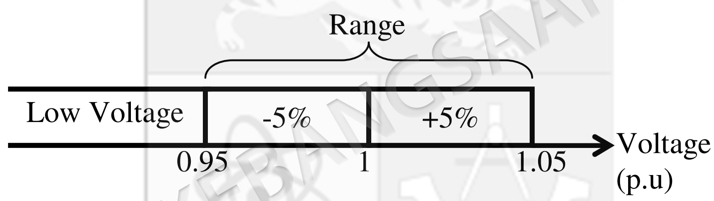

Figure 2.3 Illustration of the range of voltage limits

Risk of low voltage measures the degree of risk of a given operating point towards low voltage violation. The severity function for low voltage is defined specific to each bus (Ni et al. 2003a). The voltage magnitude of each bus determines the value of severity. The risk of a contingency associated to low voltage is written as;

$$Risk_{LV} = \Pr(E_i) \times Sev_{LV}(E_i) \tag{2.2}$$

where E_i signifies the contingency and Sev_{LV} is the severity function for low voltage.

2.3.4 Risk of Line Overload

The degree of risk of a current operating point towards violation of transmission line limit is measured by using the risk of line overload. An excessive line flow may cause a transmission line to lose clearance due to sag and lose its strength due to annealing process (Dai et al. 2001). The thermal expansion of a conductor in an overloaded transmission line results in sag and the line may touch an underlying object causing a permanent fault and subsequent outage. Annealing is a recrystallization of metal, and the process is gradual and irreversible when the grain matrix established by cold working is consumed and causing loss of tensile strength. The severity for line overload is defined specific to each transmission line. The power flow as a percentage of rating of each transmission line determines the line overload severity. The risk of a contingency associated to line overload is written as;

$$Risk_{LO} = \Pr(E_i) \times Sev_{LO}(E_i) \tag{2.3}$$

where E_i signifies the contingency and Sev_{LO} is the severity function for line overload.

2.3.5 Risk of Voltage Collapse

In recent years, major blackouts throughout the world are associated with voltage collapse (Makarov et al. 2005). Continuous increase in load demand may slowly decline the voltage magnitudes throughout the network, and as a consequence power system will be driven into a state of voltage instability and possibly will lead to voltage collapse. Uncontrolled voltage collapse may lead to catastrophic system wide collapse and blackout. The degree of risk of an operating point with respect to voltage collapse violation is given by the risk of voltage collapse. The severity function for voltage collapse is system severity function rather than a component severity function. The widely used method in determining the severity of voltage collapse is by using the percentage of available load margin (Ni et al. 2003a; Xiao 2007). The risk of a contingency associated to voltage collapse is written as;

$$Risk_{VC} = \Pr(E_i) \times Sev_{VC}(E_i) \tag{2.4}$$

where E_i signifies the contingency and Sev_{VC} is the severity function for voltage collapse.

2.4 APPROACHES IN CONTINGENCY SCREENING

Power system security analysis is the most time demanding process due to large number of possible contingencies that need to be analyzed. The basic analysis method involves evaluation of security of a power system by using the complete AC power flow calculations considering all possible contingencies (Sidhu & Cui 2000). However, this method cannot satisfy the real-time demand due to the computation time constraints. A very well accepted contingency analysis procedure is by dividing the contingencies into a set of critical and non-critical contingencies (Castro et al. 1996). The process of identifying these critical contingencies is referred to as contingency selection.

In contingency selection phase, the original list of contingencies is screened to a shorter list by eliminating large number of cases expected to have no violation (Srivani & Swarup 2008). Contingency screening based on the performance index is the most widely used method in power system (Jasmon & Lee 1993; Arya et al. 2001; Chauhan 2005; Singh & Srivastava 2007). Performance index (PI) quantitatively measures the severity of security violation resulting from contingency in which a contingency is identified as critical if its PI value is greater than zero (Jain et al. 2003). The PI value is zero if there is no security violations otherwise its value will be more than zero depending upon the extent of security violation. Various types of PI have been developed in order to quantify the extent of security violation. Voltage PI is used to measure the extent of voltage limit violation due to transmission line outage (Jasmon & Lee 1993; Jain et al. 2003). The severity of line overload associated with transmission line outage is evaluated by using the line flow PI (Singh & Srivastava 2007; Srivani & Swarup 2008).

In voltage stability analysis, contingency screening based on the power margin reduction criteria is employed in which a contingency is classified as critical if it causes a power margin reduction to be larger than the maximum permissible load (de Moura & Prada 2005). The criteria used to screen the critical contingency cases are similar to performance index since it also measures the extent of violation in terms of the difference between power reduction margin and the maximum allowable load. The larger the difference, the more severe a contingency would be.

All the above mentioned methods for contingency screening only consider the severity of security violation without taking into account the probability of occurrence. If the probability of occurrence of a contingency is low, then the risk resulting from this contingency become relatively small, and in some cases it can be neglected (Hazra & Sinha 2010). A risk based contingency analysis that considers the probability of occurrence and severity will prioritize those contingencies which are reasonably severe as well as more probable for further analysis (Hazra & Sinha 2010). Therefore, a qualitative assessment by means of classification of contingencies into critical and non-critical contingencies considering the probability of occurrence as well as severity of security violation should be employed in power system security assessment.

2.5 APPROACHES IN RISK BASED STATIC SECURITY ASSESSMENT

Considerable amount of research has been done on the RBSSA in a power system. Earlier work on the application of risk assessment in line overload can be seen in McCalley et al. (1999a) in which a predefined list of transmission line outages in the order of 'N-1' is considered. A comparison between risk based and deterministic security assessments of line overload using a limited set of contingency in the order of 'N-1' and 'N-2' was discussed in Kirschen & Jayaweera (2007) in which the risk index computed was superimposed on the deterministic security boundary. Kirschen & Jayaweera (2007) showed that the operating risk level is nonzero even within the deterministic security region. The study on the application of RBSSA considering both low voltage and line overload can be seen in (Ming Ni et al. 2003a) and (McCalley et al. 2004). Online risk based security assessment discussed in Ming Ni et al. (2003a) provides rapid online quantification of a security level in terms of line overload and low voltage considering a pre-specified contingency set in the order of 'N-1', 'N-2' and 'N-3'. McCalley et al. (2004) plotted the risk index contour with a limited set of "N-1' contingency. However, consideration of a limited set of contingency does not explicitly and accurately reflect the level of operational risk.

Ni et al. (2003b) implemented speed enhancement for low voltage and line overload risk by using component screening and voltage sensitivity techniques. The component screening is a fast screening process that is applied on the power flow solution for each contingency to eliminate the zero risk contingency from consideration. Voltage sensitivity measures the sensitivity of bus voltage magnitude to bus power injection. In order to limit the number of contingency that needs to be considered in RBSSA, contingency selection and screening method is adopted. Contingency screening and ranking for line overload and low voltage using performance index is employed in Xiao (2007), in which only critical contingencies are considered. Contingency selection using performance index may restrict system operation because it computes the hard limits from the worst contingency for a given system condition (Hazra & Sinha 2010).

The determination of probability of contingency is an important aspect in RBSSA. Poisson probability distribution function utilizing fixed failure rate of transmission line is always assumed in RBSSA (Ni et al. 2003a; Ni et al. 2003b; McCalley 2004; Pampin et al. 2010). The probability of occurrence is highly dependent on the pre-calculated failure rate. However, the failure rate of the equipment may not be constant at all conditions. The use of fixed failure rate in calculating the probability of transmission line outage will underestimate the operational risk during adverse weather condition. The application of probability estimation in transmission line outage considering the effect of weather is implemented in Xiao & McCalley (2009) and De Almeida (2010). A varying failure rate for transmission line is developed using linear regression method based on the temperature, wind speed, voltage level and geographic location (Xiao & McCalley 2009). The total probability of fault in overhead transmission line is determined by the probability of occurrence of each individual cause of failure, such as lightning, forest fires and fog combined with pollution (De Almeida 2010).

Basically there are three types of severity function adopted in RBSSA, namely, discrete, continuous and percentage of violation severity functions. The continuous severity function is often used due to its advantage to capture the impact of near violating region (McCalley et al. 2004; Xiao & McCalley 2009; Pampin et al. 2010). The application RBSSA in a practical power system network incorporating percentage of violation severity function is considered in De Almeida et al. (2010). A comparison of risk index obtained using discrete, continuous and percentage of violation severity function is discussed in Ni et al. (2003a).

2.6 APPROACHES IN RISK BASED VOLTAGE COLLAPSE ASSESSMENT

The risk based voltage collapse assessment described in McCalley et al. (1999b) and Wan et al. (2000) take into consideration three forms of system uncertainty, namely transmission line outage, short term load forecast and maximum system loading. However, for simplicity only a limited set of transmission line outage is considered. The development of voltage collapse risk assessment presented in Leite da Silva et al. (2000) takes into account the uncertainty in system loads which is assumed to be linearly dependent without considering the uncertainty due to equipment outage. Uncertainties in the occurrence of credible contingencies and load conditions are considered in the assessment of risk of voltage collapse in Pampin et al. (2010).

To reduce the computational burden of RBVCA, contingency selection is usually performed at the initial stage. Contingency screening and ranking for RBVCA implemented in Ni et al. (2003a) utilizes sensitivity technique based on the loadability so as to filter out the zero risk contingency. The selection of credible contingencies from the contingency list based on the smallest active power transfer margin is employed in Pampin et al. (2010).

The earlier approach in calculating the probability of voltage collapse is by using a pre-assigned probability of failure for the transmission lines and assuming that the load variation follows normal distribution characteristic (McCalley et al. 1999b; Wan et al. 2000). The probability of voltage collapse is defined as the conditional probability of the load margin to be less than zero. In the implementation of online RBVCA, the probability of transmission line outage is assumed to be Poisson distributed, and the probability of voltage collapse is calculated using the total probability theorem (Ni et al. 2003a). Monte Carlo simulation has been used to evaluate the probability of voltage collapse by taking into account the uncertainty in power system parameters which are assumed to be normally distributed (Arya et al. 2006).

Major blackouts throughout the world are associated with voltage collapse. To avoid voltage collapse, an appropriate planning and control actions are required. RBVCA is a refined security assessment for voltage collapse that takes into account the uncertainty in the current operating point and the extent of voltage collapse violation. Severity of voltage collapse in terms of the expected cost of interruptions is adopted in Wan et al. (2000). Severity function based on the percentage of margin calculated using loadability obtained from continuation power flow and the forecasted load is applied in Ni et al. (2003a), Ni et al. (2003b) and Pampin et al. (2010). The probabilistic load flow and Monte Carlo simulation has been used to determine the risk of voltage collapse without taking into account the severity of the voltage collapse (Leite da Silva et al. 2000).

2.7 APPLICATION OF ARTIFICIAL INTELLIGENCE IN RISK BASED SECURITY ASSESSMENT

The application of artificial intelligence (AI) based methods in power systems has gained lots of interest due to the robustness and ability to perform complex analytical process. However, only little application of AI can be seen in the RBSA. Many of the existing online RBSA methods are developed by using the outputs of post-contingency power flow simulations as the input variables (Ni et al. 2003a; Ni et al. 2003b; Berrizi et al. 2009). The online RBSSA procedure discussed in Ni et al. (2003a) and (2003b) are based on the extensive power flow computations by considering the contingencies listed in the contingency list. To speed up the RBSSA procedure, contingency screening is implemented (Ni et al. 2003a; Ni et al. 2003b), but however, it can be very time consuming if the power system size is large. To achieve fast RBSSA, artificial intelligence techniques which have the capability to perform parallel data processing with high accuracy and fast response are applied. An AI method using neural network ensemble (NNE) has been developed for assessing the risk of low voltage measurements (Chen et al. 2006). In the NNE implementation, for quantifying the risk of low voltage within an acceptable error margin, bus voltage magnitudes at all the buses in the system are required as the NNE inputs. This method is considered inefficient for fast online RBSSA because power flow simulation for every contingency must be first executed successively prior to the computation of risk by a trained NNE network. Furthermore, the implementation of NNE in Chen et al. (2006) only provides the risk of contingency but not the cumulative risk.

The determination of the probabilistic risk of voltage collapse using the radial basis function network implemented in Arya et al. (2006) only calculates the probability of collapse without taking into account the severity of voltage collapse. Online voltage collapse risk quantification using fuzzy techniques, as employed in Berrizi et al. (2009), do not take into account the probabilistic nature of power system operation. To achieve a fast risk assessment of voltage collapse that considers the likelihood of the triggering event as well as its severity, artificial intelligence techniques that can perform parallel data processing with high accuracy and fast response times must be applied.

A proper selection of system features is an important factor that needs to be considered in achieving good AI performance. The dimension of system features will substantially increase if the power system is large. It has been observed that a large number of features may actually degrade the performance of AI model if the number of training samples is small relative to the number of system features (Li et al. 2006). In general, very large data would be needed to train well an AI model. Consequently, dimensionality reduction technique should be applied since the number of training samples is usually small due to the constraints in sample availability, time and cost. Feature extraction is considered as dimensionality reduction which is a transformation of the original dataset into a new space of lower dimension. Reduction in the number of input features obtained using feature extraction technique reduces the training time without losing the main information provided by the original dataset (Sawhney & Jeyasurya 2006). Hence so as to rapidly train the AI model with good performance measures and reduced computational burden, a feature extraction technique is implemented.

2.8 CHAPTER SUMMARY

The security of a power system can be assessed by using deterministic and probabilistic approach. Deterministic approach results in high security level due to the emphasis of severe and credible contingency. As a result of this, the existing power system network is not fully utilized and therefore, it can be difficult to integrate the security into economic decision making process. In order to fully utilize the existing power system network, more refined security assessment technique is required in which in this study RBSA is proposed. RBSA is a probabilistic security assessment technique that takes into account the uncertainty in the likelihood of the triggering event and its consequence. In this study, only uncertainty in the occurrence of transmission line outage is considered. Conversely, when considering the fault on transmission line, the effect of weather should be taken into consideration since the occurrence of transmission line outage is significantly affected by the weather. To incorporate the effect of weather on the occurrence of transmission line outage, an improved model of failure rate is developed in this study. The weather dependent failure rate model is then used to compute the probability of line outage. The risk index obtained by using RBSA method provides a measurable index to reflect the degree of risk of a given operating point. However, the implementation of RBSA in a large power system network may require long computation effort. To reduce the computational burden imposed by RBSA, critical contingency selection is required. The commonly used method for critical contingency selection based on the PI technique does not consider the effect of the probability of line outage. Hence, in this research work a newly developed technique based on the risk factor is proposed wherein the probability and severity of line outage are taken into consideration. The calculation of risk index involves complex analytical process in which the risk of each critical line outage needs to be computed for every operating condition. Therefore, to achieve fast RBSA, an AI technique can be implemented so as to automate the complex analytical process. Nevertheless, very little application AI technique in RBSA can be seen in the literature. In this research work, two AI techniques, namely SVM and GRNN are proposed in predicting the risk index of a given operating condition, and their performances are compared so as to select the best AI technique for RBSA.

CHAPTER III

COMPUTATION OF CONTINGENCY PROBABILITY

3.1 INTRODUCTION

The computation of probability of contingency is an essential step in RBSA. The occurrence of contingency is unpredictable and its occurrence is estimated using stochastic technique. Under the scope of this study, only uncertainty in the transmission outage is considered. In order to compute the probability of transmission line outage, a probability model characterizing the random process associated with the transmission line outage is assumed. Historical outage data is used to estimate the parameter of the assumed probability model. Transmission line outage is a weather dependent event, therefore the effect of weather is considered in developing the probability model of transmission line outage.

3.2 FAILURE RATE ESTIMATION RELATED TO WEATHER

The parameter that characterizes the probability model of transmission line is known as failure rate (Xiao 2007). The likelihood of transmission line outage is influenced by weather condition (Kirschen & Jayaweera 2007). Therefore, the failure rate of each line with respect to weather condition should be developed in order to capture the influence of weather so as not to underestimate the risk of security violation. A good estimate of failure rate is essential for system planning and operation and therefore, sufficiently large number of samples is required. However, the historical outage data obtained from a utility for a six-year period (January 2002 – December 2007) showed that for many transmission lines, little or no outage history exists. To address this issue, a data pooling procedure is proposed in which the transmission lines are group according to geographical location and their outage data is pooled. Data pooling method has been successfully applied in estimating the performance of a generating unit (Breipohl et al. 1995).

The data pooling procedure described in Xiao et al. (2006) is applied to address the above-mentioned issues. Given a set of historical data, the estimator is improved by grouping the lines and pooling their outage history data so that data from different components but with similar characteristics are combined. As a result, the size of the database in which the probability model parameter is computed increases and a better estimator of the failure rate of a component can be obtained.

Initially, the transmission outage data are pooled by geographical area under the assumption that the weather is relatively homogenous throughout the region. The outage data is then rearranged according to its pool and weather condition, as shown in Table 3.1.

Table 3.1 Data pooled to estimate the failure rate

Pool	**Pool 1**			**........**			**Pool Q**		
Weather	W_1	….	W_M	W_1	….	W_M	W_1	….	W_M
Line Outage									

In Table 3.1, transmission lines are grouped into ‘Q’ pools and each outage in the respective pools is classified as being associated with one of ‘M’ weather conditions. Therefore, for each pool there exist M weather types. The number of failures in each column of a respective pool is indicated as n, and the total length is denoted as l. The failure rate per unit mile of a transmission line in each data pool associated with a specific weather condition is calculated as,

$$\lambda(P, wc) = \frac{\left(\frac{n}{l}\right)}{T} \tag{3.1}$$

where P is defined as the pool number, wc is the weather condition, n is the number of observed failures, l is the total length of the line experiencing the outage in pool ‘P’ under the weather condition ‘m’ and T is the sample size.

The failure rate estimation is described in terms of a flowchart as shown in Figure 3.1.

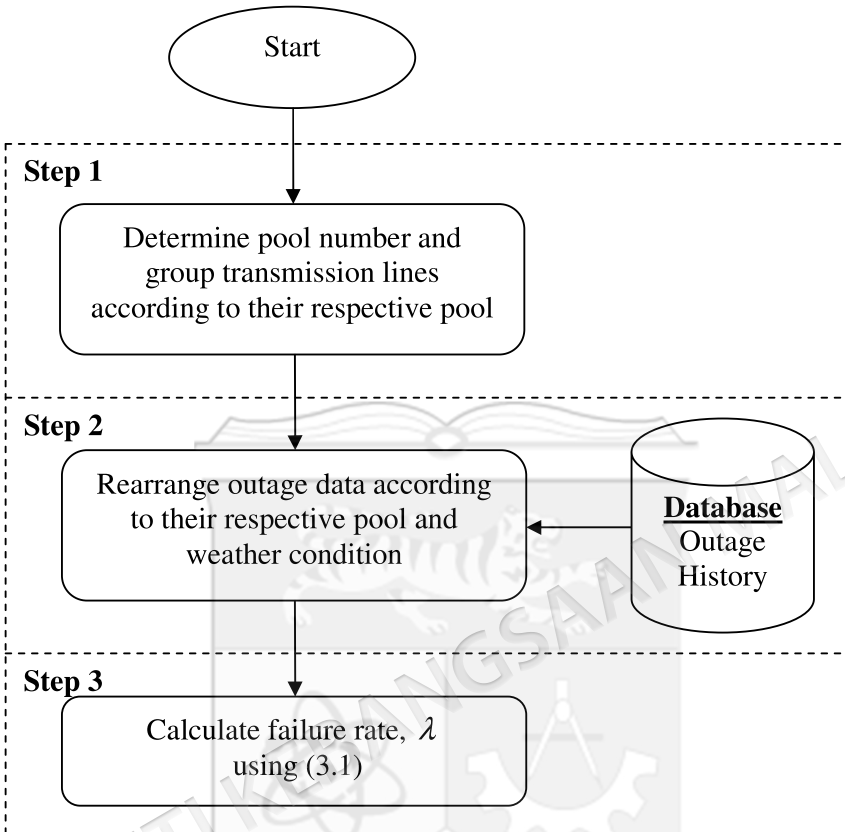

Figure 3.1 Estimation of failure rate using the data pooling method

3.3 COMPUTATION OF CONTINGENCY PROBABILITY

The probability of contingency is characterized by the failure rate of each transmission line. For a given weather condition, the failure rate with respect to weather determined in section 3.1 is used to compute the probability of transmission line outage. The probability of the next failure of a component can be represented by using Poisson model, and hence Poisson distribution function is used to model the random process associated with transmission line outage. Apart from using Poisson distribution function, Monte Carlo simulation is also employed in determining the probability of transmission line outage. The application of the non-sequential Monte Carlo in the probability estimation of voltage collapse can be seen in Arya et al. (2006).

3.3.1 Poisson Distribution

The probability of transmission line outage that can cause security violation is termed as event likelihood and it is assumed to follow the Poisson process characteristic (Ni et al. 2003a; Ni et al. 2003b; Wan et al. 2000; Xiao et al. 2006). The Poisson process counts the arrival of an event within a pre-defined time interval. The probability model of a Poisson random variable describes a phenomenon that occurs randomly in time, while the time of each occurrence is completely random and the average number of occurrences per unit time is known (Yates & Goodman 2005). The probability distribution function of a Poisson process is given by,

$$POISSON\,(x) = \frac{\lambda^{x} e^{-\lambda}}{x!} \tag{3.2}$$

where λ is the failure rate per unit time and x is the number of occurrence per unit time.

The probability for a particular transmission line to fail at least once in a given time interval can be calculated by using the cumulative distribution function. The cumulative distribution function estimates the probability that the random variable '*x*' is not larger than '*a*' and it is given by (Yates & Goodman 2005),

$$F_X(x) = POISSON(x \le a) \tag{3.3}$$

Therefore, the probability for a transmission line to fail at least once in the given time interval is given by,

$$\begin{aligned} PROB\,(F) &= POISSON\,(0 < x \le \infty) \\ &= F_X(\infty) - F_X(0) \\ &= 1 - POISSON\,(x = 0) \\ &= 1 - e^{-\lambda} \end{aligned} \tag{3.4}$$

In a transmission network, with a total of N lines, the probability for 'N-1' contingency can be derived as follows,

$$\Pr(E_i) = PROB\left(\overline{F_1} \bigcap \overline{F_2} \bigcap \cdots \bigcap F_i \bigcap \cdots \bigcap \overline{F_N}\right)$$

$$\Pr(E_i) = PROB(F_i)\prod_{j \neq i}^{N} PROB\left(\overline{F_j}\right)$$
$$= \left(1 - e^{-\lambda_i}\right) \times e^{-\sum_{j \neq i} \lambda_j} \tag{3.5}$$

The failure rate, λ of each transmission line determined by the using data pooling method is used to compute the probability of transmission line outage.

3.3.2 Monte Carlo Simulation

The Monte Carlo simulation method is the general designation for stochastic simulation using random numbers. The simulation process can be used to mimic the actual component and system behavior patterns in simulated time. Monte Carlo simulation uses random event generator that works by sampling a system state and it can be categorized into sequential and non-sequential sampling. Non-sequential Monte Carlo simulation is sometimes called the state sampling approach (Billinton & Tang 2004). The Monte Carlo simulation is based on the fact that a system state is a combination of all component states and each component state can be determined by sampling the probability of the component appearing in that state (Li 2005). The coefficient of variance, β, is often used as a stopping criterion in the Monte Carlo simulation. Non-sequential sampling is adopted in this study since it does not require chronological time dependant event. In the non-sequential method, the states of all components are sampled and a non-chronological system state is obtained (Billinton & Sankarakrishnan 1995). The basic sampling procedure of the non-sequential Monte Carlo is conducted by assuming that the behavior of each component can be categorized by probability distribution function.

Non-sequential Monte Carlo method is a stochastic simulation in which the randomness is introduced into simulation models via independent uniformly distributed random variables (Rubinstein & Kroese 2008). A pseudorandom generator which has the ability to capture the important statistical properties of true random sequence is commonly used in generating random variables. Linear congruential generator is a method used in pseudo random in which a deterministic sequence of number by means of the recursive formula are generated and it is given by (Rubinstein & Kroese 2008),

$$X_{i+1} = aX_i + c \pmod{m} \tag{3.6}$$

where the *a, c* and *m* (all positive integers) are called the multiplier, increment and modulus, respectively. The initial random number, X_0 is called the seed.

Linear congruential generator generates uniformly distributed random number. Therefore, in order to transform the uniformly distributed random number into a Poisson random variable, the inverse-transform method is applied. Let $F_x(x)$ be the cumulative distribution function of a given distribution. If *U* is a uniformly generated random number, then,

$$X = F^{-1}(U) \tag{3.7}$$

where X is a random variable.

In the Monte Carlo simulation, the state of the system containing N components is expressed by a vector, **S** which is defined as,

$$\mathbf{S} = [s_1, s_1, \ldots\ldots, s_i, \ldots\ldots\ldots s_N] \tag{3.8}$$

where s_i denotes the state of the ith component.

The state of each component can be expressed as,

$$s_i = \begin{cases} 0 \ (success), & X_i > PROB(F_i) \\ 1 \ (failure), & 0 \le X_i \le PROB(F_i) \end{cases} \tag{3.9}$$

When the number of samples is sufficiently large, the probability of each system state can be calculated as,

$$P(s) = \frac{m(s)}{M} \tag{3.10}$$

where *m(s)* is the number of occurrence of the system state and *M* is the number of samples.

By applying the non-sequential Monte Carlo simulation, the probability estimation is determined considering the procedures described as follows:

Step 1: Initialize the number of sample counter, M = 0.

Step 2: Generate random column vector, $\mathbf{U} = [u_1, u_2, ..., u_N]$ consisting of N elements, where N is the number of transmission lines.

Step 3: Transform the uniformly distributed random vector, **U** generated in step 2 into the Poisson random vector, $\mathbf{X} = [x_1, x_2, ..., x_N]$ using the inverse transform method.

Step 4: Determine vector $\mathbf{S} = [s_1, s_2, ..., s_N]$ that contains status of transmission lines by comparing each element in **X** with the respective probability of failure.

Step 5: Update M = M+1.

Step 6: Check if there is only one nonzero element in vector **S**, if yes proceed with Step 7, otherwise, repeat Step 2.

Step 7: Obtain the value of P_w^i using the following rule,

If s_i=1, then P_M^i=1 for i = 1, 2,…..,

Step 8: Estimate the probability of line outage by using,

$$p_i = \frac{\sum_{t=1}^{M} P_t^i}{M} \tag{3.11}$$

For i = 1,2,…..,N.

Step 9: Obtained coefficient of variation, β, which is given by (Arya et al. 2005),

$$\beta_i = \frac{\sqrt{\dfrac{V_i(X)}{M}}}{p_i} \tag{3.12}$$

For i = 1,2,…..,N and $V_i(X)$ is the variance of test function which is given by,

$$V_i(X) = \frac{\sum_{t=1}^{M} \left(P_t^i - p_i\right)^2}{(M-1)} \tag{3.13}$$

Step 10: If β ≤ ε, terminate the Monte Carlo simulation, otherwise repeat from Step 2 onwards. The value of ε is selected as 0.04 (Arya et al. 2006).

Step 11: Compute the relative error which is given by,

$$Error\,(\%) = \frac{|p_i - PROB(E_i)|}{p_i} \times 100 \tag{3.14}$$

where p_i is the probability calculated from the Monte Carlo simulation and $\Pr(E_i)$ is the probability calculated from the Poisson distribution.

3.4 CHAPTER SUMMARY

Failure rate of transmission lines depend on weather conditions to which they are exposed to. An improved failure rate model using data pooling method which considers the effect of weather described in this chapter provides more accurate probability estimation of the line outage. The proposed failure rate model is used in predicting the probability of transmission line outage with respect to weather condition. The probability of transmission line outage computed using weather dependent failure rate model is useful for real-time RBSA, where probability of transmission line failure with respect to weather and severity of contingency are combined to identify the risk of contingency. A procedure for probability estimation of transmission line outage using Poisson distribution function and non-sequential Monte Carlo simulation are discussed in this chapter.

CHAPTER IV

IMPLEMENTATION OF RISK BASED STATIC SECURITY ASSESSMENT AND RISK BASED VOLTAGE COLLAPSE ASSESSMENT

4.1 INTRODUCTION

In this study, the RBSA technique is applied on the static security assessment which includes low voltage and line overload, and voltage collapse assessment. Uncertainty in the occurrence of contingencies and its impact towards security violations are considered in the computation of risk index. In a power system, the list of possible contingencies includes equipment outage such as generator, transformer or transmission line outage. For this study, only uncertainty in the occurrence of transmission line outage is considered and its impact in terms of severity is adopted to uniformly quantify the extent of security violation. The probability of transmission line outage with respect to weather conditions has been described in Chapter III. For risk based static security assessment (RBSSA), the severity functions considered are of types, discrete, continuous and percentage of violation. A new severity function based on voltage collapse proximity index is proposed for risk based voltage collapse assessment (RBVCA). The computation of risk index for a given operating condition involves calculating the risks of all transmission line outages. However, in a large power system network it may be impractical to evaluate the risk of all transmission line outages since the number of transmission lines is usually very big. Therefore, in this research work, contingency screening based on the risk factor is proposed to select the critical transmission line outages.

4.2 SEVERITY FUNCTIONS FOR LOW VOLTAGE

The severity function for low voltage is defined specific to each bus (Ni et al 2003a). The voltage magnitude of each bus determines the low voltage severity of that bus. In discrete severity function, severity is assigned a value 1 if the bus voltage magnitude, V_j is lower than 0.95 and a value 0 otherwise. The diagram of discrete severity function for low voltage is shown in Figure 4.1.

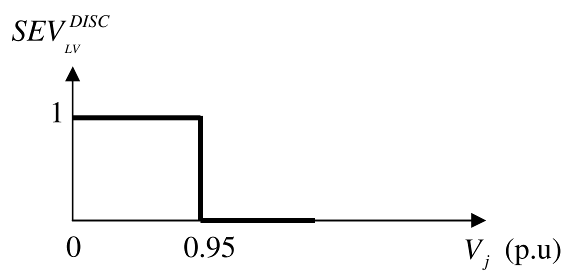

Figure 4.1 Discrete severity function for low voltage (Ni et. al 2003a)

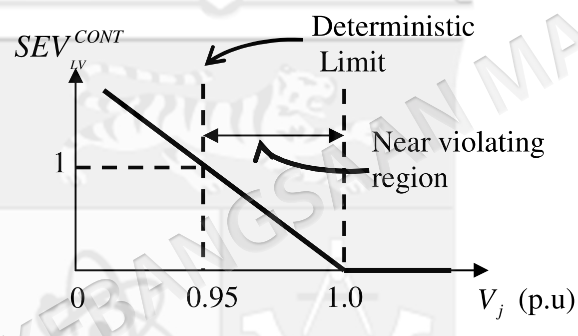

Figure 4.2 Continuous severity function for low voltage (Ni et al. 2003a)

The continuous severity function for low voltage is illustrated in Figure 4.2. At each bus, the severity function evaluates to 1 at the deterministic limit of 0.95 p.u and increases linearly as the voltage magnitude decreases. The bus voltage magnitude is at the near violating region of low voltage if its magnitude is between 0.95 to 1.0 p.u.

The percentage of violation for severity function of low voltage is given as (Xiao 2007),

$$SEV_{LV}^{PERCENT}\left(V_j\right)=\begin{cases}\dfrac{0.95-V_j}{0.95} & ,V_j \leq 0.95 \\ 0 & ,V_j > 0.95\end{cases} \tag{4.1}$$

To assess the severity of low voltage during a transmission line outage, the severity of low voltage at all buses needs to be evaluated. Therefore, for a given transmission line outage, the severity of low voltage violation is given by,

$$SEV_{LV}^{TYPE}(E_i) = \sum_{k=1}^{No.of\ bus} SEV_{LV}^{TYPE}(V_k) \tag{4.2}$$

where *TYPE* signifies the type of severity function which is either discrete, continuous or percentage of violation severity function.

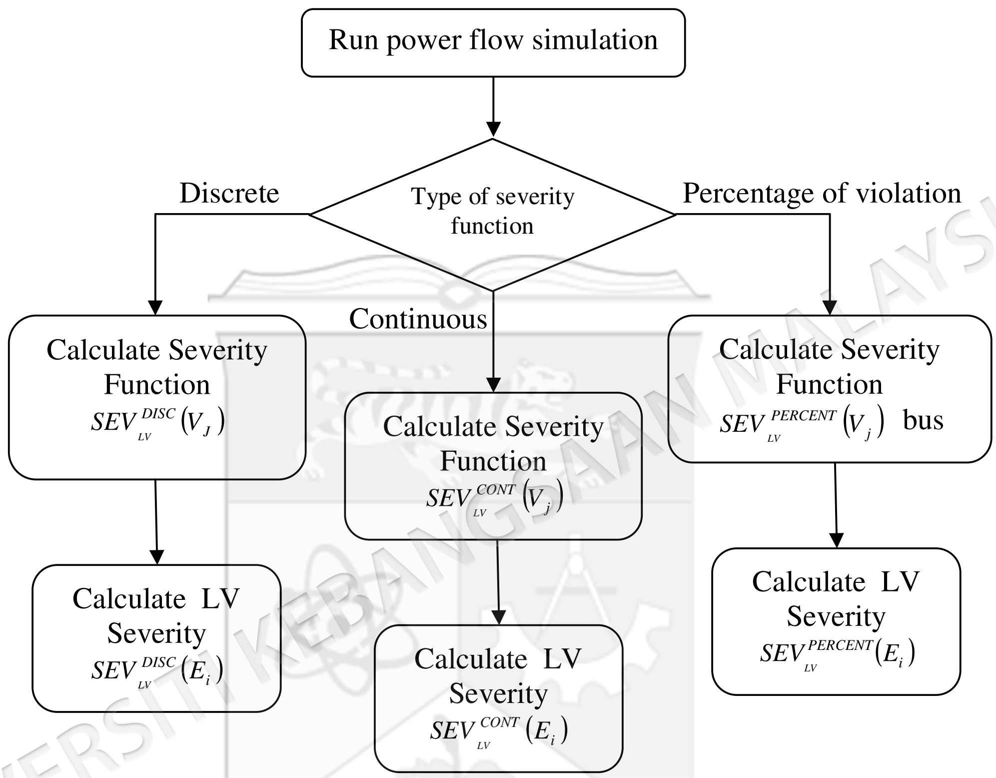

Figure 4.3 Calculation of severity function and severity of low voltage

Figure 4.3 illustrates the procedure in calculating the severity function and the severity of low voltage. To evaluate the severity function of low voltage, the bus voltage magnitudes during a transmission line outage must be examined. Therefore, line outage simulation is carried out to determine the bus voltage magnitudes.

4.3 SEVERITY FUNCTIONS FOR LINE OVERLOAD

The severity function for line overload is defined specific to each branch (Ni et al. 2003a). The ratio of power flow, L_{flow} to line rating, L_{rating}, at each line determines the overload severity. The ratio of power flow, *PR* for each line is defined as,

$$PR = \frac{L_{flow}}{L_{rating}} \tag{4.3}$$

For discrete severity function of line overload, the severity is assigned a value of 1 if the line flow is greater than the line rating and a value 0 otherwise (Ni et al. 2003a). The discrete severity function of line overload is shown in Figure 4.4.

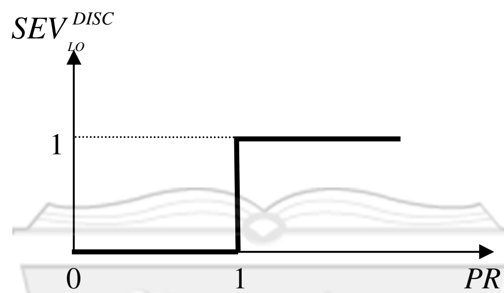

Figure 4.4 Discrete severity function of line overload

Source: Ni et al., 2003a

The continuous severity function of line overload is illustrated in Figure 4.5. At each branch, the severity function equals to 1 at the deterministic limit and increase linearly as line flow exceeds the limit (Ni et al. 2003a). The line flow at a branch is at the near violating region of line overload if the *PR* is between 0.9 to 1.0.

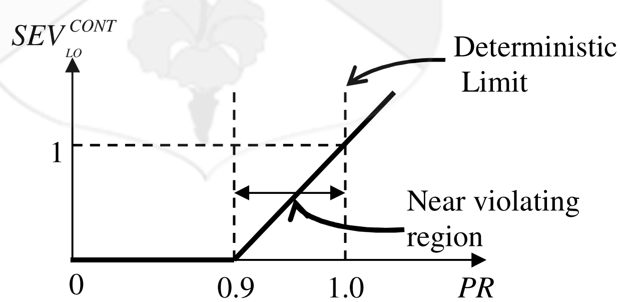

Figure 4.5 Continuous severity function for line overload

Source: Ni et al., 2003a

The percentage of violation for severity function of line overload is given as follows (Xiao 2007);

$$SEV_{LO}^{PERCENT}\left(L_j\right) = \begin{cases} \left(PR-1\right), & PR \geq 1 \\ 0, & PR < 1 \end{cases} \tag{4.4}$$

To assess the severity of line overload for each contingency, the severity function of line overload for all the lines in a power system needs to be evaluated. Therefore, for a given transmission line outage, the severity of line overload violation is given by,

$$SEV_{LO}^{TYPE}(E_i) = \sum_{t=1}^{No.of\ branch} SEV_{LO}^{TYPE}(L_t) \tag{4.5}$$

To calculate the severity function of line overload, power flow simulation is carried out to determine the power flow during transmission line outage. The diagram shown in Figure 4.6 demonstrates the procedure in calculating the severity function of line overload (LO).

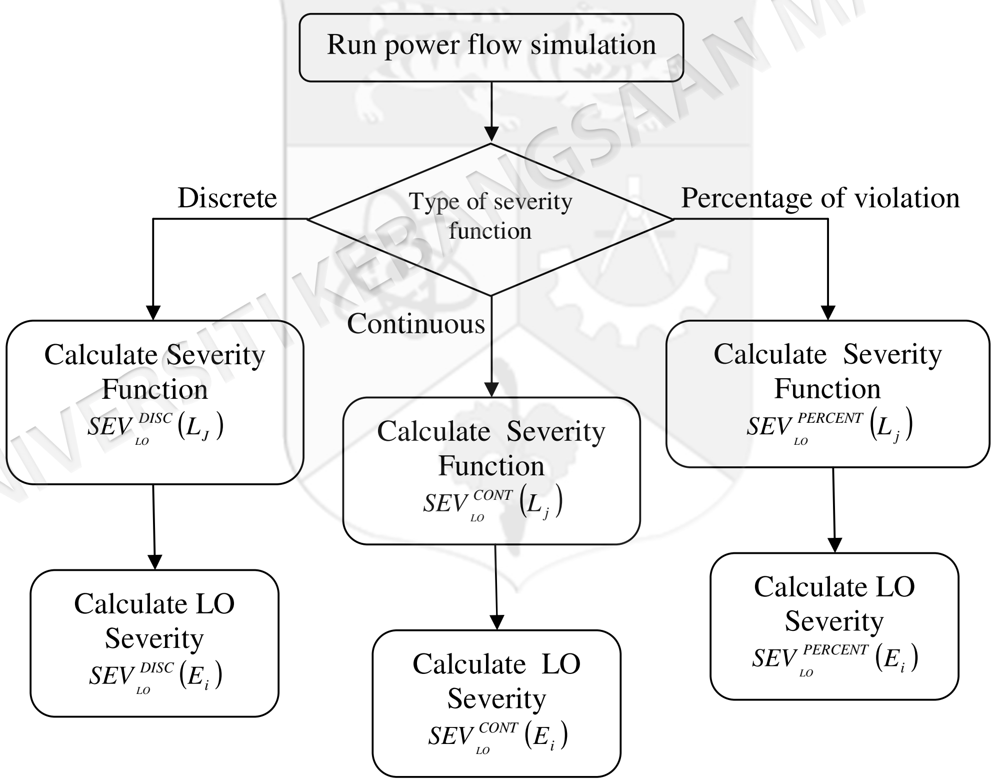

Figure 4.6 Calculation of severity function and severity of line overload

4.4 SEVERITY FUNCTION FOR VOLTAGE COLLAPSE

The percentage of loading margin is the commonly used index to quantify the severity of voltage collapse. It is defined as the percentage difference between the load and loadability, and is expressed as (Ni et al. 2003a; Xiao 2007),

$$\text{load margin} = \frac{Loadability - Load}{Load} \times 100 \tag{4.6}$$

The concept of loadability and load margin is illustrated as shown in Figure 4.7. Loadability is defined as the maximum allowable load, while the load margin quantifies the permissible load increment before a voltage collapse takes place.

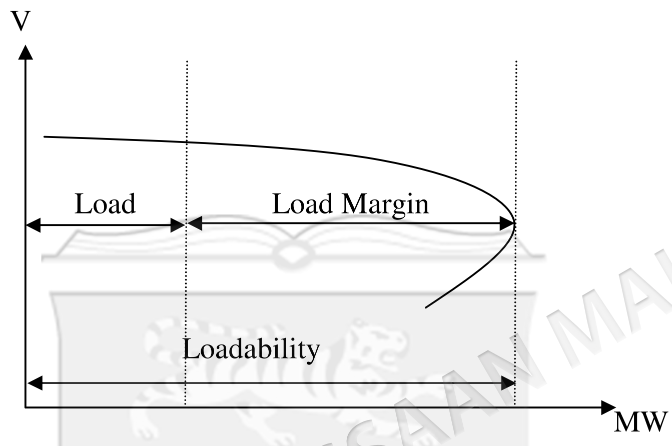

Figure 4.7 Concept of loadability and load margin

The discrete severity function of voltage collapse based on the percentage of load margin is shown in Figure 4.8. If the percent of load margin is less than zero, a voltage collapse will occur in a given contingency state for a particular operating condition. When a voltage collapse takes place, the severity function value is assigned a value of 100 (McCalley et al. 2000). This is due to the fact that the consequence is very severe and generally unacceptable. Therefore, whenever a voltage collapse occurs, the risk of contingency will become large, due to the very high severity value of 100.

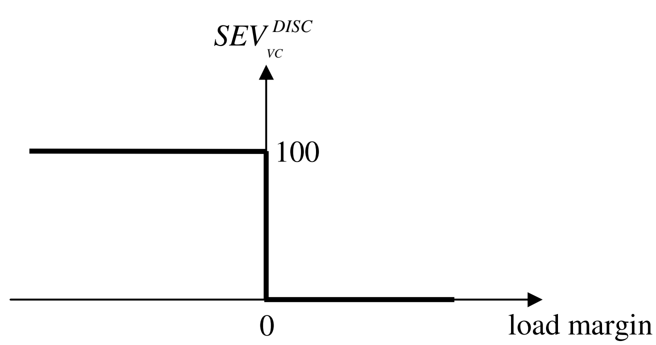

Figure 4.8 Discrete severity function of voltage collapse

Source: McCalley et al., 2000

The continuous severity function of voltage collapse is illustrated in Figure 4.9. The severity value evaluates to 1 when the percent of load margin is 10% and this value is chosen as the minimum safe margin (McCalley et al. 2000). The continuous severity function value increases as the percentage of load margin decreases.

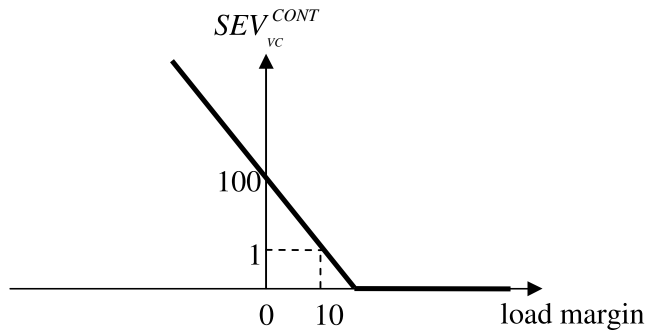

Figure 4.9 Continuous severity function of voltage collapse

Source: McCalley et al., 2000

4.4.1 New Severity Function for Voltage Collapse

In this study, a severity function based on the voltage collapse prediction index (VCPI) is proposed because the consequences are easily understood in terms of network parameters. In addition, it also reflects the relative severity of different problems, which enables a composite risk index to be calculated. VCPI is calculated at every bus using the voltage phasor measurement and network admittance matrix and it is given by the following relationship (Balamourougan et al. 2004),

$$VCPI_k = \left| 1 - \frac{\sum_{\substack{m=1 \\ m \neq k}}^{No.of\ bus} V'_m}{V_k} \right| \tag{4.7}$$

in which V'_m is given by,

$$V'_m = \frac{Y_{km}}{\sum_{\substack{j=1 \\ j \neq k}}^{No.of\ bus} Y_{kj}} V_m \tag{4.8}$$

where V_k is the voltage phasor at bus 'k', V_m is the voltage phasor at bus 'm' and Y_{km} is the admittance between bus 'k' and 'm' .

If the VCPI value is zero, the bus is considered voltage stable, and if the VCPI value is one, a voltage collapse is said to occur. The VCPI value is zero when no load is assigned to the load bus. Table 4.1 shows the variation of VCPI value with respect to the load margin.

Table 4.1 Variation of VCPI with respect to load margin

Load	**Load Margin**	**VCPI**
Load < Loadability	Loadability – Load > 0	0 < VCPI < 1
Load > Loadability	Loadability – Load < 0	VCPI = 1

From Table 4.1, it is noted that the VCPI value is between zero to one if the assigned load is less than the loadability. If the assigned load to the load bus exceeds the loadability, a voltage collapse will take place. The bus with the largest VCPI value is the weakest bus in the network. Therefore, the severity function due to transmission line outage leading to voltage collapse utilising the VCPI index is defined as follows,

$$SEV_{VC}^{NEW}(E_i) = \max(VCPI_1, VCPI_2, \ldots, VCPI_M) \tag{4.9}$$

where M is the number of buses in a power system.

4.5 TRANSMISSION LINE OUTAGE SCREENING

For large power system network, that is complex and highly interconnected, great number of possible transmission line outages may occur. Hence, an exhaustive power flow analysis is required in order to assess the security of a power system due to a long list of possible transmission line outages. To reduce the computational burden, transmission line outage screening is performed to quickly identify and filter out the critical transmission line outages which may cause security violation.

Most of the previous contingency screening methods are based on performance index, in which a contingency is screened and ranked according to the index values and its severity towards security violation (Arya et al. 2001; Flueck et al. 2002; Amjady & Esmaili 2005; de Moura & Prada 2005). A transmission line outage is considered critical if the impact towards security violation is greater than zero. However, if the probability of the transmission line outage is low, then the risk resulting from this contingency becomes relatively small, and in some cases it can be neglected (Hazra & Sinha 2010). In this RBSA study, transmission line outage screening based on the risk factor is considered. The risk factor takes into consideration the probability of transmission line outage and its severity towards security violation so as to prioritize those transmission line outages which are reasonably severe as well as more probable.

To screen the critical transmission line outages, the probability of transmission line outage and the severity of low voltage, line overload and voltage collapse at base case condition must first be computed. The probability and severity values have to be normalized between 0.1 and 0.9 using the following general equation (Basheer & Hajmeer 2000).

$$x_i = 0.1 + (0.9 - 0.1)\left(\frac{z_i - z_i^{\min}}{z_i^{\max} - z_i^{\min}}\right) \tag{4.10}$$

where x_i is the normalized value of z_i, and $z_i^{\max}$ and $z_i^{\min}$ are the maximum and minimum values of z_i in the database.

Table 4.2 Classification of probability of transmission line outage

Range	**Class**	**Probability Factor**
$0.1 \le \text{Prob}_{\text{norm}} \le 0.36$	Low (L)	1
$0.36 < \text{Prob}_{\text{norm}} \le 0.62$	Medium (M)	2
$0.62 < \text{Prob}_{\text{norm}} \le 0.9$	High (H)	3

Source: Srivastava et al., 1999

Table 4.3 Classification of severity function value

Range	**Class**	**Severity Factor**
$0.1 \le \text{SEV}_{\text{norm}} \le 0.4$	Low (L)	1
$0.4 < \text{SEV}_{\text{norm}} \le 0.8$	Medium (M)	2
$0.8 < \text{SEV}_{\text{norm}} \le 0.9$	High (H)	3

Source: Srivastava et al., 1999

The normalized values of probability of transmission line outage and its severity are then classified into low, medium or high as depicted in Tables 4.2 and 4.3, respectively. Each class in the probability of transmission line outage is assigned a probability factor value of 1, 2 or 3 corresponding to low, medium or high probability of occurrence correspondingly. Similarly, each class in the severity function value is assigned a severity factor value. The classification of probability of transmission line outage and severity function value is shown in Tables 4.2 and 4.3, respectively (Srivastava et al. 1999).

$Prob_{norm}$ is the normalized probability of transmission line outage and SEV_{norm} is the normalized severity function value.

Based on the definition of risk of line outage given in (2.2), (2.3) and (2.4), the risk factor of a line outage can be calculated as,

$$\text{Risk Factor} = \text{Probability Factor} \times \text{Severity Factor} \quad (4.11)$$

Table 4.4 Risk factor values associated with probability factor and severity factor

Probability Factor	Severity Factor	Risk Factor
1 (L)	1 (L)	1
	2 (M)	2
	3 (H)	3
2 (M)	1 (L)	2
	2 (M)	4
	3 (H)	6
3 (H)	1 (L)	3
	2 (M)	6
	3 (H)	9

Table 4.4 shows all possible risk factor values associated with the probability factor and severity factor. A transmission line outage is classified as critical if its risk factor value is greater than 1. A risk factor of 1 is chosen as the threshold for critical and non-critical contingency since the risk resulting from a transmission line outage with a risk factor of 1 is relatively small. This is due to the fact that the transmission line outage is a rare event and its probability is usually in the range of 10^{-7} to 10^{-5}, and the severity of a security violation can be as small as 10^{-2}, thus by multiplying a low probability event with low severity of security violation, the risk of transmission line outage will become even smaller. Therefore, the risk of transmission line outage with low probability of occurrence and low severity of security violation can be discarded since its risk is insignificant. Therefore, only transmission line outage with significant contribution to the risk index is considered for further analysis.

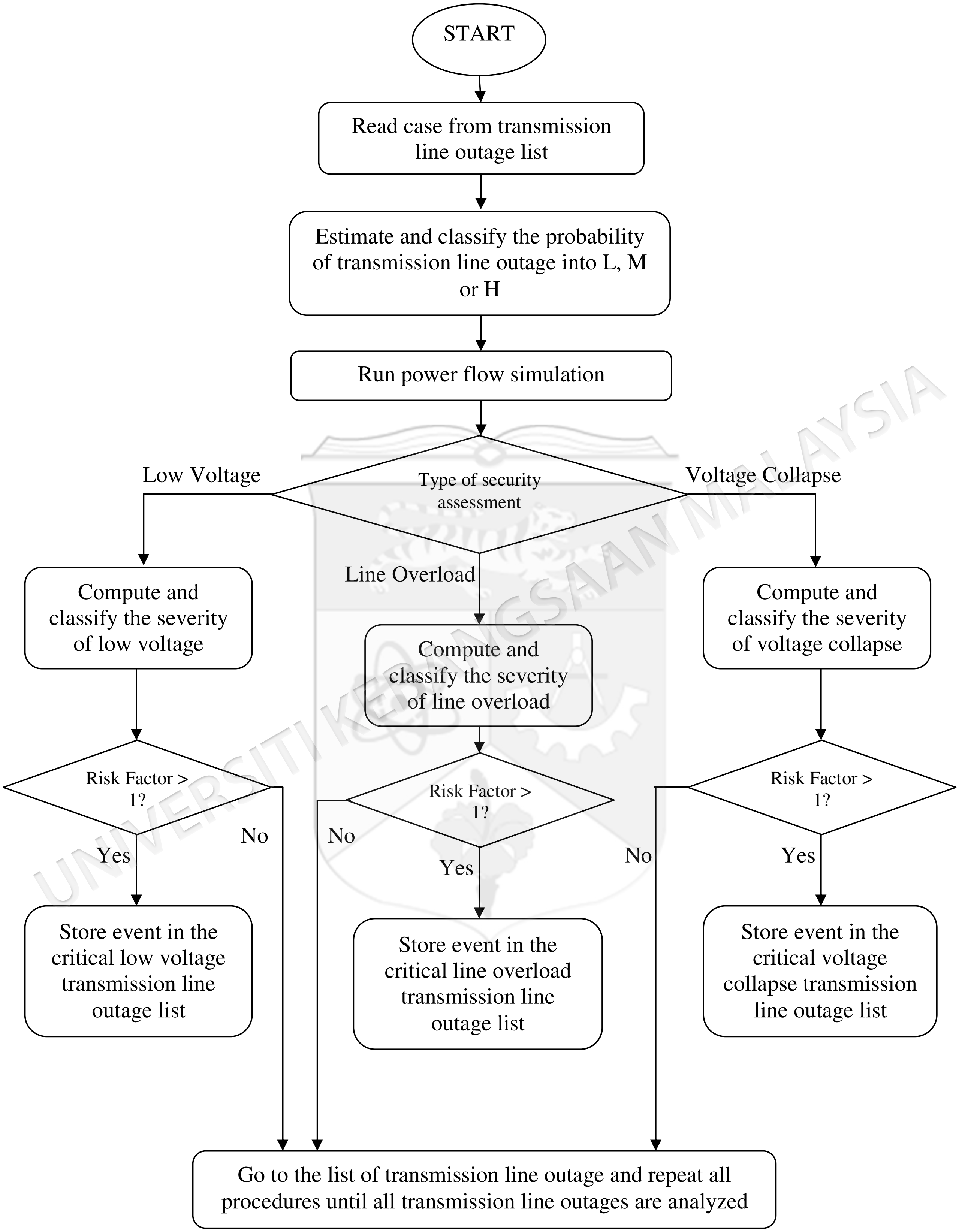

Figure 4.10 Procedure for transmission line outage screening

The screening of each transmission line outage into critical and non-critical with respect to low voltage, line overload and voltage collapse are performed and the list of critical transmission line outage with respect to each security violation are then developed. The flowchart shown in Figure 4.10 summarized the procedure for transmission line outage screening proposed in this study. From Figure 4.10, the estimated probability of transmission line outage is classified into L, M or H according to the classification shown in Table 4.2. Depending on the type of security violation considered, the severity of a transmission line outage is computed and classified into L, M or H according to the classification table shown in Table 4.3. Then, the risk factor of each transmission line outage towards low voltage, line overload and voltage are computed. The transmission line outage is considered critical if the risk factor is greater than 1. The critical transmission line outages associated with low voltage, line overload and voltage collapse is stored in each respective contingency list. These procedures are carried out for all transmission line outages considered in the study.

4.6 RISK OF CRITICAL TRANSMISSION LINE OUTAGE

Risk index of a given operating condition is evaluated by summing all risks of critical transmission line outage (McCalley et al. 1999). Therefore, risk of critical transmission line outage with respect to low voltage, line overload and voltage collapse needs to be first computed at any given operating point. The risks of critical transmission line outage associated with low voltage, $Risk_{LV}(E_i)$, line overload, $Risk_{LO}(E_i)$ and voltage collapse, $Risk_{VC}(E_i)$ consist of two elements, which are the probability and severity of low voltage, line overload and voltage collapse, respectively, and are given by,

$$Risk_{LV}(E_i) = \Pr(E_i) \times SEV_{LV}^{TYPE}(E_i) \tag{4.12}$$

$$Risk_{LO}(E_i) = \Pr(E_i) \times SEV_{LO}^{TYPE}(E_i) \tag{4.13}$$

$$Risk_{VC}(E_i) = \Pr(E_i) \times SEV_{VC}^{NEW}(E_i) \tag{4.14}$$

where $\Pr(E_i)$ is the probability of critical transmission line outage, and $SEV_{LV}^{TYPE}(E_i)$, $SEV_{LO}^{TYPE}(E_i)$ and $SEV_{VC}^{TYPE}(E_i)$ are the severity of low voltage, line overload and voltage collapse, respectively.

4.7 IMPLEMENTATION OF RISK BASED STATIC SECURITY ASSESSMENT

The implementation of RBSSA includes low voltage and line overload, since low voltage and line overload may weaken the transmission network. Severity functions are adopted to uniformly quantify the severity of network performance for low voltage and line overload. Three types of severity functions are considered in this study, namely, discrete severity function, continuous severity function and percentage of violation severity function. The RBSSA proposed in this research work computes the risk index associated with load demand considering uncertainties in the transmission line outages.

4.7.1 Risk Index Calculation for Low Voltage

The risk index calculation involves estimating the probability of transmission line outage and computes the severity function value. For a given operating condition, the probability and severity function value for all critical transmission line outages considered must be computed. The risk index of a given operating condition is equal to the combination of all the risks of critical transmission line outages.

The calculation of risk index for low voltage implemented in this study is performed by considering the steps shown in Figure 4.11. For a given weather condition, the probability of each transmission line outage is estimated using the value of failure rate calculated from the data pooling method described in Chapter III. For every critical transmission line outage and loading condition considered in the study, a contingency analysis by means of power flow simulation is carried out by using the Power System Analysis Toolbox (PSAT) (Milano 2007). The purpose of contingency analysis is to examine the magnitude of bus voltage at all buses. The value of severity function at each bus is computed by either using discrete, continuous or percentage of violation severity function. The severity of a critical transmission line outage with respect to low voltage, $SEV_{LV}^{\;TYPE}(E_i)$ and the risk of critical transmission line outage associated with low voltage, $Risk_{LV}(E_i)$, are then calculated.

For a given load and weather condition, the risk of low voltage is calculated by summing all the risk of critical transmission line outages associated with low voltage and it is given by,

$$Risk(LV) = \sum_{l=1}^{N_{LV}} Risk_{LV}(E_l) \tag{4.15}$$

where N_{LV} is the number of critical transmission line outage associated with low voltage.

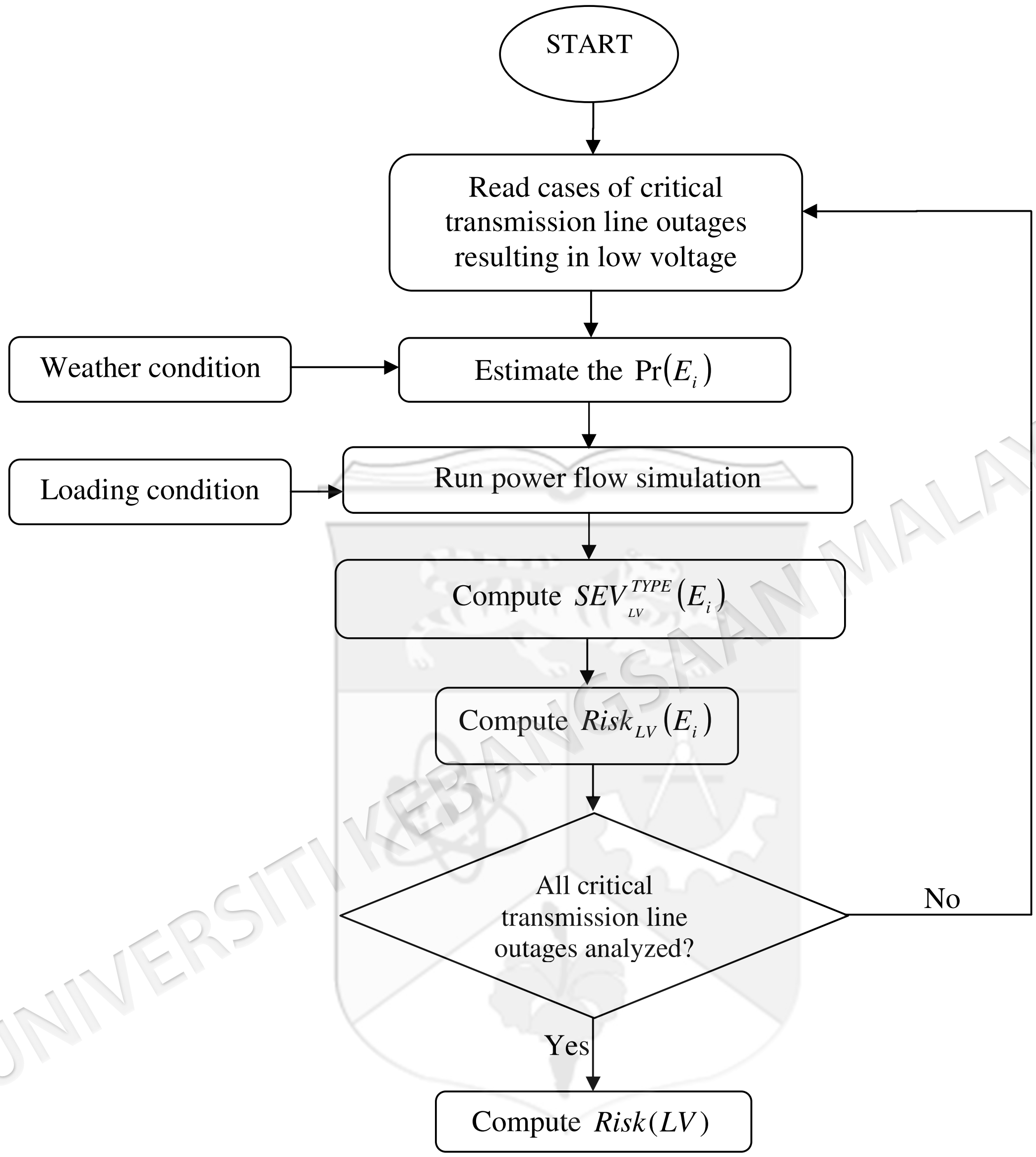

Figure 4.11 Calculation of risk index of low voltage

4.7.2 Risk Index Calculation for Line Overload

The calculation of risk index for line overload implemented in this study is performed by considering the steps shown in Figure 4.12. To calculate the risk of line overload, the probability and severity of line overload for all the critical line outages must be determined as shown in the figure.

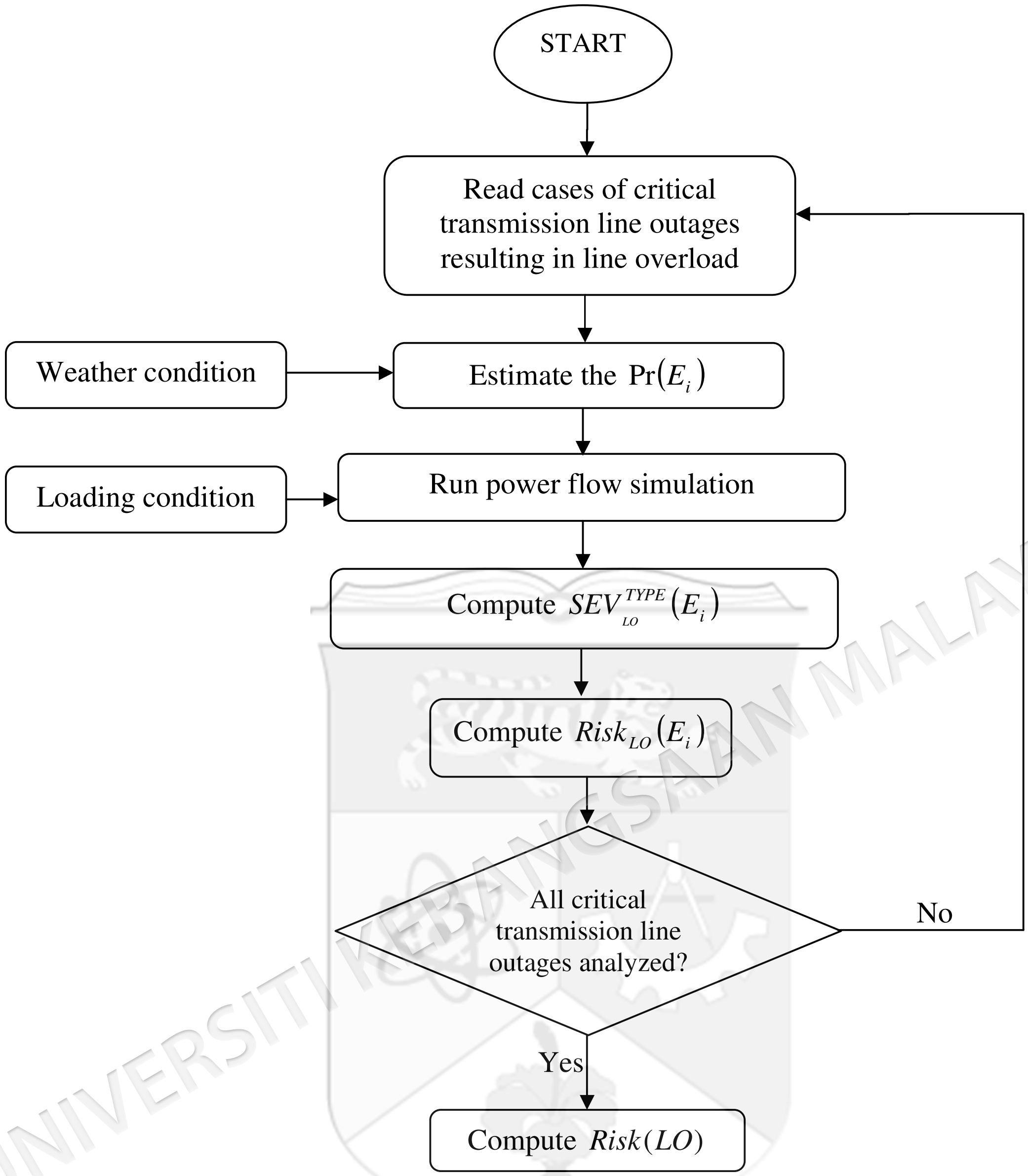

Figure 4.12 Calculation of risk index of line overload

Here, the probability of a transmission line outage with respect to weather condition is calculated by using the weather-dependent failure rate model described in Chapter III. Line outage simulations are performed using the PSAT software program to determine the power flow of all lines for the cases of the critical transmission line outages. The severity of line overload of the critical transmission line outage cases and the severity function values of all lines are computed using either discrete, continuous or percentage of violation severity function. Once the severity function of line overload, $SEV_{LO}{}^{TYPE}(E_i)$ is computed, the risk of critical transmission line outage associated with line overload can then be evaluated by multiplying the probability and severity of line overload of a critical transmission line outage.

For a given load and weather condition, the risk of line overload is obtained by summing all the risks of critical transmission line outages associated with line overload, and is given by,

$$Risk(LO) = \sum_{l=1}^{N_{LO}} Risk_{LO}(E_l) \tag{4.16}$$

where N_{LO} is the number of critical transmission line outage associated with line overload.

4.8 IMPLEMENTATION RISK BASED VOLTAGE COLLAPSE ASSESSMENT

RBVCA proposed in this study measures the degree of risk of a given operating point towards voltage collapse considering only uncertainty in transmission line outages. In the past, the loading margin computed using loadability value obtained from continuation power flow simulation is used to compute the severity of voltage collapse (Ni et al. 2003a; Ni et al. 2003b; Xiao 2007). In this research work, severity based on voltage collapse proximity index (VCPI) is proposed since the calculation of VCPI is simple and it only utilizes information obtained from AC power flow simulation.

4.8.1 Risk Index Calculation for Voltage Collapse

The calculation of risk index in RBVCA implemented in this study is performed by considering the steps shown in Figure 4.13. For a given weather condition, the probability of each critical transmission line outage considered in the study is estimated using the value of failure rate calculated from the data pooling method described in Chapter III.

For every critical transmission line outage and loading condition considered in the study, a contingency analysis is carried out. Contingency analysis by means of continuation power flow simulation is performed if the severity of voltage collapse is evaluated based on the percentage of load margin. However, if the severity of voltage collapse is assessed by using the VCPI, AC power flow simulation is performed. Both continuation and AC power flow simulations are carried out by using the PSAT program (Milano 2007). The severity of a transmission line outage with respect to voltage collapse, $SEV_{vc}^{NEW}(E_i)$ is then calculated by using (4.9).

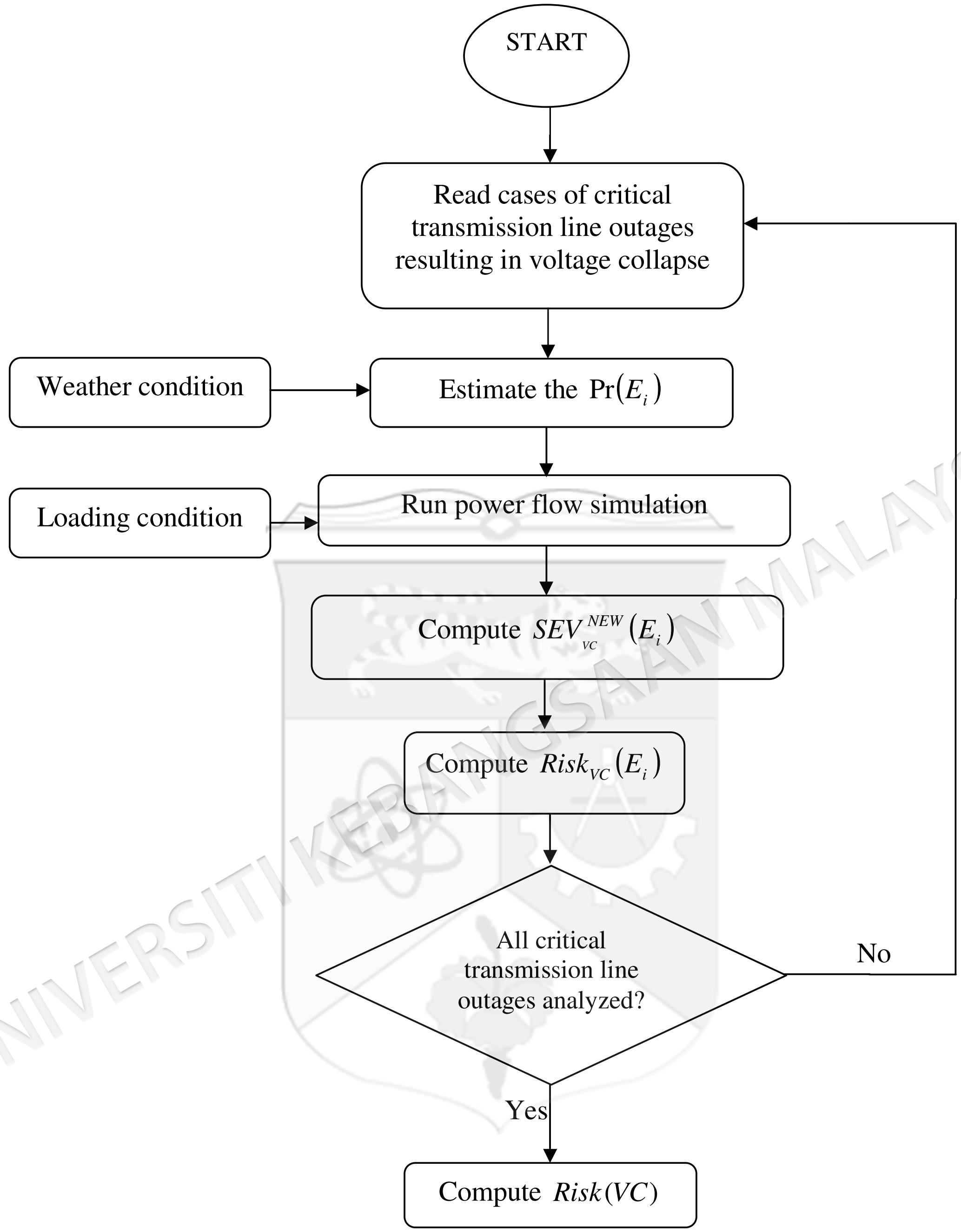

Figure 4.13 Calculation of risk index of voltage collapse

For a given load and weather condition, the risk of voltage collapse is obtained by summing all the risks of critical transmission line outages associated with voltage collapse and it is given by,

$$Risk(VC) = \sum_{l=1}^{N_{VC}} Risk_{VC}(E_l) \tag{4.17}$$

where N_{VC} is the number of critical transmission line outage associated with voltage collapse.

4.9 CHAPTER SUMMARY

The implementation of RBSSA and RBVCA considering low voltage, transmission line limit and voltage collapse violations are presented in this chapter. Transmission line outage screening by using risk factor is proposed to determine the critical transmission line outages so as to reduce the number of transmission line outage for further analysis. Only the critical transmission line outages that result in low voltage, line overload and voltage collapse are considered in the risk index calculation for low voltage, line overload and voltage collapse, respectively. To calculate the risk of a critical transmission line outage, the probability and the consequence of a critical transmission line outage in terms of its severity are considered. Three types of severity functions, namely, discrete, continuous and percentage of violation severity function are considered in the RBSSA. A new severity function based on the VCPI is proposed since it only requires information obtained from the AC power flow. For a given operating condition, the risk indices of low voltage, line overload and voltage collapse conditions are calculated by combining all the risks of critical transmission line outages associated with low voltage, line overload and voltage collapse, respectively.

CHAPTER V

APPLICATION OF SUPPORT VECTOR MACHINE AND GENERALIZED REGRESSION NEURAL NETWORK FOR RISK BASED SECURITY ASSESSMENT

5.1 INTRODUCTION

In recent years, there is a growing interest in applying the artificial intelligent techniques to solve power system related problems due to its advantage of modeling any non-linear function without knowledge of the actual model structure. In addition, the application of AI has shown great promise in power systems due to its ability to synthesize complex analytical process accurately and rapidly. However, only little application of AI can be seen in solving the RBSA problem. Previously, the application of AI in RBSA only handles a single contingency scenario in which only the risk of single transmission line outage is computed (Chen et al. 2006). The process becomes laborious if the risk index of a given operating condition needs to be evaluated by taking into account the risk of all transmission line outages. To achieve fast RBSA, AI techniques with the capability of handling all critical transmission line outages are applied. The proposed methodology uses support vector machine (SVM) and generalized regression neural network (GRNN) for prediction of the risk index associated with low voltage, line overload and voltage collapse. The purpose is to compare the performance of GRNN and SVM in predicting the risk index in RBSSA and RBVCA of a power system by incorporating a weather dependent failure rate for the probability of transmission line outage. To reduce the input dimension and the size of the GRNN and SVM, feature extraction based on the principle component analysis is adopted in this research work. If a large number of inputs are used, the size of the SVM and GRNN will increase, and the training process will be extremely slow.

5.2 SUPPORT VECTOR MACHINES

SVM which was first introduced by Vapnik in the late 1960s is an excellent tool for solving classification and regression problems with good generalization performance. The SVM which is based on the foundation of statistical learning theory is a general classification method (Vapnik 1999; Cristianini & Shawe-Taylor 2000). SVM works in the high dimensional feature space formed by the nonlinear mapping of the N-dimensional input vector, x into a K-dimensional feature space (K > N) through the use of function, φ(x). K is the number of hidden units which are also known as the support vectors.

Given a set of data points, $\{(\mathbf{x}_1, y_1),....,(\mathbf{x}_\ell, y_\ell)\}$, such that $\mathbf{x}_i \in R^n$ is an input and $y_i \in R^n$ is a target output, the estimated function is given as,

$$f(x) = \mathbf{w}^T \varphi(\mathbf{x}) + b \tag{5.1}$$

where $\mathbf{w} = [w_0, w_1, \ldots\ldots, w_k]^T$ is the weight vector matrix with $\|\mathbf{w}\|^2$ less than a user specified constant *C*.

Learning is motivated through a linear ε-insensitive loss function which is defined as,

$$L(\mathbf{x}, y, f) = \max\left(0, |y - f(\mathbf{x})| - \varepsilon\right) \tag{5.2}$$

The standard form of SVM for solving regression problems is given as,

$$min_{w,b,\xi,\xi'} \left\{ \frac{1}{2}\mathbf{w}^{\mathbf{T}}\mathbf{w} + C\sum_{i=1}^{\ell}\left(\xi_i + \xi_i'\right) \right\} \tag{5.3}$$

where ξ_i and ξ_i' are the non-negative slack variables.

Minimization of the cost function specified in (5.3) are subjected to the following boundary constraints,

$$\mathbf{w}^{\mathrm{T}}\varphi(\mathrm{x}_{\mathrm{i}}) + b - y_i \leq \varepsilon + \xi_i \tag{5.4}$$

$$y_i - \mathbf{w}^{\mathbf{T}}\varphi(\mathbf{x}_{\mathbf{i}}) - b \leq \varepsilon + \xi_i' \tag{5.5}$$

$$\xi_i \geq 0 \tag{5.6}$$

$$\xi_i' \geq 0 \tag{5.7}$$

To solve the constrained optimization problem, the Lagrangian function and multipliers are employed. The minimization of the Lagrangian function is transformed into a dual problem which is defined as,

$$max\left\{\sum_{i=1}^{\ell} y_i\left(\alpha_i-\alpha'_i\right)-\varepsilon\sum_{i=1}^{\ell}\left(\alpha_i-\alpha'_i\right)\pm\frac{1}{2}\sum_{i=1}^{\ell}\sum_{j=1}^{\ell}\left(\alpha_i-\alpha'_i\right)\left(\alpha_j-\alpha'_j\right)K\left(\mathbf{x_i},\mathbf{x_j}\right)\right\} \quad (5.8)$$

where $K\left(\mathbf{x_i},\mathbf{x_j}\right)=\varphi^T(\mathbf{x_i})\varphi(\mathbf{x_j})$.

The function described in (5.8) is subjected to the followings constraints,

$$\sum_{i=1}^{\ell}\left(\alpha_i-\alpha'_i\right)=0 \quad (5.9)$$

$$0\le\alpha_i\le C \quad (5.10)$$

$$0\le\alpha_j\le C \quad (5.11)$$

where C is defined as the regularization parameter (Smola & Schölkopf 2004).

The output of SVM network can then be expressed as,

$$f(\mathrm{x})=\sum_{i=1}^{\ell}\left(\alpha_i-\alpha'_i\right)K\left(\mathrm{x_i},\mathrm{x}\right)+b \quad (5.12)$$

where b is the bias term and the term $K\left(\mathrm{x_i},\mathrm{x}\right)$ is known as the kernel function.

In general, it is difficult to determine the type of kernel functions to use for specific data patterns. However, any function that satisfies Mercer’s condition by Vapnik can be used as a kernel function (Cristianini & Shawe-Taylor 2000). Kernels are selected based on the data structure and the type of boundaries between the classes. In this work, the radial basis function (RBF) kernel is used and it is given by,

$$K\left(\mathrm{x_i},\mathrm{x_j}\right)=\exp\left(-\frac{\left\|\mathrm{x_i},\mathrm{x_j}\right\|^2}{\sigma^2}\right) \quad (5.13)$$

where σ is a parameter that controls the width of the RBF kernel function.

The selection of the model parameters, σ^2 and C are important in order to ensure the SVM accuracy for solving the regression problem. In this work, the library for SVM (LIBSVM) is used as a tool for implementing the SVM (Chang & Lin 2001).

5.3 GENERALIZED REGRESSION NEURAL NETWORK

GRNN has the ability to draw the function estimates directly from a given training data. The network structure of GRNN as shown in Figure 5.1 comprises of two layers, namely, radial basis and special linear layers. The input neurons are made up of p neurons and a bias vector **b** where p is the dimension of input vector **x** and **b** is a column vector whose elements are set to 0.8326/SPREAD. SPREAD is a user defined parameter which is always determined by trial and error and it measures the distance of an input vector which must be from a neuron's weight vector with value 0.5 (Vapnik 1999). All the input units are fully connected to the neurons in the radial basis layer.

The input neurons receive the input vector and produce a distance vector between the input and its weight vector, w by using the Euclidean distance weight function, $\|d\|$. Then, the distance vector is passed through the radial basis layer and adjusted by the bias. The radial basis layer is made up of radial basis neuron whose transfer function is as shown in Figure 5.2 and mathematically described by,

$$a_1 = \exp\left(-n_1{}^2\right) \tag{5.14}$$

where n_1 is the output from the input units.

A pattern neuron is used to combine and process the data in a systematic fashion such that the relationship between the input and the proper response is "memorized". The radial basis layer receives input from the input units and produced output that has a maximum of one when the input is zero. Dot product operation is then performed between the output of the radial basis layer and weight vector $\mathbf{LW_{2,1}}$ in which $\mathbf{LW_{2,1}}$ equals to the target vector. The output of the dot product operation is then passed on to the special linear layer, whose transfer function is as shown in Figure 5.3. From the figure, n_2 is the output of the radial basis layer or in this case is equal to a_1. The linear transfer function, $f(\mathbf{x})$ can be written in the following form,

$$f(\mathbf{x}) = purelin(n_2) \tag{5.15}$$

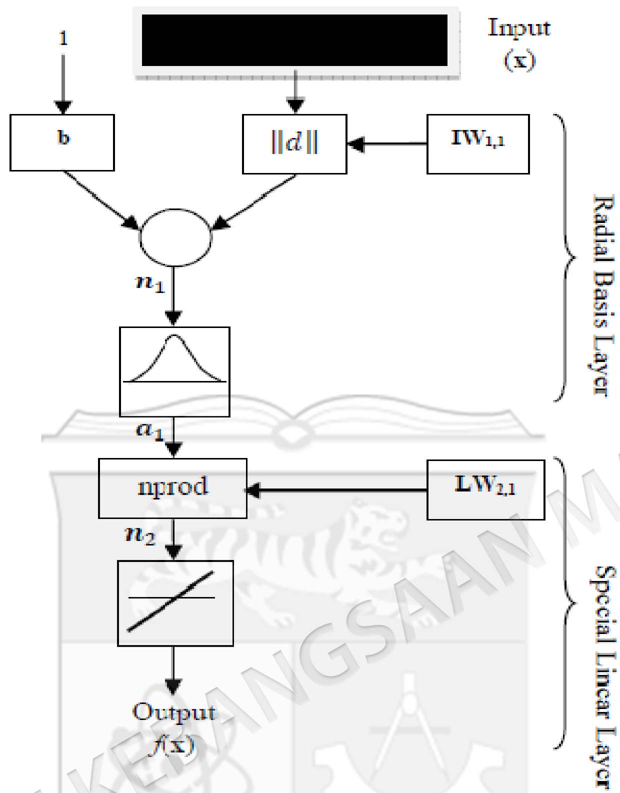

Figure 5.1 The network structure of GRNN in the MATLAB toolbox

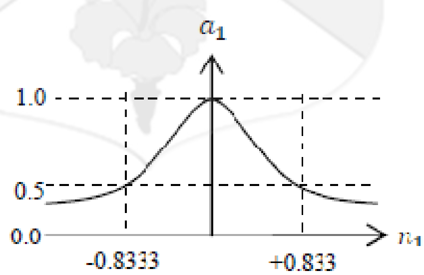

Figure 5.2 Radial basis function

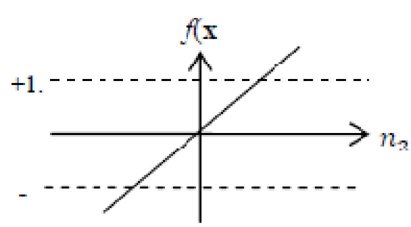

Figure 5.3 Linear transfer function

5.4 FEATURE EXTRACTION TECHNIQUE USING PRINCIPAL COMPONENT ANALYSIS

The main objective of feature extraction is to reduce the dimension of the input feature without losing the main information represented by the original input data. In feature extraction, the basic idea is to discard the data that are repetitive in nature, and to choose only the data components with maximum information with regards to the different variation of the whole set of input data. Principle component analysis (PCA) is one of the most widely used feature extraction technique. PCA is a mathematical procedure that transforms a multivariate data set into a smaller number of uncorrelated variables known as principle components (Liu & Yang 2008).

The original data are projected into a space such that variances of the variables are maximum along the coordinates of the transformed space (Sawhney & Jeyasurya 2006). The principle components whose variances are very small can be removed from the input data set, since they do not contain much information on the variation of the data set.

The transformation of the input data set into a smaller dimension by using PCA involves orthogonalizing the component of the input vector so that they become uncorrelated with each other. Then, the principle components are arranged such that principle component with the largest variation come first, while those components with small variations are eliminated since they contribute the least to the variation in the data set. The procedure of PCA mainly consists of four steps and are described as follows,

Step 1: Normalized the original data set to prevent any parameter from dominating the output value using (5.16).

$$x_{ij}* = \frac{x_{ij} - \bar{x}_j}{\varphi_j} \tag{5.16}$$

where $x_{ij}*$ is the normalized value of x_{ij}, $\bar{x}_j$ and φ_j are the mean and variance of a data set, respectively.

The data matrix $\mathbf{X}$, consists of m variables and N data set where the mean and variance of each data set are given by,

$$\bar{x}_j = \frac{1}{N}\sum_{i=1}^{N} x_{ij} \tag{5.17}$$

$$\varphi_j = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(x_{ij} - \bar{x}_j\right)^2} \tag{5.18}$$

Step 2: Calculate the correlation matrix, **R** and determine the eigenvalues of **R** and their corresponding eigenvectors. Matrix **R** is given by,

$$\mathbf{R} = \frac{1}{N-1}\mathbf{X}^{*T}\mathbf{X}^{*} \tag{5.19}$$

where $\mathbf{X}^*$ is the normalized data matrix.

The eigenvalues of **R** are arranged as follows $eig_1 > eig_2 > .... > eig_p > ..... > eig_m$ and their corresponding eigenvectors are $u_1 > u_2 > .... > u_p > ..... > u_m$.

Step 3: Calculate the accumulated contribution of variance by using,

$$\eta_{\Sigma} = \sum_{k=1}^{p}\eta_k \tag{5.20}$$

where p is the number of principle components retained for further analysis and η_k is the variance of each principle component and is given by,

$$\eta_k = \frac{eig_k}{\sum_{l=1}^{m} eig_l} \times 100 \tag{5.21}$$

Step 4: Compute the principle component by using,

$$\mathbf{Z}_{N\times p} = \mathbf{X}^{*}{}_{N\times m}\,\mathbf{U}_{m\times p} \tag{5.22}$$

where $\mathbf{U}_{m\times p}$ is the first p columns of the eigenvector matrix.

The number of principle components depends on the accumulated contribution of variance. The principle components with accumulated variance greater than 85% are retained as most information of the original variables is included (Liu & Yang 2008). In this study, the accumulated variance of 80%, 85%, 90% and 95% are chosen and their performances are compared so as to select the number of optimum principle components. PCA is performed on the original input data set by using the MATLAB toolbox.

5.5 IMPLEMENTATION OF SVM AND GRNN FOR RBSSA AND RBVCA

The AI techniques based on SVM and GRNN are proposed for prediction of risk index associated with low voltage, line overload and voltage collapse. For each risk prediction, SVM and GRNN are trained and their performances are compared so as to select the best risk prediction model.

The implementation of RBSSA and RBVCA using SVM and GRNN techniques is described as shown in Figure 5.4.

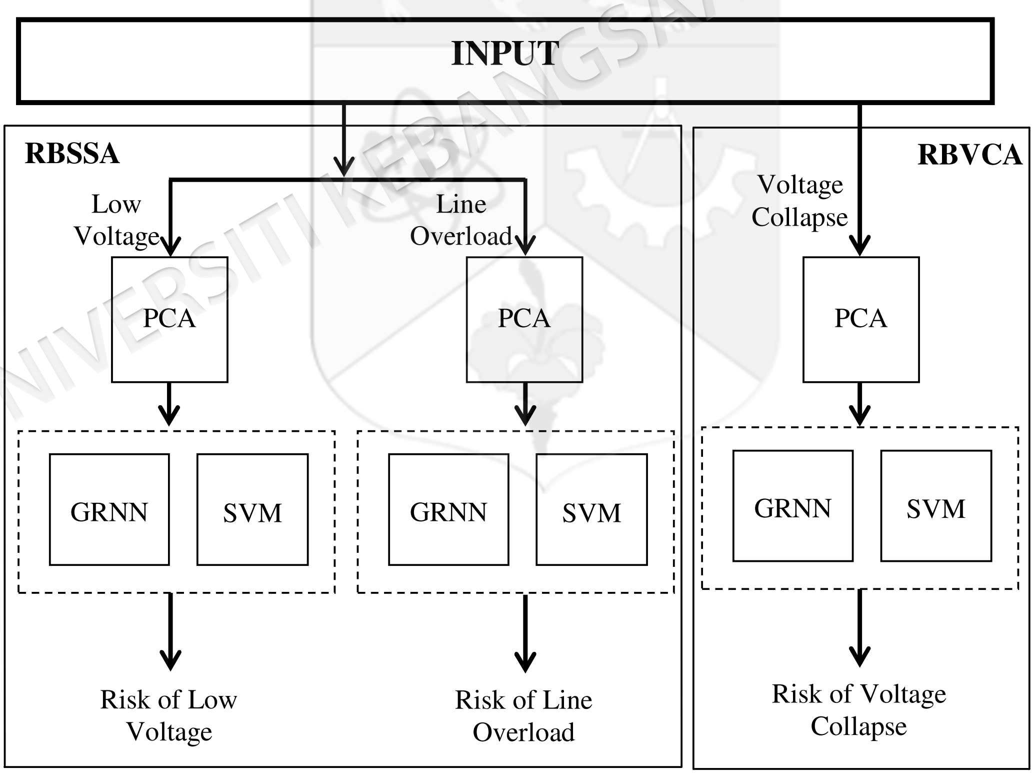

Figure 5.4 Implementation of SVM and GRNN for RBSSA and RBVCA

5.5.1 Selection of Input and Output Features

The selection of input features is an important factor to be considered in the implementation of SVM and GRNN. A large number of input features increases the complexity of the SVM and GRNN models, thus slows down the training process. Hence, it is essential to select input features which are able to clearly define the input and output mapping.

The probability of transmission line outages and their severities associated with low voltage, line overload or voltage collapse, are the two attributes that determines the risk index of a given operating condition. The severity of transmission line outage with respect to low voltage, line overload and voltage collapse is directly associated with the load demand, whereas the probability of transmission line outage is affected by the weather condition. For the developed SVM and GRNN, the load assigned to each load bus and the weather condition experienced by transmission line are selected as input features and the risk index value for low voltage, line overload and voltage collapse is the output variable. Transmission lines with more than one tie line will experience the same weather type since they are positioned at the same geographical location, therefore, only single weather type is considered. The input and output variables for the implementation of RBSSA and RBVCA using SVM and GRNN are summarized as in Table 5.1.

Table 5.1 Input and output variables for the implementation of RBSSA and RBVCA using SVM and GRNN

Variables	**Description**	**No. of features**
Input Variables	The load assigned to each load bus	Number of load buses
	The weather type (either 1,2 or 3) experienced by each transmission line	T = No. of single line + No. of double lines + No. of quadruple lines
Output Variables	Risk index	1

The input features can be written in an augmented matrix form as,

$$\mathbf{X} = [\mathbf{L} \quad | \quad \mathbf{WC}] \tag{5.23}$$

where **L** represents a matrix of load assigned to each load bus and **WC** is a matrix that characterizes the weather type experienced by transmission line and is given as follows,

$$\mathbf{L} = [L_1, L_2, ..., L_{no.of\ load\ bus}] \tag{5.24}$$

$$\mathbf{WC} = [WC_1, WC_2, ..., WC_T] \tag{5.25}$$

5.5.2 Generation of Training and Testing Data

Sufficiently large numbers of training samples have been generated prior to the implementation of the SVM and GRNN to ensure good generalization ability. The input and its corresponding output data is generated by varying the loading pattern within reasonable limits. For every load pattern, the severity associated with low voltage, line overload and voltage collapse of each critical transmission line outage is computed. To determine the severity function value, voltage magnitudes at all buses and power flows for all lines subjected to transmission line outages need to be examined. For the purpose of performing line outage simulations, the Power System Analysis Toolbox (PSAT) is used (Milano 2007). In this study, a database consisting of bus voltages and power flows at loads ranging from base case up to 30% increase in load demand is developed. To calculate the probability of critical transmission line outage, the weather condition experienced by each transmission line is randomly assigned. Then, for each load pattern, various combinations of weather are generated.

Once the input data has been generated, feature extraction based on PCA is applied so as to reduce the number of input features. This feature reduction process retained the principle components that accounts for 85% and 90% variation in the data set. A quarter of the data sets are randomly selected for testing purposes, and the remaining data are selected for training the SVM and GRNN.

5.5.3 Normalization of Data

To have a more accurate prediction result, the input and target data needs to be represented in a normalized form ranging between zero to one. This prevents any parameter from dominating the output value and also provides better convergence and accuracy of the learning process. The normalization procedure is performed using,

$$d_k = \frac{d_k^{'} - d_{k,min}}{d_{k,max} - d_{k,min}} \tag{5.26}$$

where d_k, $d_k^{'}$, $d_{k,min}$ and $d_{k,max}$ represent the normalized value, raw input or target value, minimum and maximum values of the respective features, respectively.

5.5.4 Performance Measure

To evaluate the effectiveness of the SVM and GRNN, the Mean Average Error (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE) are considered and given as,

$$MAE = \frac{\sum_{q=1}^{T} \left| y_q - f_q(\mathrm{x}) \right|}{T} \tag{5.27}$$

$$MSE = \frac{\sum_{q=1}^{T} \left| y_q - f_q(\mathrm{x}) \right|^2}{T} \tag{5.28}$$

$$RMSE = \frac{\sqrt{\sum_{q=1}^{T} \left| y_q - f_q(\mathrm{x}) \right|^2}}{T} \tag{5.29}$$

where T is the number of training sample, y and $f(\mathbf{x})$ are the target and the predicted values, respectively.

5.6 CHAPTER SUMMARY

To achieve fast and accurate RBSA, two AI techniques, namely SVM and GRNN are proposed. To reduce the number of input features, feature extraction based on PCA is proposed. In order to select the best AI technique in predicting the risk index of RBSA, the performances of SVM and GRNN are evaluated by using the MAE, MSE and RMSE. The advantage of using SVM and GRNN is that it can speed up the process of predicting the risk index value in RBA and RBVCA and hence can be used as an online tool for risk index monitoring.

CHAPTER VI

RESULTS AND DISCUSSION

6.1 TEST SYSTEMS DESCRIPTION

In this study, two test systems, namely, the IEEE 24-bus power system and the practical 87-bus power system have been used to demonstrate the effectiveness of the proposed RBSA methodologies. For the development of an improved failure rate model based on the weather condition for the estimation of probability of transmission line outages, only the 87-bus power system is considered. The effectiveness of the Monte Carlo simulation in estimating the probability of transmission line outages in RBSSA has been demonstrated on the IEEE 24-bus power system. The accuracy of SVM and GRNN techniques developed for RBSSA and RBVCA has been validated on the 87-bus power system.

The IEEE 24 bus power system consists of 35 transmission lines, 5 transformers and 17 load buses. The bus, line and reliability data of the IEEE 24 bus power system can be found in Appendix A (Grigg et al. 1999). The total real and reactive load power at base case condition is 2.85 MW + j0.58 MVar. The single line diagram of IEEE 24 bus power system is shown in Figure 6.1. The practical 87 bus power transmission network is based on the Malaysian transmission network at a voltage level of 275 kV. The network comprises of 54 load buses and lines of types 57 single, 54 double and 3 quadruple lines. The single line diagram of the test system is shown in Figure 6.2. The test system is divided into four regions, namely, Northern (N), Eastern (E), Central (C) and Southern (S) with a total real and reactive load power at base case condition of 10920 MW + j2420 MVar. The data for the practical 87 bus power is provided in Appendix B.

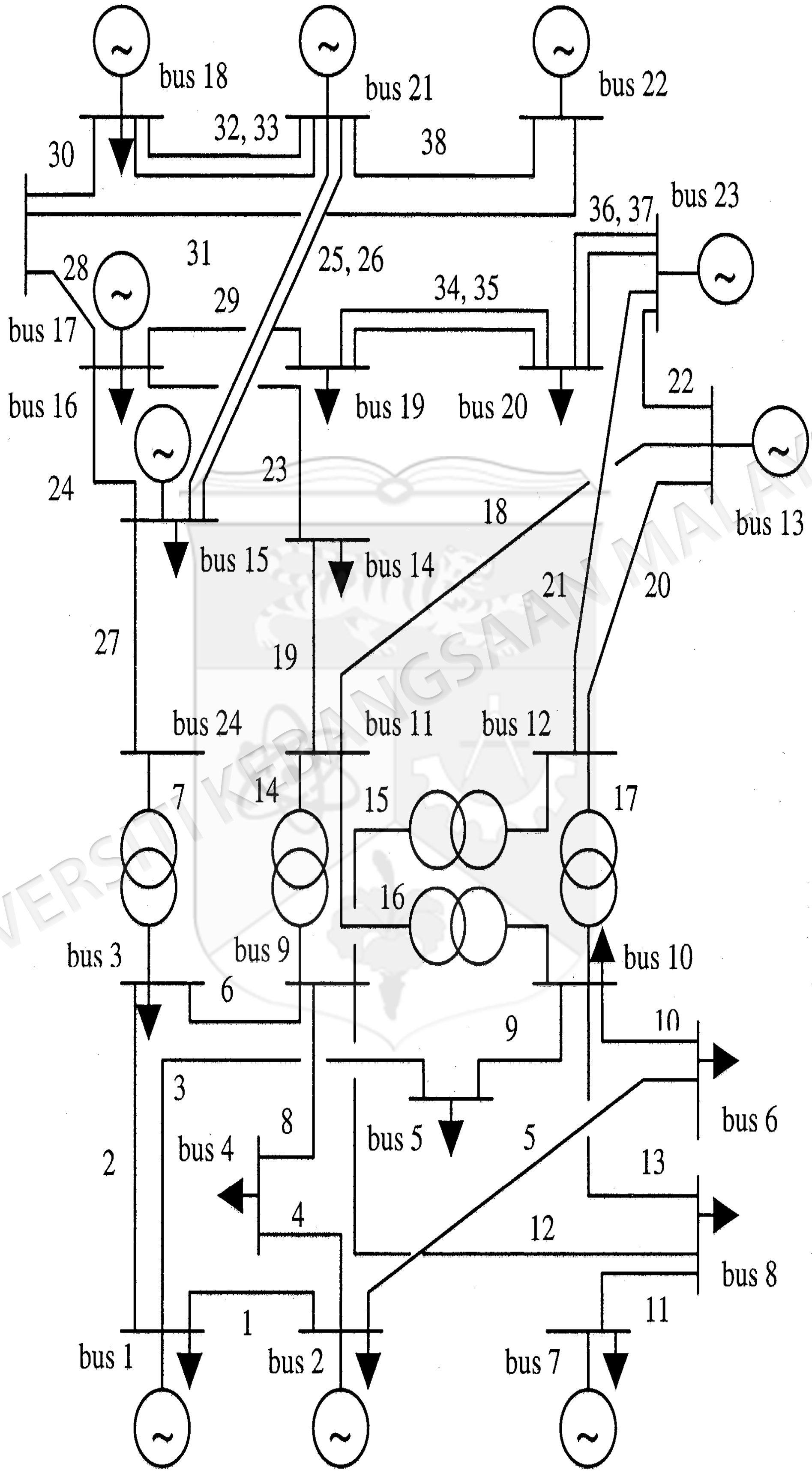

Figure 6.1 The IEEE 24 bus power system

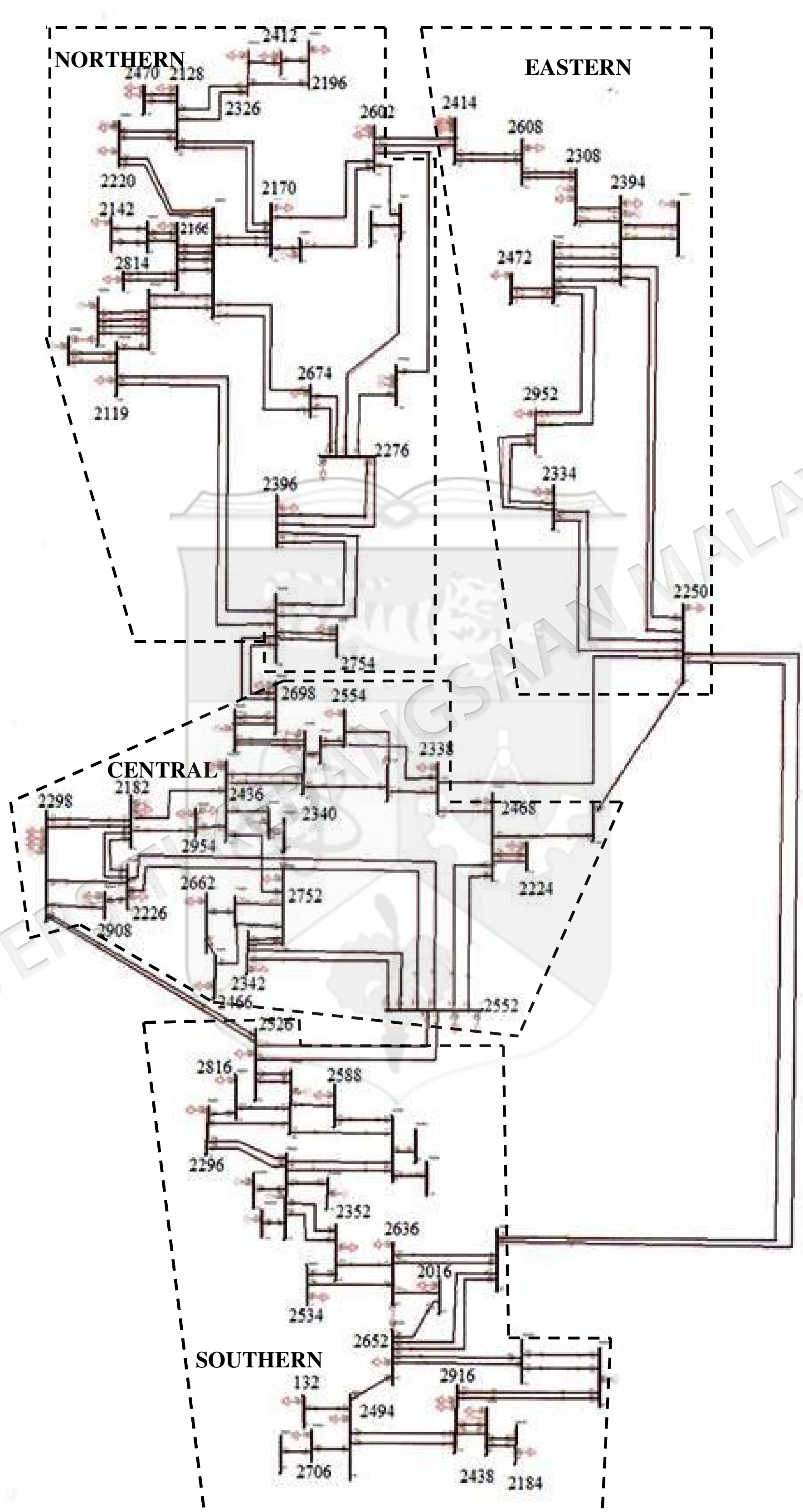

Figure 6.2 The practical 87 bus power system

6.2 RESULT OF FAILURE RATE ESTIMATION RELATED TO WEATHER

The probability of transmission line outage is characterized by its failure rate. A real historical outage data set obtained from the utility for six years period (2002 – 2007) is used to compute the failure rate of each transmission line. To estimate the failure rate of each transmission line, the data pooling method is applied such that the transmission lines are grouped according to their geographical location. Therefore, pooling is performed based on the geographical location of the transmission lines. The grouping of the transmission lines for the practical 87 bus power system according to the geographical location obtained from the utility is shown in Figure 6.3. The lines connecting two different geographical areas are grouped together as indicated by the dotted circles.

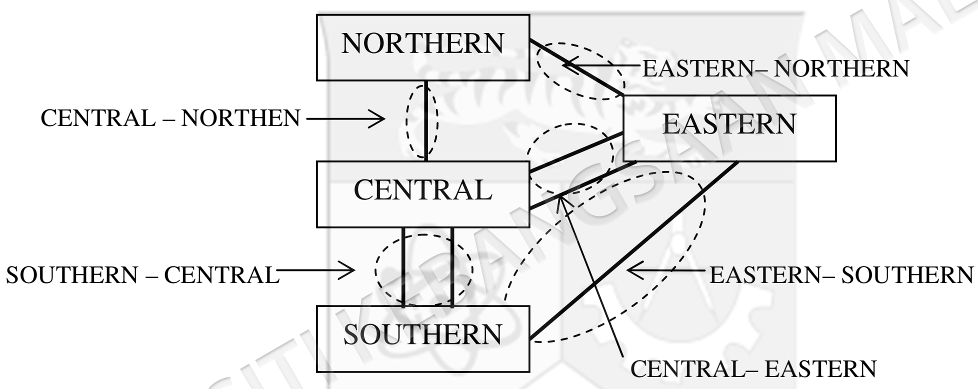

Figure 6.3 Grouping of transmission lines according to geographical location

Assuming that the weather in each group is homogeneous, data pooling is performed based on the geographical location. Table 6.1 shows the transmission line pools and the number of transmission lines in each pool. From the historical outage data obtained from January 2002 to December 2007, the weather condition can be classified as one of the three types, namely, clear, cloudy and rainy. The historical outage data obtained from the utility is used such that each transmission line outage event is grouped according to the pool and weather type. A summary of the outage data obtained from the utility for the six year period from January 2002 to December 2007 is shown in Table B.4 in Appendix B.

The failure rate per unit mile per year for each respective pool is then calculated using (3.1). The results of the failure rate related to weather conditions computed by using the data pooling method implemented on the practical 87-bus power system is tabulated as shown in Table 6.2.

Table 6.1 Transmission line pool

	Pool	No. of transmission lines
1	Northern (N)	32
2	Central (C)	32
3	Southern (S)	33
4	Eastern (E)	10
5	Northern – Central (CN)	1
6	Central – Southern (CS)	2
7	Eastern – Northern (EN)	1
8	Central – Eastern (CE)	2
9	Eastern – Southern (ES)	1

Table 6.2 Failure rate per mile per year for the practical 87-bus power system

	Failure rate (failure/ year. mile)		
Pool	**Fine**	**Cloudy**	**Rainy**
1	2.69E-03	2.42E-03	**2.72E-03**
2	1.50E-03	**5.98E-03**	4.87E-03
3	3.44E-03	2.92E-03	**4.14E-03**
4	1.09E-03	1.10E-03	**1.21E-03**
5	1.65E-03	1.65E-03	1.65E-03
6	9.11E-03	9.11E-03	9.11E-03
7	1.67E-03	1.67E-03	1.67E-03
8	1.44E-03	1.44E-03	1.44E-03
9	8.69E-04	8.69E-04	8.69E-04

From the results presented in Table 6.2, it is apparent that transmission line outage is a rare event in which the failure rate values are very low. The effect of weather on the occurrence of transmission line outage can be seen in pools 1, 2, 3 and 4. For example, in Pool 1, a transmission line outage is more likely to occur on a rainy day because the failure rate of the transmission line in Pool 1 during a rainy day is slightly higher than the failure rates associated with clear and cloudy days. However, the variation of failure rate with respect to weather condition is not revealed in pools 5, 6, 7, 8 and 9 because the values of failure rates in these five pools are constant. This may be due to the fact that only few transmission lines are located in these respective pools, and therefore, only very few historical outages occurred within the specified period.

To calculate the probability of transmission line outage, failure associated with weather condition for each line is required. The failure rate for each transmission line with respect to weather condition is calculated by multiplying the failure rate per unit mile per year by the line length. A lookup table consisting of length in miles, l and pool number, k

for each transmission line has been developed to compute the failure rate of each line. The failure rate per year of each transmission line outage associated with weather condition is represented in Table 6.3.

Table 6.3 Failure rate per year for all the lines in the practical 87-bus power system

Line #	From Bus	To Bus	Type	Geographical Location	Length (mile)	Failure rate		
						Fine	Cloudy	Rain
L1	62	2276	Single	N	82.6	0.2221	0.2003	0.2247
L2	62	2602	Single	N	22.6	0.0608	0.0548	0.0615
L3	62	2704	Single	N	0.1	0.0003	0.0002	0.0003
L4	72	2338	Single	C	8.62	0.0129	0.0516	0.042
L5	72	2340	Single	C	5.5	0.0082	0.0329	0.0268
L6	72	2554	Single	C	12.4	0.0186	0.0742	0.0604
L7	73	2338	Single	C	8.62	0.0129	0.0516	0.042
L8	73	2340	Single	C	5.5	0.0082	0.0329	0.0268
L9	73	2554	Single	C	12.4	0.0186	0.0742	0.0604
L10	132	2494	Single	S	18.8	0.0646	0.0549	0.0779
L11	2016	2636	Single	S	50.66	0.174	0.148	0.21
L12	2016	2652	Single	S	70.4	0.2418	0.2057	0.2918
L13	2072	2706	Single	S	54.2	0.1862	0.1584	0.2246
L14	2118	2119	Single	N	0.1	0.0003	0.0002	0.0003
L15	2118	2510	Quadruple	N	25.4	0.0683	0.0616	0.0691
L16	**2118**	**2722**	**Double**	**N**	**121.1**	**0.3256**	**0.2936**	**0.3294**
L17	2119	2130	Double	N	40.8	0.1097	0.0989	0.111
L18	2119	2511	Double	N	25.4	0.0683	0.0616	0.0691
L19	2128	2170	Double	N	47.9	0.1288	0.1161	0.1303
L20	2128	2220	Double	N	11.8	0.0317	0.0286	0.0321
L21	2128	2326	Double	N	44.7	0.1202	0.1084	0.1216
L22	2128	2470	Double	N	35	0.0941	0.0849	0.0952
L23	2130	2396	Double	N	9.3	0.025	0.0225	0.0253
L24	2130	2698	Double	CN	101	0.1667	0.1667	0.1667
L25	2130	2754	Double	N	39	0.1049	0.0946	0.1061
L26	2142	2248	Double	N	13.5	0.0363	0.0327	0.0367
L27	2158	2170	Single	N	108.7	0.2923	0.2636	0.2957
L28	2158	2602	Single	N	15	0.0403	0.0364	0.0408
L29	2166	2248	Double	N	8.9	0.0239	0.0216	0.0242
L30	2166	2722	Quadruple	N	12.5	0.0336	0.0303	0.034
L31	2166	2814	Double	N	19.5	0.0524	0.0473	0.053
L32	**2170**	**2602**	**Single**	**N**	**115.9**	**0.3117**	**0.281**	**0.3153**
L33	2170	2722	Double	N	26	0.0699	0.063	0.0707
L34	2182	2226	Double	C	13.3	0.0199	0.0795	0.0647
L35	2182	2298	Double	C	46.1	0.069	0.2757	0.2244
L36	2182	2436	Single	C	30.4	0.0455	0.1818	0.148

Continue …

… Continuation

L37	2182	2954	Single	C	3.56	0.0053	0.0213	0.0173
L38	2184	2438	Double	S	10.8	0.0371	0.0316	0.0448
L39	2196	2326	Single	N	52.6	0.1414	0.1275	0.1431
L40	2196	2412	Single	N	26.1	0.0702	0.0633	0.071
L41	2220	2722	Double	N	65	0.1748	0.1576	0.1768
L42	2224	2468	Double	C	4.7	0.007	0.0281	0.0229
L43	2226	2298	Single	C	27	0.0404	0.1615	0.1314
L44	2226	2552	Double	C	17.4	0.026	0.1041	0.0847
L45	2226	2908	Single	C	30.8	0.0461	0.1842	0.1499
L46	2250	2334	Double	E	96	0.1048	0.106	0.1165
L47	2250	2338	Single	CE	116	0.1667	0.1667	0.1667
L48	2250	2339	Single	CE	116	0.1667	0.1667	0.1667
L49	2250	2394	Double	E	217.8	0.2377	0.2406	0.2643
L50	2250	2880	Double	ES	191.7	0.1667	0.1667	0.1667
L51	2276	2306	Single	N	23.1	0.0621	0.056	0.0628
L52	2276	2396	Double	N	41.5	0.1116	0.1006	0.1129
L53	2276	2674	Double	N	42.6	0.1146	0.1033	0.1159
L54	2296	2410	Single	S	69.4	0.2384	0.2028	0.2876
L55	2296	2464	Double	S	21.5	0.0739	0.0628	0.0891
L56	2296	2816	Single	S	64.3	0.2209	0.1879	0.2665
L57	2298	2526	Double	CS	18.3	0.1667	0.1667	0.1667
L58	2298	2908	Single	C	18.7	0.028	0.1118	0.091
L59	2306	2602	Single	N	54.4	0.1463	0.1319	0.148
L60	2308	2394	Single	E	85.7	0.0935	0.0947	0.104
L61	2308	2608	Double	E	156	0.1703	0.1723	0.1893
L62	2326	2412	Double	N	60.7	0.1632	0.1472	0.1651
L63	2334	2952	Single	E	21.61	0.0236	0.0239	0.0262
L64	2338	2468	Double	C	22.9	0.0343	0.137	0.1115
L65	2339	2468	Single	C	22.9	0.0343	0.137	0.1115
L66	2340	2436	Single	C	42.9	0.0642	0.2566	0.2088
L67	2340	2684	Double	C	37	0.0554	0.2213	0.1801
L68	2342	2552	Double	C	14.4	0.0215	0.0861	0.0701
L69	2342	2752	Double	C	12.8	0.0192	0.0766	0.0623
L70	2352	2464	Double	S	21	0.0721	0.0614	0.087
L71	2352	2534	Double	S	46.2	0.1587	0.135	0.1915
L72	**2352**	**2636**	**Single**	**S**	**112.6**	**0.3868**	**0.329**	**0.4667**
L73	2394	2594	Single	E	41.3	0.0451	0.0456	0.0501
L74	2394	2638	Quadruple	E	0.58	0.0006	0.0006	0.0007
L75	2410	2526	Double	S	35	0.1202	0.1023	0.1451
L76	2410	2588	Double	S	3.6	0.0124	0.0105	0.0149
L77	2410	2590	Single	S	3.6	0.0124	0.0105	0.0149
L78	2410	2816	Single	S	40	0.1374	0.1169	0.1658
L79	2414	2602	Single	EN	100.1	0.1667	0.1667	0.1667
L80	2414	2608	Double	E	36.1	0.0394	0.0399	0.0438
L81	2420	2424	Double	S	0.5	0.0017	0.0015	0.0021
L82	2420	2652	Double	S	76.9	0.2642	0.2247	0.3187

Continue …

… Continuation

L83	2424	2916	Double	S	10.7	0.0368	0.0313	0.0443
L84	2436	2740	Double	C	3	0.0045	0.0179	0.0146
L85	2436	2752	Single	C	52	0.0778	0.311	0.2531
L86	2436	2954	Single	C	26.79	0.0401	0.1602	0.1304
L87	2438	2916	Single	S	3.3	0.0113	0.0096	0.0137
L88	2464	2590	Double	S	52.46	0.1802	0.1533	0.2174
L89	2464	3184	Double	S	0.5	0.0017	0.0015	0.0021
L90	2464	3185	Single	S	0.55	0.0019	0.0016	0.0023
L91	2464	3186	Single	S	0.7	0.0024	0.002	0.0029
L92	2466	2662	Single	C	2	0.003	0.012	0.0097
L93	2466	2752	Single	C	8.4	0.0126	0.0502	0.0409
L94	2467	2662	Double	C	2	0.003	0.012	0.0097
L95	2467	2752	Single	C	8.4	0.0126	0.0502	0.0409
L96	2468	2552	Single	C	26.7	0.0399	0.1597	0.13
L97	2472	2594	Double	E	1.8	0.002	0.002	0.0022
L98	2494	2652	Double	S	51.8	0.1779	0.1514	0.2147
L99	2494	2706	Single	S	14	0.0481	0.0409	0.058
L100	2494	2916	Single	S	25.5	0.0876	0.0745	0.1057
L101	2510	2511	Double	N	0.1	0.0003	0.0002	0.0003
L102	2526	2552	Single	CS	24.1	0.2195	0.2195	0.2195
L103	2534	2636	Double	S	64.2	0.2205	0.1876	0.2661
L104	2588	2590	Single	S	0.1	0.0003	0.0003	0.0004
L105	2590	2595	Single	S	0.1	0.0003	0.0003	0.0004
L106	2590	2597	Single	S	0.1	0.0003	0.0003	0.0004
L107	2594	2952	Single	E	44.99	0.0491	0.0497	0.0546
L108	2636	2652	Double	S	64	0.2198	0.187	0.2652
L109	2636	2880	Single	S	2	0.0069	0.0058	0.0083
L110	2652	2880	Double	S	62	0.213	0.1812	0.257
L111	2674	2722	Double	N	43.3	0.1164	0.105	0.1178
L112	2684	2698	Double	C	9.8	0.0147	0.0586	0.0477
L113	2740	2956	Double	C	3	0.0045	0.0179	0.0146
L114	2752	2956	Single	C	52	0.0778	0.311	0.2531

The value of failure rate signifies the number of a particular transmission line to fail in a given time interval. For example, during fine weather L1 has a failure rate of 0.2221 failure/year in which for every 10 years, L1 will fail 2.221 times. The failure rate of each transmission line is equivalent to the failure rate of its respective pool and weighted by the line length. As can be seen from Table 6.3, apart from weather condition, the failure rate of each transmission line is also affected by its line length, for example, lines L1 (82.6 miles), L2 (22.6 miles) and L3 (0.1 miles) are located at the same geographical area (northern), but their corresponding failure rate per year are different. During rainy weather the failure rate per year for L1, L2 and L3 are 0.2247 (0.00272 failure/year. mile × 82.6 mile), 0.0615 (0.00272 failure/year. mile × 22.6 mile) and 0.0003 (0.00272 failure/year. mile × 0.1 mile), correspondingly. Line L72 which is located at southern region with length of 112.6 miles has the highest failure rate with respect to weather in which during fine, cloudy and rain weather the rate of failure is 0.3868 failure/year, 0.3290 failure/year and 0.4667 failure/year, respectively. During fine weather condition, the frequency of failure of lines L16 (0.3256 failure/year), L32 (0.3117 failure/year) and L72 (0.3868 failure/year) is more than 3 times for every 10 years. The shortest transmission lines with length of 0.1 mile (L3, L14, L101, L104, L105 and L106) have the lowest rate of failure.

The failure rate of the transmission line is used to determine the probability of failure; i.e. high failure rate translates to large probability of a particular transmission line to fail and vice versa. This can be justified by referring to the Poisson probability model of transmission line outage given in (3.5). By rearranging (3.5), two components are obtained which are constant multiplier ($e^{-\sum_{k=1}^{n}\lambda_k}$) and ($e^{\lambda_i}-1$). Based on the Poisson probability model, the second component ($e^{\lambda_i}-1$) becomes more prominent if the failure rate is higher and hence result in higher probability of failure. For instance, the values of the second component of the Poisson probability model during fine weather condition for L3 (lowest failure rate) and L72 (highest failure rate) are equal to 0.0003 and 0.4723, respectively.

6.3 RESULT OF THE MONTE CARLO BASED PROBABILITY MODEL

To explore the feasibility of the Monte Carlo based probability model in RBSSA, the non-sequential Monte Carlo simulation is employed and tested on the IEEE 24 bus test system. The non-sequential Monte Carlo simulations were carried out on the Excel platform which has a built-in random number generator. A tolerance value of 0.04 is chosen as stopping criteria for the non-sequential Monte Carlo simulation. The selection of appropriate tolerance value is very important when running a Monte Carlo simulation. Large value of tolerance may lead to poor error, whereas small value of tolerance may result in unnecessary computational burden. For the study made on the IEEE RTS-96 test system, a coefficient of variation of 4% is sufficient to result in a reasonable computation error (Arya et al. 2006). The failures rates of the transmission lines for the 24 bus test system are given in Appendix A.

Table 6.4 shows the results of the probability of transmission line outages estimation by using the non-sequential Monte Carlo simulation and the Poisson model for 'N-1' contingency of transmission line outages. The results obtained from the non-sequential Monte Carlo simulation are then compared with the probability calculated by using the Poisson model described in (3.5).

Table 6.4 Probability estimation using non-sequential Monte Carlo simulation for the IEEE 24-bus power system

Line outage			**Probability of line outage**		
Line #	**From Bus**	**To Bus**	**Poisson ($\times 10^{-6}$)**	**Monte Carlo ($\times 10^{-6}$)**	**Error (%)**
L1	1	2	4.576	4.706	2.76
L2	1	3	11.223	11.765	4.6
L3	1	5	6.595	6.553	0.65
L4	2	4	8.046	7.859	2.39
L5	2	6	10.393	10.541	1.41
L6	9	3	7.799	7.494	4.06
L7	**4**	**3**	**0.341**	**0.235**	**45.11**
L8	9	4	7.31	7.706	5.14
L9	0	5	6.831	7.071	3.38
L10	0	6	6.595	6.588	0.11
L11	7	8	5.902	5.741	2.8
L12	9	8	9.324	9.506	1.91
L13	10	8	9.324	9.388	0.69
L14	**11**	**9**	**0.341**	**0.259**	**31.67**
L15	**12**	**9**	**0.341**	**0.318**	**7.28**
L16	**11**	**10**	**0.341**	**0.388**	**12.22**
L17	12	10	0.341	0.329	3.45
L18	13	11	8.297	8.624	3.79
L19	14	11	8.046	8.035	0.14
L20	13	12	8.297	8.294	0.03
L21	23	12	11.506	11.765	2.2
L22	13	23	10.667	10.612	0.52
L23	16	14	7.799	7.788	0.13
L24	16	15	6.595	6.553	0.65
L25	21	15	8.55	8.635	0.99
L26	15	24	8.55	8.459	1.08
L27	17	16	7.069	7.094	0.35
L28	19	16	6.831	6.894	0.91
L29	18	17	6.362	6.506	2.21
L30	22	14	12.079	12.165	0.71
L31	18	21	7.069	7.035	0.49
L32	19	20	7.799	7.976	2.23
L33	23	20	6.831	7.024	2.74

The results in Table 6.4 showed that the probabilities of transmission line outages estimated by using the non-sequential Monte Carlo simulation are almost similar to that obtained by the Poisson model with relative errors within 0.01% to 5% except for outages of lines L7, L14, L15 and L16. As can be seen from both the Poisson and non-sequential Monte Carlo simulation results, these 4 line outages have the lowest probabilities of outage, and therefore a small discrepancy between the results obtained using non-sequential Monte Carlo will result in a large relative error.

6.4 SCREENING OF CRITICAL TRANSMISSION LINE OUTAGES

Transmission line outage screening is performed for the purpose of selecting critical transmission line outages which may cause limit violations and to reduce the number of transmission line outages that need to be analyzed while assessing the power system's security. Screening based on risk factor which takes into account the probability of transmission line outage and its severity is proposed in this study. To reduce the computational burden in RBSA, the critical transmission line outage list is developed for low voltage, line overload and voltage collapse, respectively. The proposed method for screening the critical transmission line outages is tested on the IEEE 24-bus power system and the practical 87-bus power system. Power flow simulations were performed using the PSAT software to examine the bus voltage magnitudes and power flows during transmission line outages. To validate the effectiveness of the proposed line outage screening method, a comparison is made between the proposed screening method and the screening based on the severity of transmission line outage. The proposed screening method considers the risk factor threshold value of 1 in which a transmission line outage is considered critical if its risk factor value is greater than 1. From the severity based screening method, a transmission line outage is classified as critical if its PI is greater than the PI base case. The PI is calculated based on the continuous severity function associated with security violation (Xiao 2007). To make fair comparison, the PI is also normalized between 0.1 and 0.9 using (4.10).

6.4.1 Result of Critical Transmission Line Outage Screening for the IEEE 24-Bus Power System

To screen the critical transmission line outages, the probability of transmission line outage calculated using the failure rate of each transmission line and the severity associated with security violation at base case condition must first be computed and then normalized between 0.1 to 0.9. The probability of 'N-1' transmission line outage is computed by using the Poisson probability model described in (3.5) and the failure rate of each transmission line for the IEEE 24 bus power system provided in Appendix A. To calculate the severity factor, severity associated with low voltage and line overload calculated by using the continuous severity function is considered. Continuous severity function is used due to its ability to capture the effect of the near violating transmission line outage. For this test system, only critical transmission line outage list with respect to low voltage and line overload are developed. Using the proposed screening technique, the critical transmission line outages are screened based on the fact that the transmission line outage is considered critical if its risk factor associated with security violation is greater than 1. For comparison purposes, the result of the proposed screening method, screening based on the severity is also shown. Tables 6.5 shows the normalized PI, probability factor, severity factor, risk factor and risk values for each transmission line outage associated with low voltage where "c" and "nc" represents critical and non critical line outage.

The conventional contingency screening based on the PI method indicates that a particular transmission line outage is classified as critical if its PI is greater than the base case PI value. For the IEEE 24 bus power system, the base case normalized PI values for low voltage is 0.107. From the results presented in Table 6.5, both the PI and the proposed contingency screening methods indicate that only five out of 33 transmission line outages events are classified as non-critical line outages. The transmission line outage screening proposed in this study is able to reduce the number of power flow simulations in RBSSA, since only those transmission line outages that are critical are considered for further analysis. However, it is noted that there are differences in the critical transmission line outages identified by both methods. This is due to the fact that the PI based method only evaluates the severity of a transmission line outage regardless of its probability of occurrence while the proposed critical line outage screening method considers both probability and severity factor values. In the proposed line outage screening method for low voltage, the transmission line outage with low probability and low severity factor values is discarded from further analysis since the risk of low voltage associated with these line outages is comparatively small.

From Table 6.5, lines L1, L9, L25, L32 and L33 are classified as non critical based on the PI method but these line outages are considered critical based on the risk factor. The severities of these line outages (L1, L9, L25, L32 and L33) are considered low and their PI values are less than the base case PI, nonetheless their probability of occurrence cannot be neglected. Due to the high probability (L25) and medium probability (L1, L9, L32 and L33) of these lines outage, the risk of transmission line outage associated with low voltage contributed by those lines outage are prominent. On the other hand, lines L7, L14, L15, L16 and L17 are deemed to be critical based on the PI method but non critical based on the proposed method. Both severity and probability factor of these lines outage events (L7, L14, L15, L16 and L17) are in the low range, therefore their resulting risk of transmission line outages associated with low voltage are relatively small.

Table 6.5 Screening of critical transmission line outages that caused low voltage for the IEEE 24-bus power system

Line Outage			$PI_{Normalized}$	Probability Factor	Severity Factor	Risk Factor	$Risk_{LV}$ ($x10^{-5}$)	Method	
Line #	From Bus	To Bus						PI Method	Proposed Method
L1	1	2	0.106	2	1	2	0.697	nc	c
L2	1	3	0.219	3	1	3	2.588	c	c
L3	1	5	0.188	2	1	2	1.381	c	c
L4	2	4	0.327	3	1	3	2.461	c	c
L5	2	6	0.159	3	1	3	1.959	c	c
L6	9	3	0.136	2	1	2	1.346	c	c
L7	4	3	0.343	1	1	1	0.108	c	nc
L8	9	4	0.133	2	1	2	1.251	c	c
L9	0	5	0.100	2	1	2	1.014	nc	c
L10	0	6	0.900	2	3	6	4.65	c	c
L11	7	8	0.476	2	2	4	2.422	c	c
L12	9	8	0.119	3	1	3	1.504	c	c
L13	10	8	0.142	3	1	3	1.653	c	c
L14	11	9	0.248	1	1	1	0.085	c	nc
L15	12	9	0.307	1	1	1	0.1	c	nc
L16	11	10	0.159	1	1	1	0.064	c	nc
L17	12	10	0.157	1	1	1	0.064	c	nc
L18	13	11	0.229	3	1	3	1.978	c	c
L19	14	11	0.134	3	1	3	1.385	c	c
L20	13	12	0.219	3	1	3	1.918	c	c
L21	23	12	0.222	3	1	3	2.676	c	c
L22	13	23	0.199	3	1	3	2.32	c	c
L23	16	14	0.360	2	1	2	2.568	c	c
L24	16	15	0.127	2	1	2	1.1	c	c
L25	21	15	0.101	3	1	3	1.276	nc	c
L26	15	24	0.580	3	2	6	4.119	c	c
L27	17	16	0.122	2	1	2	1.15	c	c
L28	19	16	0.163	2	1	2	1.312	c	c
L29	18	17	0.113	2	1	2	0.998	c	c
L30	22	14	0.109	3	1	3	1.854	c	c
L31	18	21	0.107	2	1	2	1.083	c	c
L32	19	20	0.106	2	1	2	1.186	nc	c
L33	23	20	0.104	2	1	2	1.033	nc	c

To show the effectiveness of the proposed screening method in RBSA, the list of non-critical line outage and its respective risk of transmission line outage associated with low voltage obtained using PI based method and the proposed method is illustrated in Table 6.6.

Table 6.6 List of non critical line outage associated with low voltage obtained using the PI based method and the proposed method for the IEEE 24-bus power system

Screening based on PI method		**Proposed Screening method**	
Non-Critical line outage	**Risk (x10^{-5})**	**Non-Critical line outage**	**Risk (x10^{-5})**
L1	0.697	L7	0.108
L9	1.014	L14	0.085
L25	1.276	L15	0.100
L32	1.186	L16	0.064
L33	1.033	L17	0.064

Comparing the results of the non critical transmission line outage tabulated in Table 6.6, it is noted that the PI based method overlooked the effect of the probability of line outage in which the line outage event that is deemed to be non critical has reasonably high risk values whereas the proposed screening method accurately screen the non-critical line outages due to the low risk values. Thus, the proposed screening method has the ability to efficiently screen only the high risk of transmission line outage associated with low voltage for further analysis in RBSA.

The result of transmission line outage screening associated with line overload is illustrated in Table 6.7. For the results of line outages that caused line overload, the normalized base case PI value is 0.100, and this value is used to screen the critical line outages such that any line outage with normalized PI value greater than 0.100 is considered critical.

From the results shown in Table 6.7, only four transmission line outages of lines, L5, L7, L8 and L26 are with normalized PI values greater than 0.100, and these lines are considered as critical line outages based on the PI method. The screening of critical transmission line outages that result in line overload obtained using the proposed line outage screening method indicated that 29 transmission line outages have been identified as critical towards line overload. By identifying the critical transmission line outages, the number of power flow simulation is reduced since not all transmission line outages are considered in the RBSSA analysis.

Table 6.7 Screening of critical transmission line outages that caused line overload for the IEEE 24-bus power system

Line Outage			$PI_{Normalized}$	Probability Factor	Severity Factor	Risk Factor	$Risk_{LO}$ ($x10^{-5}$)	Method	
Line #	From Bus	To Bus						PI Method	Proposed Method
L1	1	2	0.100	2	1	2	0	nc	c
L2	1	3	0.100	3	1	3	0	nc	c
L3	1	5	0.100	2	1	2	0	nc	c
L4	2	4	0.100	3	1	3	0	nc	c
L5	2	6	0.900	3	3	9	1.163	c	c
L6	9	3	0.100	2	1	2	0	nc	c
L7	4	3	0.614	1	2	2	0.025	c	c
L8	9	4	0.136	2	1	2	0.034	c	c
L9	0	5	0.100	2	1	2	0	nc	c
L10	0	6	0.100	2	1	2	0	nc	c
L11	7	8	0.100	2	1	2	0	nc	c
L12	9	8	0.100	3	1	3	0	nc	c
L13	10	8	0.100	3	1	3	0	nc	c
L14	11	9	0.100	1	1	1	0	nc	nc
L15	12	9	0.100	1	1	1	0	nc	nc
L16	11	10	0.100	1	1	1	0	nc	nc
L17	12	10	0.100	1	1	1	0	nc	nc
L18	13	11	0.100	3	1	3	0	nc	c
L19	14	11	0.100	3	1	3	0	nc	c
L20	13	12	0.100	3	1	3	0	nc	c
L21	23	12	0.100	3	1	3	0	nc	c
L22	13	23	0.100	3	1	3	0	nc	c
L23	16	14	0.100	2	1	2	0	nc	c
L24	16	15	0.100	2	1	2	0	nc	c
L25	21	15	0.100	3	1	3	0	nc	c
L26	15	24	0.614	3	2	6	0.616	c	c
L27	17	16	0.100	2	1	2	0	nc	c
L28	19	16	0.100	2	1	2	0	nc	c
L29	18	17	0.100	2	1	2	0	nc	c
L30	22	14	0.100	3	1	3	0	nc	c
L31	18	21	0.100	2	1	2	0	nc	c
L32	19	20	0.100	2	1	2	0	nc	c
L33	23	20	0.100	2	1	2	0	nc	c

The most severe transmission line outage associated with line overload is the outage of line L5 with severity factor value of 3. Based on the proposed method, despite the low severity factor values, the transmission line outages are still considered critical if the probability factor values of these transmission line outages are not in the low range.

Screening based on the risk factor considers the two important attributes in the RBSA which is the probability of occurrence and the severity. The proposed screening method does not only screen line outage with medium and high severity value but it also screens line outage with medium and high probability of occurrence to be considered in RBSA. For example, outage of line L14, L15, L16 and L17 are not considered critical based on the proposed method since the probability of occurrence is low when compared with the other line outages.

6.4.2 Results of Critical Transmission Line Outage Screening for the Practical 87-Bus Power System

Transmission line outage screening based on risk factor is performed to efficiently select the critical transmission line outages associated with low voltage, line overload and voltage collapse for the practical 87-bus power system which consists of 57 single, 54 double and 3 quadruple tie lines. The probability of transmission line outage is calculated by using the Poisson probability model, whereas the severity function based on the VCPI value is used to compute the severity factor. For this test system, there exist a total of 114 (57+54+3) 'N-1' line outages, however only 107 transmission line outages are considered, since the remaining seven transmission line outages (L10, L26, L69, L89, L90, L91 and L99) result in the divergence of the power flow solution. The failure rate with respect to weather has been developed for the practical 87 bus power system. Therefore, the probability of transmission line outages will vary according to the weather condition. At a particular time and load condition, a power system consisting of N transmission lines with possible weather condition of fine, cloudy or rainy, there exist 3^N possible weather combinations. For example, if N is equal to 2, the number of possible weather combination is 9. To develop the probability factor of transmission lines for the practical 87 bus power system, 100 random weather combinations experienced by the transmission lines are generated. Out of the 100 weather combinations generated, only 3 weather combinations is shown and the probability factor value of each transmission line outage with respect to weather is shown in Appendix C.

To show the effectiveness of the proposed line outage screening method, the PI in terms of severity associated with security violation subjected to transmission line outage is also shown in Appendix C. From the result of probability factor shown in Table C.1 in Appendix C, for each line, the probability factor of transmission line outage is always consistent regardless of the weather combination. For the transmission line outage screening of the practical 87 bus power system, the probability factor values shown in Appendix C are considered

Table 6.8 Screening of critical transmission line outages that caused low voltage for the practical 87- bus power system

Line Outage From Bus	Line Outage To Bus	$PI_{Normalized}$	Probability Factor	Severity Factor	Risk Factor	$Risk_{LV}$ ($x10^{-5}$)	Method: PI Method	Method: Proposed Method
Bus62	Bus2276	0.225	2	1	2	2.983	c	c
Bus62	Bus2602	0.174	1	1	1	0.649	c	nc
Bus62	Bus2704	0.116	1	1	1	0.003	nc	nc
Bus72	Bus2338	0.166	1	1	1	0.491	c	nc
Bus72	Bus2340	0.246	1	1	1	0.099	c	nc
Bus72	Bus2554	0.124	1	1	1	0.861	c	nc
Bus73	Bus2338	0.166	1	1	1	0.149	c	nc
Bus73	Bus2340	0.246	1	1	1	0.401	c	nc
Bus73	Bus2554	0.124	1	1	1	0.861	c	nc
Bus2016	Bus2636	0.198	2	1	2	2.218	c	c
Bus2016	Bus2652	0.198	3	1	3	2.666	c	c
Bus2072	Bus2706	0.121	2	1	2	2.813	c	c
Bus2118	Bus2119	0.150	1	1	1	0.003	c	nc
Bus2118	Bus2510	0.143	1	1	1	0.799	c	nc
Bus2118	Bus2722	0.310	3	1	3	4.838	c	c
Bus2119	Bus2130	0.259	1	1	1	1.417	c	nc
Bus2119	Bus2511	0.143	1	1	1	0.809	c	nc
Bus2128	Bus2170	0.262	2	1	2	1.49	c	c
Bus2128	Bus2220	0.156	1	1	1	0.367	c	nc
Bus2128	Bus2326	0.398	2	1	2	1.658	c	c
Bus2128	Bus2470	0.180	1	1	1	1.154	c	nc
Bus2130	Bus2396	0.121	1	1	1	0.286	c	nc
Bus2130	Bus2754	0.180	2	1	2	2.095	c	c
Bus2142	Bus2248	0.762	1	2	2	1.524	c	c
Bus2158	Bus2170	0.509	3	2	6	4.653	c	c
Bus2158	Bus2602	0.124	1	1	1	0.461	c	nc
Bus2166	Bus2248	0.124	1	1	1	0.271	c	nc
Bus2166	Bus2722	0.135	1	1	1	0.346	c	nc
Bus2166	Bus2814	0.156	1	1	1	0.552	c	nc
Bus2170	Bus2602	0.411	3	2	6	4.243	c	c
Bus2170	Bus2722	0.164	1	1	1	0.745	c	nc
Bus2182	Bus2226	0.135	1	1	1	0.931	c	nc
Bus2182	Bus2298	0.119	3	1	3	0.797	c	c
Bus2182	Bus2436	0.169	2	1	2	1.831	c	c
Bus2182	Bus2954	0.150	1	1	1	0.244	c	nc
Bus2184	Bus2438	0.116	1	1	1	0.421	nc	nc
Bus2196	Bus2326	0.387	2	1	2	1.986	c	c
Bus2196	Bus2412	0.182	1	1	1	0.756	c	nc

Continue …

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Bus2220	Bus2722	0.315	2	1	2	2.406	c	c
Bus2224	Bus2468	0.161	1	1	1	0.326	c	nc
Bus2226	Bus2298	0.124	2	1	2	1.571	c	c
Bus2226	Bus2552	0.113	1	1	1	0.293	nc	nc
Bus2226	Bus2908	0.124	2	1	2	2.264	c	c
Bus2250	Bus2334	0.305	1	1	1	1.529	c	nc
Bus2250	Bus2338	0.209	2	1	2	2.131	c	c
Bus2250	Bus2339	0.251	2	1	2	2.182	c	c
Bus2250	Bus2394	0.379	3	1	3	3.892	c	c
Bus2250	Bus2880	0.483	2	2	4	2.454	c	c
Bus2276	Bus2306	0.661	1	2	2	0.847	c	c
Bus2276	Bus2396	0.150	1	1	1	1.342	c	nc
Bus2276	Bus2674	0.129	1	1	1	1.379	c	nc
Bus2296	Bus2410	0.124	3	1	3	3.726	c	c
Bus2296	Bus2464	0.116	1	1	1	0.722	nc	nc
Bus2296	Bus2816	0.121	2	1	2	2.761	c	c
Bus2298	Bus2526	0.140	2	1	2	2.047	c	c
Bus2298	Bus2908	0.116	1	1	1	1.06	nc	nc
Bus2306	Bus2602	0.180	2	1	2	1.628	c	c
Bus2308	Bus2394	0.127	1	1	1	1.228	c	nc
Bus2308	Bus2608	0.127	2	1	2	2.334	c	c
Bus2326	Bus2412	0.392	2	1	2	2.295	c	c
Bus2334	Bus2952	0.166	1	1	1	0.305	c	nc
Bus2338	Bus2468	0.222	1	1	1	0.412	c	nc
Bus2339	Bus2468	0.116	2	1	2	1.633	nc	c
Bus2340	Bus2436	0.214	3	1	3	3.447	c	c
Bus2340	Bus2684	0.363	1	1	1	0.726	c	nc
Bus2342	Bus2552	0.228	1	1	1	0.258	c	nc
Bus2352	Bus2464	0.318	1	1	1	0.789	c	nc
Bus2352	Bus2534	0.900	2	3	6	3.436	c	c
Bus2352	Bus2636	0.368	3	1	3	6.038	c	c
Bus2394	Bus2594	0.137	1	1	1	0.526	c	nc
Bus2394	Bus2638	0.116	1	1	1	0.007	nc	nc
Bus2410	Bus2526	0.143	2	1	2	1.218	c	c
Bus2410	Bus2588	0.119	1	1	1	0.139	c	nc
Bus2410	Bus2590	0.119	1	1	1	0.168	c	nc
Bus2410	Bus2816	0.153	1	1	1	1.677	c	nc
Bus2414	Bus2602	0.116	2	1	2	2.018	nc	c
Bus2414	Bus2608	0.121	1	1	1	0.449	c	nc
Bus2420	Bus2424	0.113	1	1	1	0.019	nc	nc
Bus2420	Bus2652	0.166	3	1	3	4.304	c	c
Bus2424	Bus2916	0.100	1	1	1	0.35	nc	nc
Bus2436	Bus2740	0.135	1	1	1	0.051	c	nc
Bus2436	Bus2752	0.360	3	1	3	3.669	c	c
Bus2436	Bus2954	0.188	2	1	2	1.615	c	c
Bus2438	Bus2916	0.140	1	1	1	0.109	c	nc
Bus2464	Bus2590	0.124	2	1	2	1.853	c	c

Continue …

… Continuation

Bus2466	Bus2662	0.140	1	1	1	0.11	c	nc
Bus2466	Bus2752	0.140	1	1	1	0.471	c	nc
Bus2467	Bus2662	0.137	1	1	1	0.034	c	nc
Bus2467	Bus2752	0.145	1	1	1	0.143	c	nc
Bus2468	Bus2552	0.196	2	1	2	0.475	c	c
Bus2472	Bus2594	0.116	1	1	1	0.022	nc	nc
Bus2494	Bus2652	0.337	2	1	2	2.056	c	c
Bus2494	Bus2916	0.150	1	1	1	1.04	c	nc
Bus2510	Bus2511	0.116	1	1	1	0.003	nc	nc
Bus2526	Bus2552	0.116	2	1	2	2.733	nc	c
Bus2534	Bus2636	0.196	2	1	2	3.551	c	c
Bus2588	Bus2590	0.116	1	1	1	0.003	nc	nc
Bus2590	Bus2595	0.116	1	1	1	0.003	nc	nc
Bus2590	Bus2597	0.116	1	1	1	0.005	nc	nc
Bus2594	Bus2952	0.233	1	1	1	0.668	c	nc
Bus2636	Bus2652	0.212	2	1	2	2.419	c	c
Bus2636	Bus2880	0.119	1	1	1	0.077	c	nc
Bus2652	Bus2880	0.209	3	1	3	3.442	c	c
Bus2674	Bus2722	0.156	1	1	1	1.261	c	nc
Bus2684	Bus2698	0.158	1	1	1	0.169	c	nc
Bus2740	Bus2956	0.496	1	1	1	0.061	c	nc
Bus2752	Bus2956	0.358	3	1	3	1.029	c	c

Line outage screening associated with low voltage using the PI method for the practical 87-bus power system is based on the normalized base case PI value of 0.116 in which a transmission line outage is critical if the PI value is greater than the normalized base case PI value. Referring to Table 6.8, based on the PI method a total of 91 transmission line outage events are classified as critical lines towards low voltage. Using the proposed line outage screening method, the result of critical transmission line outages that caused low voltage shows a reduction in the number of identified critical lines, in which out of the 107 transmission line outages considered, only 46 line outages give risk factor value greater than 1, as a consequence these lines are deemed to be critical from the low voltage perspective.

Comparing the result of the PI method to the proposed line outage screening method shown in Table 6.8, more than 50% of the transmission line outage events are considered non critical based on the proposed screening method. The proposed screening method based on the risk factor identifies the critical line outage by considering the probability and severity of a transmission line outage. On the other hand, transmission line outage screening performed based on the PI value result in unnecessary computational burden since the transmission line outage that is supposed to be critical from the severity point of view may have a low probability factor, hence the risk resulted from this line outage is rather small. For example, the risk associated with line outage of line connecting bus 2118 to bus 2119 is only 0.0003, and it is identified as critical line outage based on the PI method but non critical according to the risk factor value. By considering only line outage that has significant risk contribution in RBSA, the proposed screening method is able to reduce the computation of power flow for all line outages.

Table 6.9 Screening of critical transmission line outages that caused line overload for the practical 87- bus power system

Line Outage		$PI_{Normalized}$	Probability Factor	Severity Factor	Risk Factor	$Risk_{LO}$ ($x10^{-5}$)	Method	
From Bus	To Bus						PI Method	Proposed Method
Bus62	Bus2276	0.100	2	1	2	0	nc	c
Bus62	Bus2602	0.100	1	1	1	0	nc	nc
Bus62	Bus2704	0.100	1	1	1	0	nc	nc
Bus72	Bus2338	0.402	1	2	2	0.367	c	c
Bus72	Bus2340	0.399	1	2	2	0.07	c	c
Bus72	Bus2554	0.100	1	1	1	0	nc	nc
Bus73	Bus2338	0.402	1	2	2	0.111	c	c
Bus73	Bus2340	0.399	1	2	2	0.284	c	c
Bus73	Bus2554	0.100	1	1	1	0	nc	nc
Bus2016	Bus2636	0.101	2	1	2	0.006	c	c
Bus2016	Bus2652	0.100	3	1	3	0.001	nc	c
Bus2072	Bus2706	0.100	2	1	2	0	nc	c
Bus2118	Bus2119	0.508	1	3	3	0.003	c	c
Bus2118	Bus2510	0.100	1	1	1	0	nc	nc
Bus2118	Bus2722	0.101	3	1	3	0.007	c	c
Bus2119	Bus2130	0.347	1	2	2	0.823	c	c
Bus2119	Bus2511	0.100	1	1	1	0	nc	nc
Bus2128	Bus2170	0.100	2	1	2	0	nc	c
Bus2128	Bus2220	0.100	1	1	1	0	nc	nc
Bus2128	Bus2326	0.100	2	1	2	0	nc	c
Bus2128	Bus2470	0.100	1	1	1	0	nc	nc
Bus2130	Bus2396	0.100	1	1	1	0	nc	nc
Bus2130	Bus2754	0.100	2	1	2	0	nc	c
Bus2142	Bus2248	0.100	1	1	1	0	nc	nc
Bus2158	Bus2170	0.100	3	1	3	0	nc	c
Bus2158	Bus2602	0.100	1	1	1	0	nc	nc
Bus2166	Bus2248	0.100	1	1	1	0	nc	nc
Bus2166	Bus2722	0.100	1	1	1	0	nc	nc
Bus2166	Bus2814	0.100	1	1	1	0	nc	nc
Bus2170	Bus2602	0.100	3	1	3	0	nc	c
Bus2170	Bus2722	0.100	1	1	1	0	nc	nc
Bus2182	Bus2226	0.297	1	2	2	0.463	c	c
Bus2182	Bus2298	0.100	3	1	3	0	nc	c

Continue …

… Continuation

Bus2182	Bus2436	0.451	2	3	6	1.589	c	c
Bus2182	Bus2954	0.114	1	1	1	0.009	c	nc
Bus2184	Bus2438	0.100	1	1	1	0	nc	nc
Bus2196	Bus2326	0.100	2	1	2	0	nc	c
Bus2196	Bus2412	0.100	1	1	1	0	nc	nc
Bus2220	Bus2722	0.100	2	1	2	0	nc	c
Bus2224	Bus2468	0.100	1	1	1	0	nc	nc
Bus2226	Bus2298	0.100	2	1	2	0	nc	c
Bus2226	Bus2552	0.100	1	1	1	0	nc	nc
Bus2226	Bus2908	0.100	2	1	2	0	nc	c
Bus2250	Bus2334	0.220	1	1	1	0.422	c	nc
Bus2250	Bus2338	0.100	2	1	2	0	nc	c
Bus2250	Bus2339	0.100	2	1	2	0	nc	c
Bus2250	Bus2394	0.280	3	2	6	1.545	c	c
Bus2250	Bus2880	0.335	2	2	4	1.213	c	c
Bus2276	Bus2306	0.190	1	1	1	0.147	c	nc
Bus2276	Bus2396	0.900	1	3	3	2.684	c	c
Bus2276	Bus2674	0.100	1	1	1	0	nc	nc
Bus2296	Bus2410	0.100	3	1	3	0	nc	c
Bus2296	Bus2464	0.100	1	1	1	0	nc	nc
Bus2296	Bus2816	0.101	2	1	2	0.009	c	c
Bus2298	Bus2526	0.258	2	2	4	0.811	c	c
Bus2298	Bus2908	0.101	1	1	1	0.002	c	nc
Bus2306	Bus2602	0.100	2	1	2	0	nc	c
Bus2308	Bus2394	0.142	1	1	1	0.13	c	nc
Bus2308	Bus2608	0.104	2	1	2	0.027	c	c
Bus2326	Bus2412	0.100	2	1	2	0	nc	c
Bus2334	Bus2952	0.516	1	3	3	0.314	c	c
Bus2338	Bus2468	0.411	1	2	2	0.308	c	c
Bus2339	Bus2468	0.100	2	1	2	0	nc	c
Bus2340	Bus2436	0.100	3	1	3	0	nc	c
Bus2340	Bus2684	0.406	1	2	2	0.495	c	c
Bus2342	Bus2552	0.100	1	1	1	0	nc	nc
Bus2352	Bus2464	0.490	1	3	3	0.702	c	c
Bus2352	Bus2534	0.228	2	1	2	0.764	c	c
Bus2352	Bus2636	0.300	3	2	6	2.688	c	c
Bus2394	Bus2594	0.100	1	1	1	0	nc	nc
Bus2394	Bus2638	0.435	1	2	2	0.006	c	c
Bus2410	Bus2526	0.100	2	1	2	0	nc	c
Bus2410	Bus2588	0.100	1	1	1	0	nc	nc
Bus2410	Bus2590	0.100	1	1	1	0	nc	nc
Bus2410	Bus2816	0.100	1	1	1	0	nc	nc
Bus2414	Bus2602	0.100	2	1	2	0	nc	c
Bus2414	Bus2608	0.156	1	1	1	0.065	c	nc
Bus2420	Bus2424	0.100	1	1	1	0	nc	nc
Bus2420	Bus2652	0.101	3	1	3	0.004	c	c
Bus2424	Bus2916	0.127	1	1	1	0.024	c	nc

Continue …

… Continuation

Bus2436	Bus2740	0.216	1	1	1	0.015	c	nc
Bus2436	Bus2752	0.231	3	1	3	1.075	c	c
Bus2436	Bus2954	0.268	2	2	4	0.666	c	c
Bus2438	Bus2916	0.289	1	2	2	0.052	c	c
Bus2464	Bus2590	0.100	2	1	2	0	nc	c
Bus2466	Bus2662	0.100	1	1	1	0	nc	nc
Bus2466	Bus2752	0.100	1	1	1	0	nc	nc
Bus2467	Bus2662	0.100	1	1	1	0	nc	nc
Bus2467	Bus2752	0.100	1	1	1	0	nc	nc
Bus2468	Bus2552	0.100	2	1	2	0	nc	c
Bus2472	Bus2594	0.100	1	1	1	0	nc	nc
Bus2494	Bus2652	0.104	2	1	2	0.016	c	c
Bus2494	Bus2916	0.100	1	1	1	0	nc	nc
Bus2510	Bus2511	0.100	1	1	1	0	nc	nc
Bus2526	Bus2552	0.100	2	1	2	0	nc	c
Bus2534	Bus2636	0.100	2	1	2	0	nc	c
Bus2588	Bus2590	0.100	1	1	1	0	nc	nc
Bus2590	Bus2595	0.100	1	1	1	0	nc	nc
Bus2590	Bus2597	0.100	1	1	1	0	nc	nc
Bus2594	Bus2952	0.251	1	2	2	0.241	c	c
Bus2636	Bus2652	0.101	2	1	2	0.006	c	c
Bus2636	Bus2880	0.100	1	1	1	0	nc	nc
Bus2652	Bus2880	0.102	3	1	3	0.018	c	c
Bus2674	Bus2722	0.100	1	1	1	0	nc	nc
Bus2684	Bus2698	0.128	1	1	1	0.012	c	nc
Bus2740	Bus2956	0.658	1	3	3	0.071	c	c
Bus2752	Bus2956	0.659	3	3	9	1.285	c	c

The results of transmission line outage screening associated with line overload for the 87 bus power system are as shown in Table 6.9. Here, the normalized base case PI value for line overload is 0.100. From the PI based line outage screening method, the line outages with PI value greater than 0.100 are considered as critical events, in which for this case, 42 transmission line outages have been identified as critical line outages. The proposed line outage screening method identified 59 critical line outages out of the 107 transmission line outages are critical based on the fact that the risk factor values for these critical line outages are greater than 1.

The result of the screening method based on the PI technique shown in Table 6.9 indicates only line outage that is considerably severe with PI > 0, is identified as critical line outage without considering the probability of occurrence. As can be seen in Table 6.9, transmission line outage screening based on risk factor does not only capture the severity of a line outage but it also consider uncertainty in the occurrence of line outage in which line outage that is likely to occur (probability factor > 1) and reasonably severe (severity factor > 1) is classified as critical line outage. Risk is a product of probability and severity, and therefore for transmission line outage screening in RBSA study, besides severity of line outage, the probability of occurrence should also be taken into consideration.

Table 6.10 Screening of critical transmission line outages that caused voltage collapse for the practical 87- bus power system

Line Outage		$PI_{Normalized}$	Probability Factor	Severity Factor	Risk Factor	$Risk_{VC}$ ($x10^{-5}$)	Method	
From Bus	**To Bus**						**PI Method**	**Proposed Method**
Bus62	Bus2276	0.100	2	1	2	0.287	c	c
Bus62	Bus2602	0.100	1	1	1	0.064	c	nc
Bus62	Bus2704	0.050	1	1	1	0	nc	nc
Bus72	Bus2338	0.075	1	1	1	0.043	c	nc
Bus72	Bus2340	0.075	1	1	1	0.008	c	nc
Bus72	Bus2554	0.050	1	1	1	0.067	nc	nc
Bus73	Bus2338	0.075	1	1	1	0.013	c	nc
Bus73	Bus2340	0.075	1	1	1	0.033	c	nc
Bus73	Bus2554	0.050	1	1	1	0.067	nc	nc
Bus2016	Bus2636	0.100	2	1	2	0.225	c	c
Bus2016	Bus2652	0.075	3	1	3	0.225	c	c
Bus2072	Bus2706	0.050	2	1	2	0.219	nc	c
Bus2118	Bus2119	0.075	1	1	1	0	c	nc
Bus2118	Bus2510	0.050	1	1	1	0.063	nc	nc
Bus2118	Bus2722	0.050	3	1	3	0.325	nc	c
Bus2119	Bus2130	0.100	1	1	1	0.148	c	nc
Bus2119	Bus2511	0.050	1	1	1	0.064	nc	nc
Bus2128	Bus2170	0.050	2	1	2	0.109	nc	c
Bus2128	Bus2220	0.050	1	1	1	0.028	nc	nc
Bus2128	Bus2326	0.050	2	1	2	0.112	nc	c
Bus2128	Bus2470	0.050	1	1	1	0.086	nc	nc
Bus2130	Bus2396	0.050	1	1	1	0.024	nc	nc
Bus2130	Bus2754	0.050	2	1	2	0.159	nc	c
Bus2142	Bus2248	0.050	1	1	1	0.087	nc	nc
Bus2158	Bus2170	0.100	3	1	3	0.386	c	c
Bus2158	Bus2602	0.075	1	1	1	0.043	c	nc
Bus2166	Bus2248	0.050	1	1	1	0.021	nc	nc
Bus2166	Bus2722	0.050	1	1	1	0.027	nc	nc
Bus2166	Bus2814	0.050	1	1	1	0.042	nc	nc
Bus2170	Bus2602	0.100	3	1	3	0.368	c	c
Bus2170	Bus2722	0.050	1	1	1	0.057	nc	nc
Bus2182	Bus2226	0.050	1	1	1	0.075	nc	nc
Bus2182	Bus2298	0.050	3	1	3	0.063	nc	c
Bus2182	Bus2436	0.075	2	1	2	0.177	c	c

Continue …

… Continuation

Bus2182	Bus2954	0.075	1	1	1	0.021	c	nc
Bus2184	Bus2438	0.050	1	1	1	0.033	nc	nc
Bus2196	Bus2326	0.050	2	1	2	0.134	nc	c
Bus2196	Bus2412	0.050	1	1	1	0.057	nc	nc
Bus2220	Bus2722	0.050	2	1	2	0.167	nc	c
Bus2224	Bus2468	0.050	1	1	1	0.025	nc	nc
Bus2226	Bus2298	0.050	2	1	2	0.122	nc	c
Bus2226	Bus2552	0.050	1	1	1	0.023	nc	nc
Bus2226	Bus2908	0.050	2	1	2	0.178	nc	c
Bus2250	Bus2334	0.225	1	1	1	0.221	c	nc
Bus2250	Bus2338	0.275	2	1	2	0.451	c	c
Bus2250	Bus2339	0.275	2	1	2	0.456	c	c
Bus2250	Bus2394	0.275	3	1	3	0.762	c	c
Bus2250	Bus2880	0.275	2	1	2	0.457	c	c
Bus2276	Bus2306	0.200	1	1	1	0.11	c	nc
Bus2276	Bus2396	0.075	1	1	1	0.128	c	nc
Bus2276	Bus2674	0.050	1	1	1	0.106	nc	nc
Bus2296	Bus2410	0.075	3	1	3	0.33	c	c
Bus2296	Bus2464	0.050	1	1	1	0.056	nc	nc
Bus2296	Bus2816	0.050	2	1	2	0.212	nc	c
Bus2298	Bus2526	0.050	2	1	2	0.174	nc	c
Bus2298	Bus2908	0.050	1	1	1	0.082	nc	nc
Bus2306	Bus2602	0.100	2	1	2	0.179	c	c
Bus2308	Bus2394	0.000	1	1	1	0.054	nc	nc
Bus2308	Bus2608	0.000	2	1	2	0.091	nc	c
Bus2326	Bus2412	0.050	2	1	2	0.155	nc	c
Bus2334	Bus2952	0.100	1	1	1	0.033	c	nc
Bus2338	Bus2468	0.175	1	1	1	0.063	c	nc
Bus2339	Bus2468	0.275	2	1	2	0.362	c	c
Bus2340	Bus2436	0.075	3	1	3	0.319	c	c
Bus2340	Bus2684	0.200	1	1	1	0.104	c	nc
Bus2342	Bus2552	0.050	1	1	1	0.019	nc	nc
Bus2352	Bus2464	0.225	1	1	1	0.136	c	nc
Bus2352	Bus2534	0.800	2	3	6	1.287	c	c
Bus2352	Bus2636	0.425	3	2	6	1.619	c	c
Bus2394	Bus2594	0.075	1	1	1	0.047	c	nc
Bus2394	Bus2638	0.050	1	1	1	0.001	nc	nc
Bus2410	Bus2526	0.100	2	1	2	0.135	c	c
Bus2410	Bus2588	0.050	1	1	1	0.011	nc	nc
Bus2410	Bus2590	0.050	1	1	1	0.013	nc	nc
Bus2410	Bus2816	0.075	1	1	1	0.166	c	nc
Bus2414	Bus2602	0.050	2	1	2	0.149	nc	c
Bus2414	Bus2608	0.025	1	1	1	0.028	nc	nc
Bus2420	Bus2424	0.050	1	1	1	0.001	nc	nc

Continue …

… Continuation

Bus2420	Bus2652	0.125	3	1	3	0.535	c	c
Bus2424	Bus2916	0.050	1	1	1	0.028	nc	nc
Bus2436	Bus2740	0.050	1	1	1	0.004	nc	nc
Bus2436	Bus2752	0.075	3	1	3	0.314	c	c
Bus2436	Bus2954	0.100	2	1	2	0.164	c	c
Bus2438	Bus2916	0.050	1	1	1	0.008	nc	nc
Bus2464	Bus2590	0.075	2	1	2	0.171	c	c
Bus2466	Bus2662	0.050	1	1	1	0.008	nc	nc
Bus2466	Bus2752	0.050	1	1	1	0.036	nc	nc
Bus2467	Bus2662	0.050	1	1	1	0.003	nc	nc
Bus2467	Bus2752	0.050	1	1	1	0.011	nc	nc
Bus2468	Bus2552	0.100	2	1	2	0.047	c	c
Bus2472	Bus2594	0.050	1	1	1	0.002	nc	nc
Bus2494	Bus2652	0.150	2	1	2	0.252	c	c
Bus2494	Bus2916	0.050	1	1	1	0.088	nc	nc
Bus2510	Bus2511	0.050	1	1	1	0	nc	nc
Bus2526	Bus2552	0.050	2	1	2	0.226	nc	c
Bus2534	Bus2636	0.275	2	1	2	0.761	c	c
Bus2588	Bus2590	0.050	1	1	1	0	nc	nc
Bus2590	Bus2595	0.050	1	1	1	0	nc	nc
Bus2590	Bus2597	0.050	1	1	1	0	nc	nc
Bus2594	Bus2952	0.175	1	1	1	0.096	c	nc
Bus2636	Bus2652	0.100	2	1	2	0.255	c	c
Bus2636	Bus2880	0.050	1	1	1	0.006	nc	nc
Bus2652	Bus2880	0.125	3	1	3	0.4	c	c
Bus2674	Bus2722	0.050	1	1	1	0.095	nc	nc
Bus2684	Bus2698	0.075	1	1	1	0.017	c	nc
Bus2740	Bus2956	0.075	1	1	1	0.005	c	nc
Bus2752	Bus2956	0.075	3	1	3	0.088	c	c

RBVCA requires an exhaustive power flow analysis, and to reduce the computational effort, transmission line outage screening is performed in order to shortlist only the critical line outages. From the results of transmission line outage screening associated with voltage collapse as shown in Table 6.10, out of the 107 transmission line outage events considered, only 48 and 43 transmission line outage events are considered to be critical with respect to voltage collapse as identified by the PI method and the proposed line outage screening method, respectively. In this case, the critical lines identified by the PI method consider the normalized base case PI value of 0.050. The PI based screening method only considers the severity of a line outage with respect to voltage collapse in which only line outage with PI value greater than 0.050 is identified as critical. But some of the line outages that have greater impact on the power system may have very low probability occurrence. For example, based on the result presented in Table 6.10, line outages for lines connecting bus 73 to bus 2340, bus 2334 to bus 2952 and bus 2740 to bus 2956, having PI values greater than 0.050 are classified as critical, but the probability of occurrence are low and as a consequence, the risk of voltage collapse associated with these line outages are moderately small with risk value less than 0.047. Another example shows that the line outage for line connecting bus 2118 to bus 2722, having risk value associated to voltage collapse greater than 0.047 is considered as critical by the proposed screening method but not critical based on the PI method. The probability of occurrence of this line outage (bus 2118 to bus 2722) is significant, and hence lead to a higher risk of voltage collapse. The proposed screening method based on the risk factor accounts for both severity and likelihood of transmission line outage, and therefore provides more accurate result of line outage screening when compared with the PI based method.

6.5 RISK BASED STATIC SECURITY ASSESSMENT CONSIDERING THE EFFECT OF DIFFERENT SEVERITY FUNCTIONS

Three types of severity functions, namely discrete, continuous and percentage of violation severity function are considered in the RBSSA. To investigate the effect of different severity functions, the risk index associated with load demand is calculated by using three different severity functions. This study is implemented on the IEEE 24-bus and the practical 87-bus power systems. The Poisson probability model is used to calculate the probability of transmission line outages for both test systems. Only transmission line outage that is deemed to be critical is considered in the risk index calculation. The severity associated with low voltage and line overload based on discrete, continuous and percentage of violation severity functions for every critical transmission line outage is considered. To calculate the severity function, the bus voltage magnitudes and power flows at every transmission line outage are obtained by performing power flow simulations using the PSAT software program.

6.5.1 Result of the RBSSA Considering the Effect of Different Severity Functions for the IEEE 24-bus Power System

To investigate the effect of different severity functions in the RBSSA study so as to select the best severity indicator of security violation, the risk index values used to evaluate the risk of low voltage and line overload with respect to load increase are plotted. For the IEEE 24-bus power system, only critical transmission line outages screened using the risk factor method in the order of 'N-1' are considered. The failure rates of the transmission lines provided in the Appendix A are used to compute the probability of transmission line outages. In the calculation of the risk index values, the load is increased from base case to 25% increase of base case load. 0% increase in load indicates the base case load condition. The risk index values of low voltage and line overload with respect to the total load for the IEEE 24 bus power system are shown Tables 6.11 and 6.12.

The risk index curves calculated by using the three different severity functions associated with risk of low voltage and risk of line overload are shown in Figures 6.4 and 6.5, respectively.

Table 6.11 Risk index of low voltage for the IEEE 24-bus power system

% increase in load from base case	**Type of severity function used to assess the severity of low voltage**		
	Percent ($\times 10^{-4}$)	**Continuous ($\times 10^{-4}$)**	**Discrete ($\times 10^{-4}$)**
0	0.019	5.088	0.291
5	0.021	6.035	0.291
10	0.027	7.575	0.291
15	0.028	8.923	0.403
20	0.032	10.798	0.611
25	0.039	13.235	0.895

Table 6.12 Risk index of line overload for the IEEE 24-bus power system

% increase in load from base case	**Type of severity function used to assess the severity of line overload**		
	Percent ($\times 10^{-5}$)	**Continuous ($\times 10^{-5}$)**	**Discrete ($\times 10^{-5}$)**
0	0.012	1.837	0
5	0.033	2.944	1.928
10	0.083	6.941	1.928
15	0.176	14.555	2.659
20	0.356	24.391	5.172
25	0.012	1.837	0

The curves in Figure 6.4 show that similar pattern of risk of low voltage curves are obtained for the three different severity functions. Risk of low voltage measures the degree of risk of an operating point towards low voltage, in which the higher the risk of low voltage, the more risky an operating point would be. All risk index curves shown in Figure 6.4 revealed that the risk of low voltage increases as load is increased from base case to 25% increase from base case load. This implies that as load is increased from base case, the bus voltages of the IEEE 24-bus power system are in higher risk of low voltage. It is also noted that for all the load conditions shown in Figure 6.4, the risk of low voltage calculated using the continuous severity function always result in higher risk index value compared to the risk of low voltage calculated using the other two severity functions. This is because the risk of low voltage calculated using the continuous severity function reflects the extent of low voltage violation as well as the effect of a voltage near to violation. At the loads from base case to 10% increase in base case load, the risk of low voltage calculated using the discrete severity function gives a constant risk index value. This is because the severity of low voltage computed using discrete severity function evaluates to 1 if the bus voltage magnitude is less than 0.95 but it does not measure the extent of low voltage violation. Therefore, the risk index calculated using discrete severity function does not represent the degree of risk at different operating points. It is also obvious from Figure 6.4, that the risk of low voltage computed using percentage of violation severity function always result in the smallest risk index value. This is due to the fact that the extent of security violation assessed using the percentage of violation severity function is in terms of percentage of violation which results in smaller severity function values.

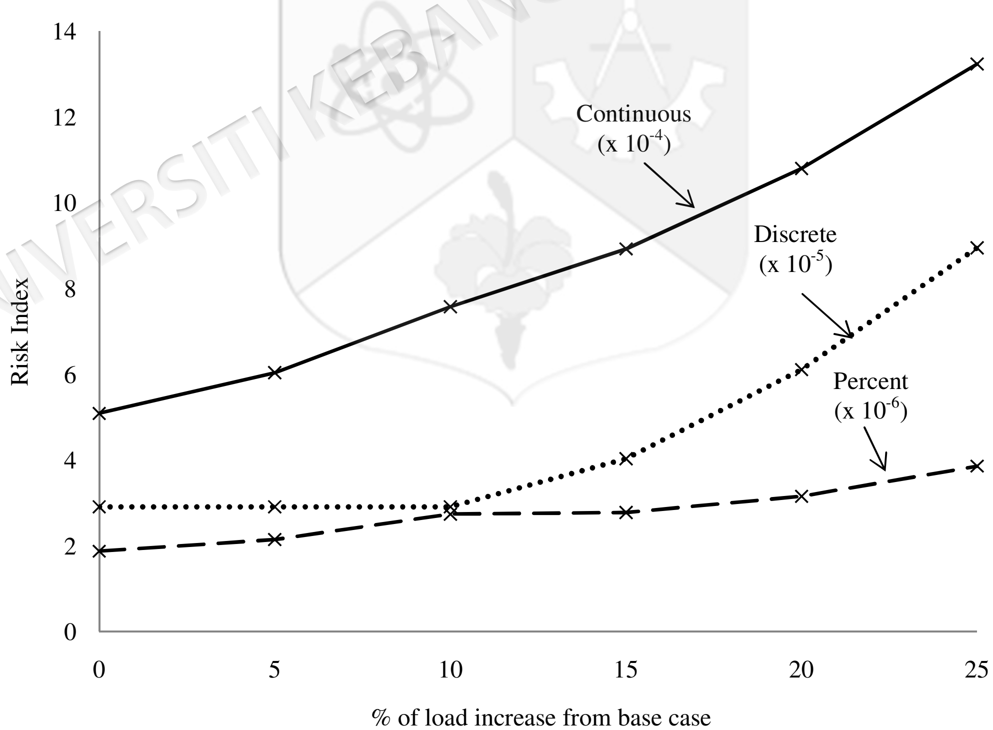

Figure 6.4 Risk of low voltage for the IEEE 24-bus power system

Figure 6.5 shows the risk of line overload values calculated using the discrete, line overload risk increases as load is increased from base case to 25% increase in base case load. It is noted that from base case to 20% increase in base case load, the risk of line overload computed using the discrete and percentage of violation severity functions is relatively small when compared with the risk of line overload determined using the continuous severity function. Nevertheless, as load is increased from 20% to 25% increase in base case load, a significant rise in risk of line overload computed using the discrete severity function can be seen. This shows that as load changes from 20% to 25% increase in base case load, more lines in the power systems become overloaded. It is also obvious that the risk of line overload evaluated using the continuous severity function always yield higher risk index value when compared with the other two severity functions. This is due to the fact that the continuous severity function gives nonzero severity values when the line flows are close to violation. To illustrate this, consider a transmission line outage that results in a near violation where the line flow is 480 MVA and the line limit is 500 MVA, the continuous, discrete and percentage of violation severity function calculated for this line is 0.6, 0 and 0, respectively. The results of the implementation of different severity functions in RBSSA have shown that continuous severity function is the most desirable as it can capture the effect of the near violating transmission line outage that the other two severity functions cannot.

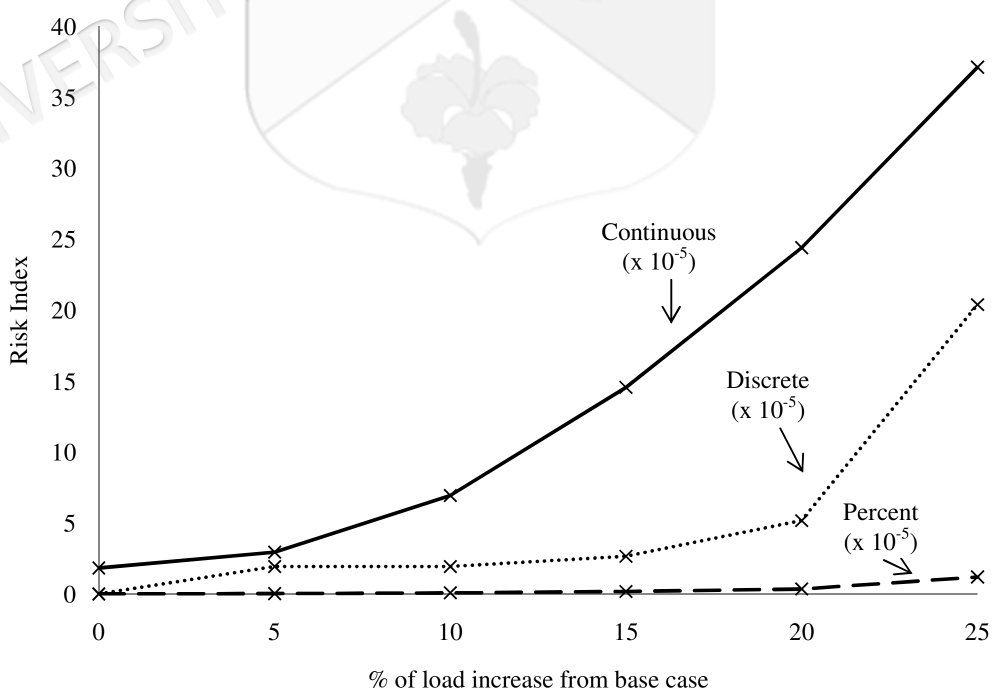

Figure 6.5 Risk of line overload for the IEEE 24-bus power system

6.5.2 Result of the RBSSA Considering the Effect of Different Severity Functions for the Practical 87-Bus Power System

To illustrate the effect of different severity function, the risk index values associated with low voltage and line overload during fine weather are plotted against the load by considering three different severity functions, and the load is increased from base case to 25% increase in base case load. Figures 6.6 and 6.7 show the variation of the risk index values for the practical 87-bus power system associated with low voltage and line overload, respectively. The value of risk index for both low voltage and line overload with respect to load calculated for the practical 87-bus power system is presented in Tables 6.13 and 6.14.

Table 6.13 Risk index of low voltage for the practical 87-bus power system

% increase in load from base case	Type of severity function used to assess the severity of low voltage		
	Percent ($x\ 10^{-3}$)	Continuous ($x\ 10^{-3}$)	Discrete ($x\ 10^{-3}$)
0	0	4.6968	0.0141
5	0.0002	7.3063	0.0141
10	0.0175	11.1756	0.1019
15	0.0084	15.441	0.9142
20	0.0932	21.4426	6.5879
25	0.3606	29.6211	13.8891

Table 6.14 Risk index of line overload for the practical 87-bus power system

% increase in load from base case	Type of severity function used to assess the severity of line overload		
	Percent ($x\ 10^{-2}$)	Continuous ($x\ 10^{-2}$)	Discrete ($x\ 10^{-2}$)
0	0.0035	0.072	0.0188
5	0.0058	0.1746	0.0342
10	0.2223	0.3535	0.0342
15	0.6339	4.3477	1.7653
20	1.0032	9.1122	2.2926
25	1.1754	15.3743	3.0965

From Figure 6.6, the minimum value of risk index occurs at base case, while the maximum risk index takes place when the load demand is increased to 25% from the base case load. The risk of low voltage for the practical 87-bus power system increases as load is increases from base case to 25% increase in the base case load. It can be seen from the increasing value of risk of low voltage calculated using all severity functions. The risk of low voltage computed by using the continuous severity function is greater than the risk of low voltage computed by using the discrete and percentage of violation severity functions. This is as a result of the nonzero continuous severity function is obtained when the magnitude of bus voltage fall below 1.0 p.u, whereas the other two severity function only evaluates to more than zero if the bus voltage magnitude is less than 0.95 p.u. It is also eminent from Figure 6.5 that the risk of low voltage calculated using the percentage of violation severity function leads to the smallest risk index value as compared to the other severity functions. The severity of low voltage assessed using the percentage of violation severity function yield smaller severity value because the severity is measured in terms of percentage. At base case load, the risk of low voltage computed using continuous severity function is relatively large when compared with the risk calculated using discrete and percentage of violation severity function. This is due to the fact that at base case load, more buses in the practical 87-bus power system are in the near violating state because the bus voltage magnitude is less than 1.0 p.u.

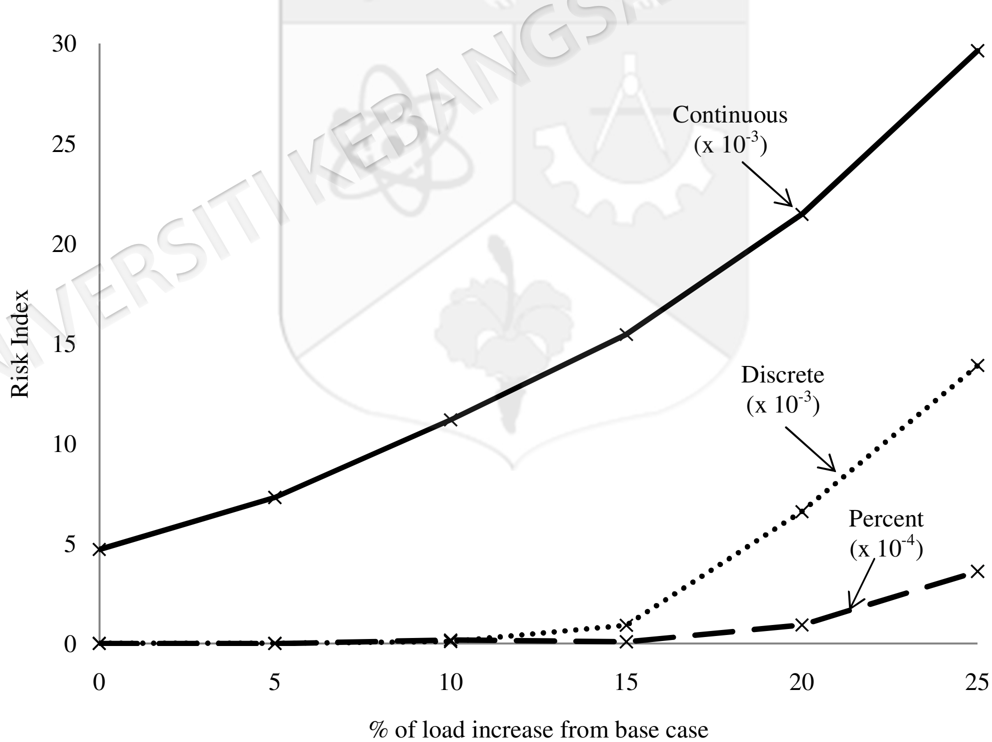

Figure 6.6 Risk of low voltage for the practical 87-bus power system

Figure 6.7 shows that the risk index values associated with risk of line overload calculated by using the continuous severity result in higher values compared with using the to 25% increase from base case load. It is also obvious that percentage of violation severity function always result in the smallest risk index value. This is as a result of the severity of low voltage violation is calculated based on the percent of the extent of security violation. At load between base case and 10% increase in base case load, the risk of line overload computed using all severity functions is comparatively low because at this point most of the line power flow in the practical 87-bus power sytem does not exceed the line rating. When load is raised beyond 10% from the base case load, it is noted that more lines in the test system are in the near violating state in which the line flow has exceeded 90% of the line rating. As a consequence, the risk of line overload calculated using the continuous severity function increases significantly.

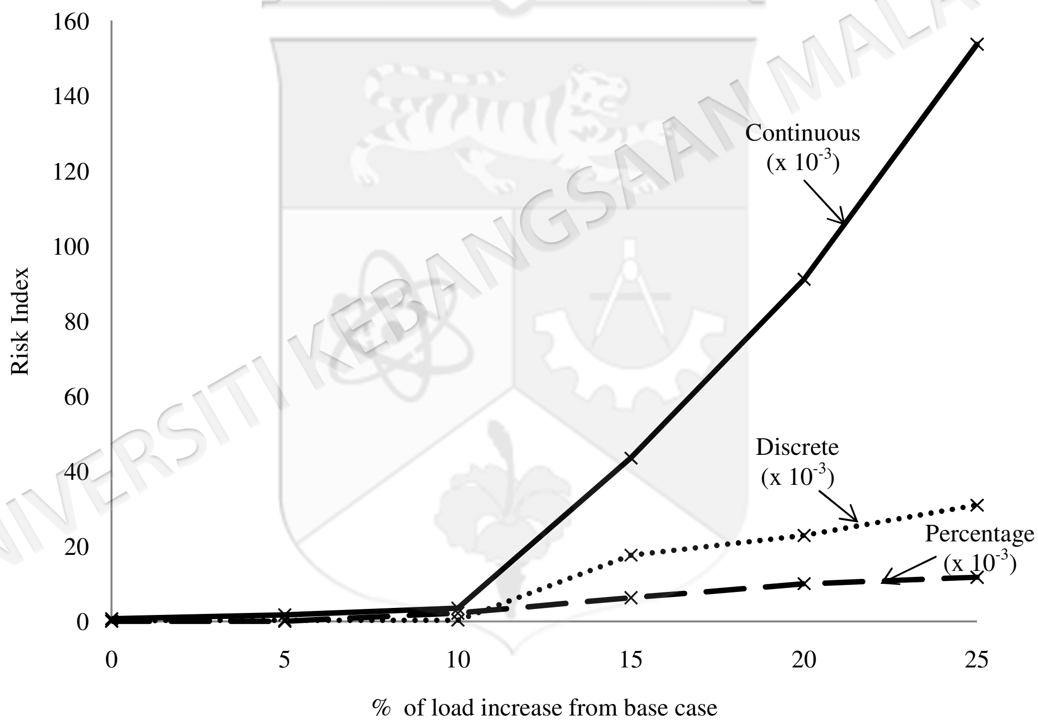

Figure 6.7 Risk of line overload for the practical 87-bus power system

6.6 RISK BASED VOLTAGE COLLAPSE ASSESSMENT USING VOLTAGE COLLAPSE PREDICTION INDEX AS A NEW SEVERITY FUNCTION

The RBVCA employing the new severity function based on the VCPI is tested on the practical 87-bus power system by considering only the critical transmission line outages prone to voltage collapse. The risk of voltage collapse calculated using the proposed severity function is compared with the risk of voltage collapse evaluated using the screening the critical transmission line outages presented earlier, the identified 43 critical transmission line outages are considered in RBVCA. To calculate the risk of voltage collapse using the proposed severity function, the bus voltage magnitude at different loading conditions are obtained through the power flow simulations carried out using the PSAT software. For comparison purposes, the risk index of voltage collapse calculated by using the severity function based on percent of load margin. To facilitate this, a continuation power flow at different loading is performed by using the PSAT software. For comparison purposes, the variation in risk of voltage collapse with respect to load during fine weather is shown. Risk index obtained using both severity functions are tabulated in Table 6.15.

Table 6.15 Risk index of voltage collapse for the practical 87-bus power system

% increase in load from base case	**Type of severity function used to assess the severity of voltage collapse**	
	Continuous	**Proposed RBVCA**
0	0	6.240
3	0	11.296
6	0	16.174
9	0	27.095
12	0	37.946
15	0	43.769
18	0	55.058
21	10.670	64.098
24	37.445	68.803
27	64.219	75.996
30	69.955	77.464

Figure 6.8 shows the variation of the risk index values with respect to load increase obtained using the continuous severity function based on the percent of load margin and the severity based on the VCPI. From the figure, it is noted that the risk of voltage collapse calculated based on the continuous severity function determined using the percent of load margin for the practical 87-bus power system is 0 as load is increased from base case to 18% increase from base case load. On the other hand, the risk of voltage determined considering the VCPI value as the severity function capture a nonzero risk of voltage collapse at all load conditions shown in Figure 6.8. The reason is as load is increased, the distance of the current operating point to the point of collapse becomes closer. In parallel with this, the severity associated to voltage collapse is also increase. The proposed severity function for voltage collapse based on the VCPI value is able to reflect the relative severity of different operating point.

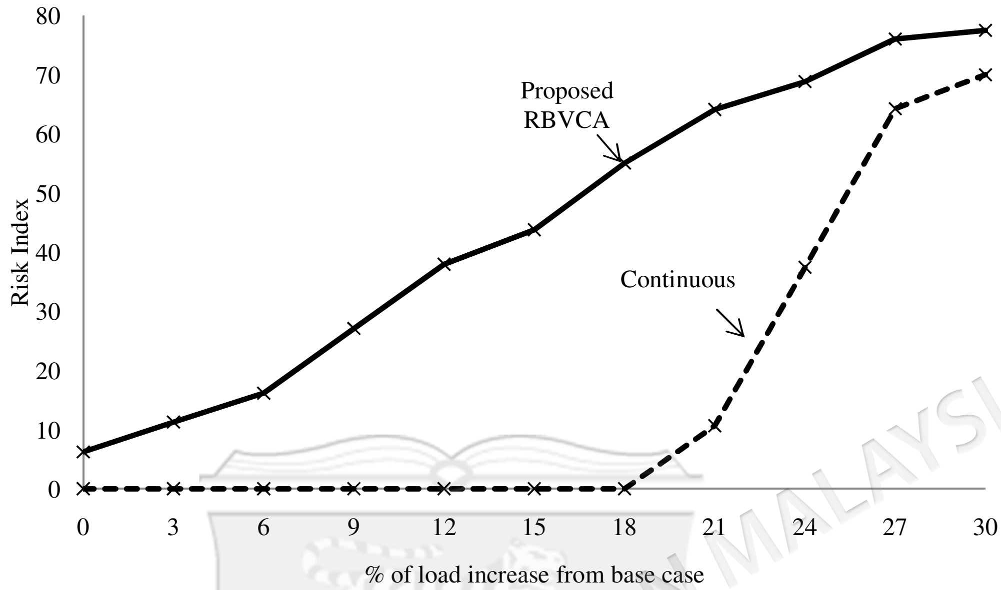

Figure 6.8 Risk of voltage collapse for the practical 87-bus power system

6.7 RISK BASED STATIC SECURITY ASSESSMENT USING ARTIFICIAL INTELLIGENT TECHNIQUES

To predict the risk of low voltage and risk of line overload for a given operating load and weather condition in RBSSA, AI techniques, namely, the SVM and GRNN are developed for the practical 87-bus power system. The continuous severity function is used for calculating the risk index due to its capability in capturing near violating condition. In order to obtain the most accurate risk prediction model, the risk index predicted by SVM and GRNN are compared and their performances are evaluated in terms of the MAE, MSE and RMSE. To reduce the number of input features to the SVM and GRNN, a feature extraction technique based on the PCA is incorporated in the SVM and GRNN implementation. The performances of the SVM and GRNN with reduced input features are also evaluated and compared.

In the development of the SVM and GRNN, real load and weather condition data are used and selected as input variables and the risk of low voltage and risk of line overload are the output variables. Numerical values of 1, 2 and 3 are assigned to represent fine, cloudy and rainy weather conditions, respectively. Table 6.16 summarizes the selected input features in which the total number of input features is 161.

Table 6.16 Selected input features for SVM and GRNN

Feature description	Number of features
MVA load at the 54 load buses	54
Weather condition at the 107 transmission lines	107

Sufficiently large numbers of training and testing data sets have been generated prior to the training of the SVM and GRNN to ensure good generalization ability. To calculate the severity of security violation, the data sets consist of bus voltages and line flows at 18 different load conditions, ranging from base case up to 25% increase in base case load are developed. For each load condition, 35 weather conditions are generated and this gives a size of 18 x 35 or 630 collected data. 80% of the data sets are used for training the SVM and GRNN while the remaining 20% are used for testing. The selection of the training and testing data sets are made randomly. For training and testing purposes, the input and output data are normalized between zero and one.

6.7.1 SVM and GRNN Results in Predicting Risk of Low Voltage for the 87-Bus Power System

In this section, the results of the risk of low voltage predicted by using SVM and GRNN for the practical 87-bus power system are presented. Initially, the number of input features selected for predicting the risk of low voltage is 161, but after feature extraction using PCA, the number of input features are reduced as shown in Table 6.17. The number of principle components is selected based on the total variance percentage of approximately 80%, 85%, 90% and 95%.

To ensure that the SVM can achieve the best generalization ability, the regularization parameter, C and the width of the RBF kernel function have to be chosen carefully. To attain good generalization accuracy in the implementation of GRNN, the SPREAD is adjusted heuristically. To select the optimum parameters for SVM and GRNN, training process are carried out using different parameters values and their accuracies are evaluated in terms of MAE, MSE and RMSE. The MATLAB toolbox is used to implement the GRNN while the LIBSVM is used to execute the SVM. The performance evaluations of the SVM and GRNN with and without PCA are tabulated as shown in Tables 6.18 and 6.19 respectively.

Table 6.17 Reduced input features for SVM and GRNN using PCA in low voltage risk prediction

Feature Extraction	Total Percentage of Variance	Number of input features
Without PCA	-	161
With PCA	80%	19
	85%	23
	90%	28
	95%	35

The values of C and σ^2 are varied over the set of values, and the training is carried out for each pair of C and σ^2. As can be seen from Table 6.18, given a value of C, the variation of σ^2 does not have much influence on the accuracy. The minimum MAE (0.03703), MSE (0.00198) and RMSE (0.04454) in the prediction of risk of low voltage using SVM are obtained when the user defined parameters C and σ^2 are tuned to 5 and 0, respectively. The most accurate risk of low voltage predicted using SVM is achieved by applying the feature extraction based on PCA which retained 28 principle components with a total variance of 90%.

Table 6.18 Performance evaluation of the SVM for the practical 87-bus power used in predicting the risk of low voltage

Feature Extraction	Total Percent of Variance	User defined parameter		Performance measures		
		C	σ^2	MAE	MSE	RMSE
Without PCA	-	1	0	0.06996	0.0054	0.0737
		5	0	0.06695	0.0051	0.07142
		5	1	0.06670	0.0054	0.07148
With PCA	80%	5	0	0.05816	0.00381	0.0617
	85%	5	0	0.04016	0.00232	0.0482
	90%	**5**	**0**	**0.03703**	**0.00198**	**0.04454**
	95%	5	0	0.03704	0.00199	0.04460

The evaluation of prediction performance of GRNN in risk assessment of low voltage shown in Table 6.19 indicates that the best accuracy is obtained when the SPREAD is adjusted to 0.10. In terms of the performance measure, the GRNN incorporating feature extraction based on PCA which retained 23 principle components with a total variance of 85% provides the lowest MAE (0.0097), MSE (0.00035) and RMSE (0.01866). Table 6.20 shows the comparison between the real risk index of low voltage and predicted risk index of low voltage of the GRNN with PCA which retains 85% of the total variance obtained during the testing stage.

Table 6.19 Performance evaluation of the GRNN for the practical 87-bus power used in predicting the risk of low voltage

Feature Extraction	Total Percent of Variance	User defined parameter SPREAD	Performance measures		
			MAE	MSE	RMSE
Without PCA	-	0.1	0.01494	0.00079	0.02815
		0.2	0.01781	0.00082	0.0287
		1	0.02943	0.0016	0.0399
With PCA	80%	0.1	0.01101	0.00040	0.02000
	85%	**0.1**	**0.00970**	**0.00035**	**0.01866**
	90%	0.1	0.01064	0.00036	0.01906
	95%	0.1	0.01064	0.00036	0.01906

Table 6.20 Comparison between real, y_{LV} and predicted, $f(x)_{LV}$ risk index of low voltage obtained using PCA based GRNN with total variance of 85%

y_{LV}	$f(x)_{LV}$	$\|y_{LV}-f(x)_{LV}\|$	y_{LV}	$f(x)_{LV}$	$\|y_{LV}-f(x)_{LV}\|$
0.53472	0.53292	0.0018	0.81932	0.78791	0.0314
0.41645	0.4159	0.0005	0.70536	0.67335	0.032
0.48443	0.42941	0.055	0.55654	0.55647	0.0001
0.48643	0.46747	0.019	0.21454	0.21972	0.0052
0.51764	0.51753	0.0001	0.48121	0.48133	0.0001
0.53473	0.53461	0.0001	0.53816	0.53793	0.0002
0.38778	0.38795	0.0002	0.51326	0.51288	0.0004
0.65341	0.63111	0.0223	0.52944	0.52818	0.0013
0.23409	0.24298	0.0089	0.30082	0.35433	0.0535
0.27519	0.2901	0.0149	0.71982	0.67783	0.042
0.37291	0.35558	0.0173	0.38394	0.38108	0.0029
0.72119	0.73056	0.0094	0.46621	0.46605	0.0002
0.73095	0.74917	0.0182	0.33681	0.33658	0.0002
0.40139	0.40166	0.0003	0.67567	0.65225	0.0234
0.32162	0.32917	0.0076	0.41555	0.41525	0.0003
0.29476	0.31962	0.0249	0.58837	0.58821	0.0002
0.24943	0.25484	0.0054	0.62032	0.65575	0.0354
0.60051	0.5712	0.0293	0.71982	0.67783	0.042

Continue …

… Continuation

0.46378	0.51678	0.053	0.19845	0.18708	0.0114
0.69334	0.69371	0.0004	0.65716	0.65777	0.0006
0.57265	0.53472	0.0379	0.41517	0.35589	0.0593
0.43248	0.4344	0.0019	0.22378	0.21696	0.0068
0.44526	0.44628	0.001	0.34237	0.34072	0.0016
0.70528	0.67088	0.0344	0.5116	0.51169	0.0001
0.52832	0.53056	0.0022	0.6114	0.61135	0.0001
0.43704	0.43648	0.0006	0.69334	0.69371	0.0004
0.2404	0.25405	0.0137	0.58733	0.58766	0.0003
0.76706	0.75921	0.0078	0.70536	0.67335	0.032
0.60067	0.623	0.0223	0.3018	0.31085	0.0091
0.57423	0.55659	0.0176	0.45309	0.44919	0.0039
0.65655	0.66585	0.0093	0.35698	0.34946	0.0075
0.62032	0.65575	0.0354	0.3672	0.36456	0.0026
0.6723	0.67196	0.0003	0.48946	0.48957	0.0001
0.61317	0.67064	0.0575	0.41645	0.4159	0.0005
0.69254	0.71487	0.0223	0.51804	0.51816	0.0001
0.67761	0.67413	0.0035	0.57026	0.53709	0.0332
0.53867	0.57653	0.0379	0.37428	0.36997	0.0043
0.51804	0.51816	0.0001	0.63163	0.62671	0.0049
0.55854	0.55848	0.0001	0.73095	0.74917	0.0182
0.30606	0.30669	0.0006	0.69334	0.69371	0.0004
0.59908	0.62792	0.0288	0.71283	0.74318	0.0304
0.32668	0.353	0.0263	0.71408	0.73368	0.0196
0.32255	0.31727	0.0053	0.53144	0.48026	0.0512
0.50932	0.50609	0.0032	0.53144	0.48026	0.0512
0.43384	0.43283	0.001	0.354	0.35381	0.0002
0.32255	0.31727	0.0053	0.6875	0.65362	0.0339
0.21221	0.20921	0.003	0.75304	0.73502	0.018

6.7.2 SVM and GRNN Results in Predicting Risk of Line Overload for the 87-Bus Power System

In this section, the results of the risk of line overload predicted by using SVM and GRNN for the practical 87-bus power system are presented. Feature extraction based on PCA is applied to reduce the number of input features for faster training time and better accuracy of prediction. The input features are reduced from 161 to 23 and 28 for total variance of 85% and 90%, respectively as shown in Table 6.21. The SVM and GRNN are trained by using both the original and reduced input so as to evaluate the performance of the developed AI techniques. To achieve the best generalization ability of the SVM and GRNN, the training and testing processes are carried by using different user defined parameters values. The performance evaluations of the SVM and GRNN with and without PCA used in the prediction of risk of line overload are tabulated in Tables 6.22 and 6.23, respectively. Training and testing are carried using various set of C and σ^2.

Table 6.21 Reduced input features for SVM and GRNN using PCA in line overload risk

Feature Extraction	**Total Percentage of Variance**	**Number of input features**
Without PCA	-	161
With PCA	80%	19
	85%	23
	90%	28
	95%	35

For choosing the optimum values of the parameters C and σ^2 of the RBF kernel, a large number of studies had been carried out by varying the values of these two parameters. The range of variation of these two parameters, which had been considered, is as follows, C, from 1 to 10, andσ^2 , from 0 to 10.For comparison purposes, only significant results are shown in Table 6.22.

Table 6.22 Performance evaluation of the SVM in predicting risk of line overload

Feature Extraction	**Total Percent of Variance**	**User defined parameter**		**Performance measures**		
		C	σ^2	**MAE**	**MSE**	**RMSE**
Without PCA	-	1	0	0.0831	0.01311	0.11451
		4	1	0.03452	0.01279	0.11309
		4	0	0.08721	0.01292	0.11365
With PCA	80%	4	1	0.04862	0.00422	0.06496
	85%	4	1	0.04506	0.00266	0.05159
	90%	**4**	**1**	**0.04176**	**0.00239**	**0.04888**
	95%	4	1	0.04177	0.00240	0.04899

From the result presented in Table 6.22, the variation in C does not have much influence on the accuracy of the prediction while variation in σ^2 improves the accuracy of the developed SVM. The performance of SVM in the prediction of risk of line overload is the most favorable if parameters C and σ^2 are set to 4 and 1 correspondingly. The results shown in Table 6.22 showed that the SVM with 28 input features by using PCA that accounts for 90% of the total variance is sufficient to predict the risk of line overload with better accuracy in terms of MAE (0.04176), MSE (0.00239) and RMSE (0.04888).

Table 6.23 Performance evaluation of the GRNN in predicting risk of line overload

Feature Extraction	Total Percent of Variance	User defined parameter SPREAD	Performance measures		
			MAE	MSE	RMSE
Without PCA	-	0.1	0.01096	0.00085	0.0291
		0.2	0.01331	0.00098	0.0312
		1	0.03187	0.0042	0.065
With PCA	80%	0.1	0.01001	0.00063	0.02510
	85%	0.1	0.00964	0.00033	0.01811
	90%	**0.1**	**0.00854**	**0.00031**	**0.01766**
	95%	0.1	0.00856	0.00032	0.01789

The performance of the developed GRNN with original input features shown in Table 6.23 proves that the best accuracy is obtained when the SPREAD is tuned to 0.1. Comparing the result of the GRNN without PCA and with PCA shown in Table 6.23, it is noted that the overall accuracy of the employed PCA that considers 85% of total variance is better than the performance of the developed GRNN without PCA. The lowest performance measures in terms of MAE (0.00854), MSE (0.00031) and RMSE (0.01766) of the developed GRNN is attained when the feature extraction based on PCA takes into account 28 principles components with a total variance of 90%. Table 6.24 shows the testing result of risk index prediction for line overload attained using the GRNN with PCA that retained 90% of the total variance.

Table 6.24 Comparison between real, y_{LO} and predicted, $f(x)_{LO}$ risk of line overload obtained using PCA based GRNN with total variance of 90% for the practical 87-bus power system

y_{LO}	$f(x)_{LO}$	$\lvert y_{LO}-f(x)_{LO}\rvert$	y_{LO}	$f(x)_{LO}$	$\lvert y_{LO}-f(x)_{LO}\rvert$
0.34634	0.35145	0.0051	0.59096	0.59033	0.0006
0.37	0.38725	0.0173	0.27247	0.27518	0.0027
0.35465	0.35625	0.0016	0.41197	0.44385	0.0319
0.60108	0.6031	0.002	0.40032	0.39784	0.0025
0.39553	0.39193	0.0036	0.25064	0.25917	0.0085
0.57351	0.57334	0.0002	0.42736	0.42611	0.0013
0.74256	0.70242	0.0401	0.48073	0.48425	0.0035
0.70736	0.61728	0.0901	0.40782	0.40834	0.0005
0.3516	0.35538	0.0038	0.43195	0.40027	0.0317
0.52783	0.52758	0.0002	0.243	0.24363	0.0006

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0.52928	0.53	0.0007	0.42232	0.42249	0.0002
0.48824	0.54365	0.0554	0.77319	0.77245	0.0007
0.72719	0.72166	0.0055	0.3162	0.32647	0.0103
0.74407	0.72552	0.0186	0.65618	0.67733	0.0212
0.26635	0.27186	0.0055	0.35465	0.35625	0.0016
0.35804	0.35515	0.0029	0.7311	0.7315	0.0004
0.43897	0.39017	0.0488	0.64745	0.64466	0.0028
0.34443	0.34474	0.0003	0.4768	0.48783	0.011
0.29114	0.30565	0.0145	0.69951	0.69898	0.0005
0.29969	0.3007	0.001	0.65618	0.67733	0.0212
0.34044	0.3392	0.0012	0.76035	0.76181	0.0015
0.48961	0.48986	0.0003	0.40058	0.39276	0.0078
0.71092	0.70852	0.0024	0.59163	0.59369	0.0021
0.35922	0.35702	0.0022	0.49041	0.50496	0.0146
0.55883	0.51008	0.0488	0.62918	0.68559	0.0564
0.70246	0.70798	0.0055	0.67367	0.61633	0.0573
0.36112	0.36148	0.0004	0.65116	0.6172	0.034
0.47199	0.47156	0.0004	0.37972	0.37891	0.0008
0.43591	0.42772	0.0082	0.63254	0.61632	0.0162
0.30651	0.30369	0.0028	0.58185	0.58211	0.0003
0.65287	0.61727	0.0356	0.7483	0.74764	0.0007
0.40058	0.39276	0.0078	0.61443	0.61471	0.0003
0.68896	0.68875	0.0002	0.61795	0.61932	0.0014
0.48961	0.48986	0.0003	0.30839	0.30784	0.0005
0.23993	0.24352	0.0036	0.67737	0.67821	0.0008
0.61935	0.61756	0.0018	0.49091	0.50491	0.014
0.2865	0.27262	0.0139	0.40032	0.39784	0.0025
0.55902	0.55908	0.0001	0.56491	0.53	0.0349
0.30651	0.30369	0.0028	0.73009	0.71069	0.0194
0.22693	0.22198	0.0049	0.72719	0.72166	0.0055
0.19169	0.1959	0.0042	0.64853	0.64873	0.0002
0.55096	0.55272	0.0018	0.58402	0.58217	0.0019
0.5381	0.56995	0.0318	0.62029	0.58547	0.0348
0.58402	0.58217	0.0019	0.61443	0.61471	0.0003
0.39689	0.39276	0.0041	0.70246	0.70798	0.0055
0.243	0.24363	0.0006	0.33642	0.30838	0.028
0.29523	0.28466	0.0106	0.64825	0.64835	0.0001
0.22077	0.21643	0.0043	0.74039	0.73435	0.006
0.60895	0.55862	0.0503	0.17109	0.17496	0.0039

6.8 RISK BASED VOLTAGE COLLAPSE ASSESSMENT USING SVM and GRNN FOR THE PRACTICAL 87-BUS POWER SYSTEM

SVM and GRNN are also applied in RBVCA for prediction of risk of voltage collapse on the practical 87-bus power system. The input features shown in Table 6.16 are also used in predicting the risk of voltage collapse. By employing PCA for feature extraction, the number of input features is reduced depending on the total percent of variation as shown in Table 6.25. The output variable of the developed SVM and GRNN is the risk of voltage collapse. The accuracy of the risk of voltage collapse predicted using SVM and GRNN are compared in terms of MAE, MSE and RMSE. The training and testing data sets are generated by performing voltage collapse simulations considering load increase from base case to 30% increase in base case load. For each load condition, 100 weather combinations are generated. Therefore, a total of 1100 data sets have been generated in which 733 data sets are selected randomly for training while the remaining 367 data sets are used for testing. The input and output data are normalized in the range between zero and one. The values of the user-defined parameters used to predict the risk of voltage collapse in the developed SVM and GRNN and their respective performance measures are summarized in Tables 6.26 and 6.27, respectively.

Table 6.25 Reduced input features of SVM and GRNN for predicting the risk of voltage collapse

Feature Extraction	Total Percent of Variance	Number of input features
Without PCA	-	161
With PCA	80%	41
	85%	48
	90%	59
	95%	65

Tables 6.26 and 6.27 show the SVM and GRNN results for RBVCA, respectively. The values of C and σ^2 are varied over the set of values, and the training is carried out for each pair of C and σ^2. As can be seen from Table 6.18, given a value of C, the variation of σ^2 degrades the performance of the SVM in predicting the risk index for voltage collapse. The best accuracy for SVM used to predict the risk of voltage collapse is obtained when the user defined parameters C and σ^2 are adjusted to 3 and 0, respectively. From the results presented in Table 6.26, improvement in the performance measures can be seen when feature extraction is applied. The 48 principle components which accounts for a total

variance of 85% is adequate to predict the risk of voltage collapse with good accuracy in which the MAE, MSE and RMSE are 0.03374, 0.00173 and 0.04157, respectively.

Table 6.26 Performance evaluation of the SVM for predicting the risk of voltage collapse

Feature Extraction	Total Percent of Variance	User defined parameter		Performance measures		
		C	σ^2	MAE	MSE	RMSE
Without PCA	-	5	0	0.049	0.0035	0.05916
		5	1	0.0967	0.0127	0.11269
		3	0	0.0418	0.0027	0.05196
With PCA	80%	3	0	0.03690	0.00201	0.04483
	85%	**3**	**0**	**0.03374**	**0.00173**	**0.04157**
	90%	3	0	0.03535	0.00183	0.04279
	95%	3	0	0.03533	0.00180	0.04243

In order to attain good generalization ability for the GRNN, SPREAD should be adjusted to 0.1. The GRNN results with and without PCA as shown in Table 6.27 proved that better accuracy is obtained when using PCA in which the values of MAE, MSE and RMSE are 0.01193, 0.00067 and 0.02588, respectively. However, increasing the total percent of variance in the risk voltage collapse prediction does not show improvement in accuracy. Thus, GRNN with PCA that retained 48 principle components which accounts for a total of 85% variance is considered the best model in predicting the risk of voltage collapse.

Table 6.27 Performance evaluation of the GRNN for predicting the risk of voltage collapse

Feature Extraction	Total Percent of Variance	User defined parameter	Performance measures		
		SPREAD	MAE	MSE	RMSE
Without PCA	-	0.1	0.015	0.00095	0.03074
		0.2	0.0216	0.0018	0.04243
		0.3	0.0291	0.0033	0.05745
With PCA	80%	0.1	0.01701	0.00099	0.03146
	85%	**0.1**	**0.01193**	**0.00067**	**0.02588**
	90%	0.1	0.01509	0.00074	0.02727
	95%	0.1	0.01501	0.00069	0.02627

Comparisons between the SVM and GRNN results are then made in terms of accuracy in predicting the risk of voltage collapse. The results showed that the GRNN with

PCA that accounts for the 85% of the total variance gives the most accurate prediction of risk of voltage collapse because it provides the lowest MAE (0.01193), MSE (0.00067) and RMSE (0.02588) values. Out of 367 data used to validate the developed GRNN with 48 principle components, only 138 data result in nonzero prediction error. Some of the result of the nonzero prediction obtained during the testing stage is shown in Table 6.28. The result of risk prediction tabulated in Table 6.31 shows that the maximum absolute error is 0.0938.

Table 6.28 Comparison between real, y_{VC} and predicted, $f(x)_{VC}$ risk of voltage collapse obtained using PCA based GRNN with total variance of 85%

y_{VC}	$f(x)_{VC}$	$\lvert y_{VC}-f(x)_{VC}\rvert$	y_{VC}	$f(x)_{VC}$	$\lvert y_{VC}-f(x)_{VC}\rvert$
0.31821	0.31185	0.0064	0.15635	0.13199	0.0244
0.05929	0.05896	0.0003	0.28495	0.27896	0.006
0.47016	0.43665	0.0335	0.63105	0.56999	0.0611
0	0.01454	0.0145	0.10815	0.09169	0.0165
0.10301	0.12412	0.0211	0.20824	0.29785	0.0896
0.255	0.23582	0.0192	0.41081	0.40275	0.0081
0.66467	0.65839	0.0063	0.13263	0.10247	0.0302
0.3514	0.32581	0.0256	0.08161	0.05121	0.0304
0.04494	0.04464	0.0003	0.44407	0.52108	0.077
0.29297	0.27135	0.0216	0.03804	0.0125	0.0255
0.22385	0.21886	0.005	0.24987	0.26315	0.0133
0.03709	0.06173	0.0246	0.10394	0.05486	0.0491
0.06074	0.0366	0.0241	0.98045	0.94209	0.0384
0.0566	0.03315	0.0234	0.04177	0.04205	0.0003
0.10932	0.09143	0.0179	0.17803	0.21094	0.0329
0.14289	0.16637	0.0235	0.22731	0.19434	0.033
0.35853	0.31543	0.0431	0.5258	0.50732	0.0185
0.21905	0.2592	0.0402	0.16914	0.17912	0.01
0.28676	0.30905	0.0223	0.40155	0.38871	0.0128
0.28328	0.27928	0.004	0.52359	0.48638	0.0372
0.05149	0.02025	0.0312	0.30576	0.27462	0.0311
0.31821	0.31185	0.0064	0.21405	0.30715	0.0931
0.18557	0.1584	0.0272	0.56682	0.51143	0.0554
0.05503	0.05547	0.0004	0.5258	0.50732	0.0185
0.98045	0.94209	0.0384	0.18215	0.26198	0.0798
0.07698	0.11983	0.0428	0.03892	0.08629	0.0474
0.67176	0.64567	0.0261	0.25408	0.2594	0.0053
0.09698	0.13686	0.0399	0.46207	0.45302	0.0091
0.03773	0.08349	0.0458	0.36292	0.35577	0.0072
0.62058	0.55806	0.0625	0.58019	0.48638	0.0938
0.98045	0.94209	0.0384	0.15635	0.13199	0.0244

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0.24742	0.24014	0.0073	0.12034	0.2134	0.0931
0.07473	0.09183	0.0171	0.08217	0.126	0.0438
0.03614	0.03641	0.0003	0.23344	0.16146	0.072
0.07698	0.11983	0.0428	0.1263	0.14532	0.019
0.33543	0.28921	0.0462	0.19252	0.20406	0.0115
0.25408	0.2594	0.0053	0.29653	0.29003	0.0065
0.03016	0.09056	0.0604	0.06914	0.01483	0.0543

6.9 CHAPTER SUMMARY

The results of all the work in this thesis are presented in this chapter. Initially, the failure rate of the transmission line with respect to weather is computed using the data pooling method. The failure rate calculated using real historical data is then used to determine the probability of line outage with respect to weather condition. Next, probability of transmission line outage calculated using the non-sequential Monte Carlo simulation is presented. From the simulation result, it is shown that the non-sequential Monte Carlo is able to estimate the probability of transmission line outage with insignificant difference when compared with the Poisson model. This shows that the non-sequential Monte Carlo simulation can also be used to estimate the probability of line outage. Monte Carlo requires an extensive computational effort, but with the advancement in the current computing resources this is no longer impossible.

The computational burden in RBSA is reduced by implementing a new transmission line outage screening based on risk factor which takes into account probability and severity of line outage. Comparing the result of the transmission line outage screening based on the proposed screening method and the PI based method, it is shown that the PI method result in unnecessary computational burden because it overlooked the effect of the probability of line outage, hence the line that is classified as critical by using PI method may have a very low risk.

To select the best indicator of the extent of security violation in RBSSA, the effect of different severity function is studied. From the results presented, the continuous severity function is the most accurate in RBSSA because of its ability to zoom into the consequence of near violating line outage. For RBVCA, the new severity function based on VCPI proposed in this study has the ability to measure the relative degree of risks at different operating points. Finally, the SVM and GRNN results in predicting the risk index for both

RBSSA and RBVCA are presented. GRNN with optimized user defined parameter is the most accurate prediction model for RBSSA and RBVCA when compared to SVM. The risk prediction results showed that GRNN with PCA gives better performance in terms of accuracy by means of MAE, MSE and RMSE.

CHAPTER VII

CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORKS

7.1 CONCLUSION

A comprehensive RBSA incorporating low voltage, line overload and voltage collapse analyses considering uncertainty in transmission line outage, and the development of new AI techniques for prediction of risk index in power system have been presented in this thesis. The first objective of this research work is to develop an improved failure rate model based on weather condition for the estimation of probability of line outage. To achieve this objective, the data pooling method based on the real historical outage data has been employed to calculate the failure rate of each line with respect to fine, cloudy and rainy weather by assuming that the weather is relatively homogenous throughout a geographical location. The improved failure rate model can capture the effect of different weather conditions since the failure rate per year for each transmission line with respect to weather condition shows that the frequency of failure varies according to the weather. Hence, better estimates of probability of line outage can be made. The probability of line outage is estimated by using the Poisson probability distribution function which considers the failure rate of each line as the parameter to characterize the occurrence of line outage.

To accomplish the second objective of the research which is to investigate the effectiveness of the Monte Carlo simulation in estimating the probability of line outage, the non-sequential Monte Carlo simulation is proposed. The non-sequential Monte Carlo simulation which uses random event generator is used to mimic the behavior of line outage. When the number of samples is sufficiently large, the probability of each system state can be estimated from the average rate of system state's occurrence. The results obtained proved that the non-sequential Monte Carlo simulation can accurately estimate the probability of line outage comparable to the analytical probability method based on the Poisson model.

The third objective of the research is to develop the critical transmission line outage list with respect to low voltage, line overload and voltage collapse so as to reduce the number of power flow simulations that need to be performed in RBSA. The calculation of risk index in RBSA necessitates an extensive power flow simulations in order to examine the power system behavior due to transmission line outage. To reduce the number of power flow simulations and to obtain the critical transmission line outage list, a new transmission line outage screening method is proposed using the risk factor which considers the severity and probability of line outage. The proposed screening method based on the risk factor accounts for both severity and likelihood of transmission line outage, and therefore provides more accurate result of line outage screening as compared to the PI based method. The proposed screening technique was tested on the IEEE 24-bus and the practical 87-bus power systems. The results revealed that only line outage with significant risk is identified as critical in which the severity and probability of occurrence are comparatively high.

To address the fourth objective of this thesis which is to develop a fast and accurate method for the assessment of RBSSA, AI techniques were applied due to their ability to synthesis complex analytical process rapidly and accurately. To achieve fast risk prediction in RBSSA, the two AI techniques, namely, SVM and GRNN incorporated with PCA as a feature extraction technique are used by handling all the critical transmission line outages. Given the load and weather conditions, the risk of low voltage and line overload can be predicted by using the developed SVM and GRNN models. The SVM and GRNN were implemented on the practical 87-bus power system and the results showed that the GRNN with reduced features provide the most accurate risk prediction.

The final objective of the research is to develop a fast and accurate risk prediction method in RBVCA. To achieve this objective, a new severity function for voltage collapse based on the VCPI and two AI techniques; SVM and GRNN are used to predict the risk of voltage collapse. A comparison is made between the risk of voltage collapse calculated by using the continuous severity function based on load margin and the proposed severity function based on the VCPI. Results proved that the proposed severity function is able to accurately measure the degree of risk for different operating conditions. In this research work, the GRNN and SVM overcome the shortcoming of the laborious computing effort required by the conventional RBVCA which has to evaluate the risk index by taking into account the risk of all transmission line outages. The feature extraction technique based on PCA is also used to reduce the training time and improve the prediction accuracy of GRNN and SVM. The developed GRNN with feature extraction based on PCA is more accurate than the SVM in predicting the risk of voltage collapse.

In conclusion, all the proposed research objectives are met and the results are promising. The proposed techniques developed in this thesis have accomplished the requirements of RBSA in power systems which are high accuracy, computationally fast and applicable for real-time risk monitoring.

7.2 SIGNIFICANT CONTRIBUTIONS IN THE RESEARCH

The main contributions of this research work are summarized as follows:

i) The improved failure rate model using real historical outage data for the transmission line outage that considers the effect of weather provides better estimate of probability of line outage compared to the of constant failure rate model which does not capture the effect of weather.

ii) The proposed technique for transmission line outage screening using the risk factor has been proven to accurately select the critical line outages compared to the conventional screening method based on the PI value.

iii) The two new AI techniques, SVM and GRNN, proposed for predicting the risk of low voltage and line overload given the load and weather conditions provide fast and accurate RBSA prediction. The proposed techniques can handle all the critical line outages and hence reduce the computational burden required in predicting the risk index. The performance of GRNN has been verified to be more accurate than SVM. The incorporation of PCA as feature extraction technique helps in reducing further the GRNN training time while improving the accuracy. The PCA managed to reduce more than 80% of the original features of the system.

iv) The proposed severity function based on the VCPI for RBVCA is proven to be superior to the existing severity function based on load margin because it has the ability to measure the degree of risk of different operating conditions.

v) The two new AI techniques, SVM and GRNN, proposed for predicting the risk of voltage collapse utilizing the new severity function based on VCPI value is proven to provide fast and accurate RBVCA prediction. The simulation results proved that the GRNN incorporated with feature reduction based on PCA is more precise than the SVM.

7.3 SUGGESTIONS FOR FUTURE WORKS

In this study, the developed RBSA analysis considers the uncertainty in the occurrence of transmission line outage and the effect of weather in the frequency of line outage. For future investigations related to this research work, the following issues may be addressed in RBSA which include,

i) To verify the proposed techniques developed in this thesis with real operating data to enable real-time implementation of RBSA.

ii) To consider uncertainties in the operating conditions such as uncertainty in load and generation patterns.

iii) To develop a software tool to incorporate the system security level into an advanced decision-support tool in selecting the most effective alternatives in maneuvering power system into more secure and efficient regions of operation.

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APPENDIX A

IEEE 24-BUS POWER SYSTEM DATA

Table A.1 Branch data for the IEEE 24-bus power system

No.	From Bus	To Bus	Length (mile)	Failure Rate	R (p.u)	X (p.u)	B (p.u)	Rating (MVA)
L1	1	2	3	0.24	0.003	0.014	0.461	175
L2	1	3	55	0.51	0.055	0.211	0.057	175
L3	1	5	22	0.33	0.022	0.085	0.023	175
L4	2	4	33	0.39	0.033	0.127	0.034	175
L5	2	6	50	0.48	0.05	0.192	0.052	175
L6	9	3	31	0.38	0.031	0.119	0.032	175
L7	4	3	27	0.36	0.027	0.104	0.028	175
L8	9	4	23	0.34	0.023	0.088	0.024	175
L9	0	5	16	0.33	0.014	0.061	2.459	175
L10	0	6	16	0.3	0.016	0.061	0.017	175
L11	7	8	43	0.44	0.043	0.165	0.045	175
L12	9	8	43	0.44	0.043	0.165	0.045	175
L13	10	8	33	0.4	0.006	0.048	0.1	500
L14	11	9	29	0.39	0.005	0.042	0.088	500
L15	12	9	33	0.4	0.006	0.048	0.1	500
L16	11	10	67	0.52	0.012	0.097	0.203	500
L17	12	10	60	0.49	0.011	0.087	0.182	500
L18	13	11	27	0.38	0.005	0.059	0.082	500
L19	14	11	12	0.33	0.002	0.017	0.036	500
L20	13	12	34	0.41	0.006	0.049	0.103	500
L21	23	12	34	0.41	0.006	0.049	0.103	500
L22	13	23	36	0.41	0.007	0.052	0.109	500
L23	16	14	18	0.35	0.003	0.026	0.055	500
L24	16	15	16	0.34	0.003	0.023	0.049	500
L25	21	15	10	0.32	0.002	0.014	0.03	500
L26	15	24	73	0.54	0.014	0.105	0.221	500
L27	17	16	18	0.35	0.003	0.026	0.055	500
L28	19	16	18	0.35	0.003	0.026	0.055	500
L29	18	17	27.5	0.38	0.005	0.04	0.083	500
L30	22	14	27.5	0.38	0.005	0.04	0.083	500
L31	18	21	15	0.34	0.003	0.022	0.046	500
L32	19	20	15	0.34	0.003	0.022	0.046	500
L33	23	20	47	0.45	0.009	0.068	0.142	500

Table A.2 Bus data for the IEEE 24-bus power system

Bus	Bus Name	Bus Type	MW Load	MVAR Load	Base kV
1	Abel	2	108	22	138
2	Adams	2	97	20	138
3	Adler	1	180	37	138
4	Agricola	1	74	15	138
5	Aiken	1	71	14	138
6	Alber	1	136	28	138
7	Alder	2	125	25	138
8	Alger	1	171	35	138
9	Ali	1	175	36	138
10	Allen	1	195	40	138
11	Anna	1	0	0	230
12	Archer	1	0	0	230
13	Arne	3	265	54	230
14	Arnold	2	194	39	230
15	Arthur	2	317	64	230
16	Asser	2	100	20	230
17	Aston	1	0	0	230
18	Astor	2	333	68	230
19	Attar	1	181	37	230
20	Attila	1	128	26	230
21	Attlee	2	0	0	230
22	Aubrey	2	0	0	230
23	Austen	2	0	0	230
24	Avery	1	0	0	230

Bus Type:

1 Load Bus (no generation).

2 Generator or plant bus.

3 Swing bus.

APPENDIX B

PRACTICAL 87-BUS POWER SYSTEM DATA

Table B. 1 Branch data for the practical 87-bus power system

No	From Bus Number	To Bus Number	Line R (pu)	Line X (pu)	Charging (pu)	Rate (MVA)
1	62	2276	0.00496	0.03188	0.24764	587
2	62	2602	0.00136	0.00874	0.06787	487
3	62	2704	0	0.0002	0.0015	587
4	72	2338	0.00052	0.00333	0.02584	587
5	72	2340	0.00033	0.00211	0.0164	587
6	72	2554	0.00057	0.0047	0.03792	683
7	73	2338	0.00052	0.00333	0.02584	587
8	73	2340	0.00033	0.00211	0.0164	587
9	73	2554	0.00057	0.0047	0.03792	683
10	132	2494	0.000828	0.006822	0.055044	282
11	2016	2636	0.00233	0.0192	0.154918	683
12	2016	2652	0.003238	0.026682	0.215283	683
13	2072	2706	0.00249	0.02054	0.16574	683
14	2118	2119	0	0.0001	0	0
15	2118	2510	0.00117	0.00963	0.07767	683
16	2118	2510	0.00117	0.00963	0.07767	683
17	2118	2510	0.00117	0.00963	0.07767	683
18	2118	2510	0.00117	0.00963	0.07767	683
19	2118	2722	0.0023	0.0436	0.3821	1762
20	2118	2722	0.0023	0.0436	0.3821	1762
21	2119	2130	0.00188	0.01546	0.12477	683
22	2119	2130	0.00188	0.01546	0.12477	683
23	2119	2511	0.00117	0.00963	0.07767	683
24	2119	2511	0.00117	0.00963	0.07767	683
25	2128	2170	0.00287	0.01849	0.1436	587
26	2128	2170	0.00287	0.01849	0.1436	587
27	2128	2220	0.00054	0.00447	0.03608	573
28	2128	2220	0.00054	0.00447	0.03608	573
29	2128	2326	0.00268	0.01725	0.13401	587
30	2128	2326	0.00268	0.01725	0.13401	587
31	2128	2470	0.00161	0.01327	0.10703	573
32	2128	2470	0.00161	0.01327	0.10703	573
33	2130	2396	0.00043	0.00352	0.02844	573
34	2130	2396	0.00043	0.00352	0.02844	573
35	2130	2698	0.00465	0.03828	0.30886	683
36	2130	2698	0.00465	0.03828	0.30886	683
37	2130	2754	0.00179	0.01478	0.11926	683
38	2130	2754	0.00179	0.01478	0.11926	683
39	2142	2248	0.00601	0.0009	1.05687	500
40	2142	2248	0.00601	0.0009	1.05687	500
41	2158	2170	0.005	0.0412	0.3324	587
42	2158	2602	0.00069	0.00569	0.04587	587
43	2166	2248	0.00041	0.00337	0.02722	683
44	2166	2248	0.00041	0.00337	0.02722	683
45	2166	2722	0.00058	0.00474	0.03822	683

Continue ...

... Continuation

46	2166	2722	0.00058	0.00474	0.03822	683
47	2166	2722	0.00058	0.00474	0.03822	683
48	2166	2722	0.00058	0.00474	0.03822	683
49	2166	2814	0.0009	0.00739	0.05963	683
50	2166	2814	0.0009	0.00739	0.05963	683
51	2170	2602	0.00533	0.04393	0.35442	683
52	2170	2722	0.00119	0.00985	0.07945	683
53	2170	2722	0.00119	0.00985	0.07945	683
54	2182	2226	0.00061	0.00504	0.04067	587
55	2182	2226	0.00061	0.00504	0.04067	587
56	2182	2298	0.00212	0.01747	0.14097	683
57	2182	2298	0.00212	0.01747	0.14097	683
58	2182	2436	0.00182	0.01172	0.09099	683
59	2182	2954	0.00016	0.00135	0.01089	683
60	2184	2438	0.0005	0.00409	0.03303	683
61	2184	2438	0.0005	0.00409	0.03303	683
62	2196	2326	0.00316	0.0203	0.15769	487
63	2196	2412	0.0012	0.00989	0.07981	683
64	2220	2722	0.00124	0.0234	0.20508	1762
65	2220	2722	0.00124	0.0234	0.20508	1762
66	2224	2468	0.00012	0.00124	0.42083	500
67	2224	2468	0.00012	0.00124	0.42083	500
68	2226	2298	0.00124	0.01023	0.08257	683
69	2226	2552	0.0008	0.00659	0.05315	587
70	2226	2552	0.0008	0.00659	0.05315	587
71	2226	2908	0.00142	0.01169	0.09431	683
72	2250	2334	0.00576	0.03707	0.28793	587
73	2250	2334	0.00576	0.03707	0.28793	587
74	2250	2338	0.00696	0.04476	0.34777	587
75	2250	2339	0.00696	0.04476	0.34777	587
76	2250	2394	0.01307	0.08407	0.65299	587
77	2250	2394	0.01307	0.08407	0.65299	587
78	2250	2880	0.00882	0.07267	0.58631	683
79	2250	2880	0.00882	0.07267	0.58631	683
80	2276	2306	0.00139	0.00892	0.06925	487
81	2276	2396	0.00249	0.01602	0.12442	487
82	2276	2396	0.00249	0.01602	0.12442	487
83	2276	2674	0.00196	0.01613	0.13018	683
84	2276	2674	0.00196	0.01613	0.13018	683
85	2296	2410	0.00319	0.02631	0.21229	683
86	2296	2464	0.00099	0.00815	0.06575	683
87	2296	2464	0.00099	0.00815	0.06575	683
88	2296	2816	0.00296	0.02438	0.19669	683
89	2298	2526	0.00084	0.00692	0.05584	687
90	2298	2526	0.00084	0.00692	0.05584	687
91	2298	2908	0.00086	0.00709	0.05718	683
92	2306	2602	0.00326	0.021	0.16309	487
93	2308	2394	0.00514	0.0331	0.25705	487
94	2308	2394	0.00514	0.0331	0.25705	487
95	2308	2608	0.00936	0.06022	0.46769	487
96	2308	2608	0.00936	0.06022	0.46769	487

Continue ...

... Continuation

97	2326	2412	0.00279	0.02301	0.18562	683
98	2334	2952	0.00099	0.00819	0.06608	683
99	2334	2952	0.00099	0.00819	0.06608	683
100	2338	2468	0.00105	0.00868	0.07003	683
101	2339	2468	0.00105	0.00868	0.07003	683
102	2340	2436	0.00197	0.01625	0.1311	587
103	2340	2436	0.00197	0.01625	0.1311	587
104	2340	2684	0.0017	0.01402	0.11315	683
105	2340	2684	0.0017	0.01402	0.11315	683
106	2342	2552	0.00066	0.00545	0.04394	683
107	2342	2552	0.00066	0.00545	0.04394	683
108	2342	2752	0.00059	0.00487	0.03926	683
109	2342	2752	0.00059	0.00487	0.03926	683
110	2352	2464	0.00126	0.00811	0.06296	487
111	2352	2464	0.00126	0.00811	0.06296	487
112	2352	2534	0.00212	0.01749	0.14113	683
113	2352	2636	0.00518	0.04267	0.34433	587
114	2394	2594	0.00247	0.01592	0.12367	587
115	2394	2594	0.00247	0.01592	0.12367	587
116	2394	2594	0.00247	0.01592	0.12367	587
117	2394	2594	0.00247	0.01592	0.12367	587
118	2394	2638	0.00002	0.0002	0.00504	900
119	2394	2638	0.00002	0.0002	0.00504	900
120	2410	2526	0.00161	0.01328	0.10712	683
121	2410	2526	0.00161	0.01328	0.10712	683
122	2410	2588	0.00017	0.00137	0.0111	683
123	2410	2590	0.00017	0.00137	0.0111	683
124	2410	2816	0.00184	0.01516	0.12232	683
125	2414	2602	0.00601	0.03864	0.30013	487
126	2414	2602	0.00601	0.03864	0.30013	487
127	2414	2608	0.00217	0.01394	0.10826	487
128	2414	2608	0.00217	0.01394	0.10826	487
129	2420	2424	0.00022	0.00003	0.03914	650
130	2420	2424	0.00022	0.00003	0.03914	650
131	2420	2652	0.00148	0.02771	0.24267	683
132	2420	2652	0.00148	0.02771	0.24267	683
133	2424	2916	0.00049	0.00407	0.03281	683
134	2424	2916	0.00049	0.00407	0.03281	683
135	2436	2740	0.00027	0.00114	0.00917	1435
136	2436	2752	0.00239	0.01972	0.15911	683
137	2436	2954	0.00123	0.01015	0.08192	683
138	2438	2916	0.00015	0.00125	0.01009	683
139	2438	2916	0.00015	0.00125	0.01009	683
140	2464	2590	0.00315	0.02025	0.15728	587
141	2464	2590	0.00315	0.02025	0.15728	587
142	2464	3184	0.00002	0.0001	0.01541	454
143	2464	3185	0.00003	0.00011	0.01695	454
144	2464	3186	0.00003	0.00014	0.02157	454
145	2466	2662	0.00005	0.00053	0.17908	500
146	2466	2752	0.00039	0.0032	0.02581	687
147	2466	2752	0.00039	0.0032	0.02581	683
148	2467	2662	0.00005	0.00053	0.17908	500
149	2467	2752	0.00039	0.00318	0.02569	573
150	2468	2552	0.00123	0.01012	0.08165	683

Continue ...

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151	2468	2552	0.00123	0.01012	0.08165	683
152	2472	2594	0.00011	0.00069	0.00537	587
153	2472	2594	0.00011	0.00069	0.00537	587
154	2494	2652	0.00238	0.01963	0.1584	683
155	2494	2706	0.000644	0.005306	0.042812	683
156	2494	2916	0.00117	0.00967	0.07798	687
157	2494	2916	0.00117	0.00966	0.07798	683
158	2510	2511	0	0.0001	0	0
159	2526	2552	0.00111	0.00912	0.07361	683
160	2526	2552	0.00111	0.00912	0.07361	683
161	2534	2636	0.00296	0.02435	0.19648	683
162	2588	2590	0	0.00034	0.00027	683
163	2590	2595	0	0.0001	0	0
164	2590	2597	0	0.0001	0	0
165	2594	2952	0.00207	0.01705	0.13758	683
166	2594	2952	0.00207	0.01705	0.13758	683
167	2636	2652	0.00294	0.02426	0.19571	683
168	2636	2880	0.00009	0.00076	0.00612	683
169	2636	2880	0.00009	0.00076	0.00612	683
170	2652	2880	0.00118	0.0223	0.19561	1762
171	2652	2880	0.00118	0.0223	0.19561	1762
172	2674	2722	0.00199	0.01642	0.13252	683
173	2674	2722	0.00199	0.01642	0.13252	683
174	2684	2698	0.00045	0.00371	0.02997	683
175	2684	2698	0.00045	0.00371	0.02997	683
176	2740	2956	0.00027	0.00114	0.00917	1435
177	2752	2956	0.00239	0.01972	0.15911	683

Table B.2 Load data for the practical 87-bus power system

No.	Bus Number	Pload (MW)	Qload (Mvar)	Pload (pu)	Qload (pu)
1	132	90.5	5.7	0.905	0.057
2	2016	173.6	3.4	1.736	0.034
3	2119	115.2	58.6	1.152	0.586
4	2128	195	44	1.95	0.44
5	2142	164	62	1.64	0.62
6	2166	198.9	4.2	1.989	0.042
7	2170	192	69.1	1.92	0.691
8	2182	102.5	66.9	1.025	0.669
9	2184	83	15.2	0.83	0.152
10	2196	110	22	1.1	0.22
11	2220	30	10	0.3	0.1
12	2220	0	0	0	0
13	2224	319.4	150.9	3.194	1.509
14	2226	324.4	143.1	3.244	1.431
15	2250	151.8	28.8	1.518	0.288
16	2276	195.5	42.3	1.955	0.423
17	2296	202.4	59.9	2.024	0.599
18	2298	-16.5922	-2.1037	-0.16592	-0.02104
19	2298	19.7985	18.7456	0.197985	0.187456
20	2298	0	0	0	0
21	2308	99.2	21.4	0.992	0.214
22	2326	117.8	26.8	1.178	0.268
23	2334	131.2	25.2	1.312	0.252
24	2338	0	0	0	0
25	2338	325.1	115.5	3.251	1.155
26	2340	259.9	26.5	2.599	0.265
27	2342	251.1	9.6	2.511	0.096
28	2352	317.4	6.6	3.174	0.066
29	2352	198.9	37.5	1.989	0.375
30	2394	161.6	25.8	1.616	0.258
31	2396	0	0	0	0
32	2412	96.4	10.6	0.964	0.106
33	2414	0	0	0	0
34	2414	0	0	0	0
35	2414	10.7798	3.6637	0.107798	0.036637
36	2436	357.2	165.2	3.572	1.652
37	2438	0	0	0	0
38	2466	196.2	134.4	1.962	1.344
39	2468	338.1	65.1	3.381	0.651
40	2470	1.1702	-2.264	0.011702	-0.02264
41	2470	1.9444	-2.8077	0.019444	-0.02808
42	2472	23.9667	9.3196	0.239667	0.093196
43	2494	254.6	23.3	2.546	0.233
44	2526	455	82.6	4.55	0.826
45	2534	181.6	7.2	1.816	0.072
46	2534	182	7.6	1.82	0.076
47	2552	539	103.4	5.39	1.034
48	2554	39.6	15.9	0.396	0.159
49	2588	150.3	20.2	1.503	0.202
50	2602	0.3585	-1.9193	0.003585	-0.01919
51	2608	208.8	46.2	2.088	0.462

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52	2636	215.7	24.6	2.157	0.246
53	2652	185.2	20.3	1.852	0.203
54	2662	132.8	92.2	1.328	0.922
55	2674	46.9	12.3	0.469	0.123
56	2698	325.4	80.2	3.254	0.802
57	2706	92.6	7.5	0.926	0.075
58	2752	684.9	237	6.849	2.37
59	2754	233.8	63.2	2.338	0.632
60	2814	152.7	35.3	1.527	0.353
61	2816	351.6	19.5	3.516	0.195
62	2908	248.5103	-153.16	2.485103	-1.5316
63	2916	0	0	0	0
64	2916	252.2	46.2	2.522	0.462
65	2952	98	24.8	0.98	0.248
66	2954	160.8	65.4	1.608	0.654
67	2954	190.6	62.2	1.906	0.622

Table B.3 Machine data for the practical 87-bus power system

No.	Bus Number	Pgen (MW)	Pmax (MW)	Pmin (MW)	Qgen (Mvar)	Qmax (Mvar)	Qmin (Mvar)	Mbase (MVA)
1	2158	80	85	0	29.1807	52.68	-31.22	100
2	2182	230	255	0	31.7854	158.03	-93.67	300
3	2298	728.1	680	0	337.2166	421.43	-249.8	800
4	2306	80	85	0	-21.1714	52.68	-31.22	100
5	2306	74	85	0	-19.5836	52.68	-31.22	100
6	2308	330	340	0	-14.626	210.71	-124.9	400
7	2394	590	595	0	220.4401	368.75	-218.57	700
8	2410	380	382.5	0	-35.4162	237.05	-140.51	450
9	2414	593.1	595	0	-156.571	368.75	-218.57	700
10	2424	165	170	0	100.198	105.36	-62.45	200
11	2436	1600	1615	0	353.366	1000.89	-593.27	1900
12	2438	23	25.5	0	0	15.8	-9.37	30
13	2464	400	425	0	148.012	263.39	-156.12	500
14	2510	1064.3	1105	0	-74.5345	684.82	-405.92	1300
15	2511	630	637.5	0	-74.5345	395.09	-234.19	750
16	2552	300	340	0	-56.742	210.71	-124.9	400
17	2602	533.4459	722.5	0	-206.477	447.77	-265.41	850
18	2638	720	722.5	0	-72.3083	447.77	-265.41	850
19	2684	630	637.5	0	375.426	395.09	-234.19	750
20	2740	800	850	0	342.8551	526.78	-312.25	1000
21	3184	231.4	255	0	54.9586	158.03	-93.67	300
22	3185	231.4	255	0	28.7782	158.03	-93.67	300
23	3186	238.6	255	0	20.6554	158.03	-93.67	300

Table B.4 Summary of the transmission lines outages between January 2002 to December 2007 for the practical 87-bus power system.

Pool	No. of Failure	Total Outage (mile)	Weather Type
1	49	3037.1	Fine
	21	1443.5	Cloudy
	84	5146.8	Rain
2	31	1002.59	Fine
	9	250.8	Cloudy
	42	1438.19	Rain
3	16	776.3	Fine
	6	342.2	Cloudy
	28	1126	Rain
4	31	4733.51	Fine
	14	2112.4	Cloudy
	32	4394.81	Rain
5	14	1414	Fine
	6	606	Cloudy
	9	909	Rain
6	1	18.3	Fine
	1	18.3	Cloudy
	2	36.6	Rain
7	3	300.3	Fine
	1	100.1	Cloudy
	7	700.7	Rain
8	9	1044	Fine
	1	116	Cloudy
	9	1044	Rain
9	7	1341.9	Fine
	4	766.8	Cloudy
	12	2300.4	Rain

APPENDIX C

TRANSMISSION LINE OUTAGE SCREENING FOR THE PRACTICAL 87-BUS POWER SYSTEM

Table C.1 The probability factor of transmission line outage associated with weather combination for the practical 87-bus power system

Line Outage		Weather 1		Weather 2		Weather 3	
		Weather Type	Probability Factor	Weather Type	Probability Factor	Weather Type	Probability Factor
Bus62	Bus2276	Fine	2	Rainy	2	Rainy	2
Bus62	Bus2602	Rainy	1	Rainy	1	Cloudy	1
Bus62	Bus2704	Rainy	1	Cloudy	1	Fine	1
Bus72	Bus2338	Cloudy	1	Cloudy	1	Rainy	1
Bus72	Bus2340	Fine	1	Fine	1	Fine	1
Bus72	Bus2554	Fine	1	Cloudy	1	Cloudy	1
Bus73	Bus2338	Fine	1	Fine	1	Fine	1
Bus73	Bus2340	Cloudy	1	Rainy	1	Cloudy	1
Bus73	Bus2554	Cloudy	1	Fine	1	Cloudy	1
Bus2016	Bus2636	Cloudy	2	Cloudy	2	Fine	2
Bus2016	Bus2652	Fine	3	Rainy	3	Cloudy	2
Bus2072	Bus2706	Fine	2	Rainy	2	Rainy	2
Bus2118	Bus2119	Rainy	1	Fine	1	Rainy	1
Bus2118	Bus2510	Rainy	1	Cloudy	1	Fine	1
Bus2118	Bus2722	Rainy	3	Rainy	3	Rainy	3
Bus2119	Bus2130	Cloudy	1	Fine	1	Rainy	1
Bus2119	Bus2511	Fine	1	Rainy	1	Rainy	1
Bus2128	Bus2170	Fine	2	Fine	2	Cloudy	1
Bus2128	Bus2220	Cloudy	1	Cloudy	1	Fine	1
Bus2128	Bus2326	Rainy	2	Cloudy	1	Fine	1
Bus2128	Bus2470	Fine	1	Rainy	1	Rainy	1
Bus2130	Bus2396	Fine	1	Rainy	1	Rainy	1
Bus2130	Bus2754	Rainy	2	Fine	2	Cloudy	2
Bus2142	Bus2248	Cloudy	1	Fine	1	Cloudy	1
Bus2158	Bus2170	Rainy	3	Fine	3	Fine	3
Bus2158	Bus2602	Rainy	1	Cloudy	1	Fine	1
Bus2166	Bus2248	Rainy	1	Fine	1	Fine	1
Bus2166	Bus2722	Cloudy	1	Fine	1	Cloudy	1
Bus2166	Bus2814	Rainy	1	Cloudy	1	Cloudy	1
Bus2170	Bus2602	Cloudy	3	Cloudy	3	Cloudy	3
Bus2170	Bus2722	Fine	1	Rainy	1	Cloudy	1
Bus2182	Bus2226	Rainy	1	Fine	1	Cloudy	1
Bus2182	Bus2298	Cloudy	3	Cloudy	3	Fine	1
Bus2182	Bus2436	Cloudy	2	Cloudy	2	Rainy	2

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Bus2182	Bus2954	Fine	1	Fine	1	Cloudy	1
Bus2184	Bus2438	Cloudy	1	Rainy	1	Fine	1
Bus2196	Bus2326	Fine	2	Cloudy	2	Rainy	2
Bus2196	Bus2412	Cloudy	1	Cloudy	1	Cloudy	1
Bus2220	Bus2722	Fine	2	Cloudy	2	Rainy	2
Bus2224	Bus2468	Rainy	1	Cloudy	1	Cloudy	1
Bus2226	Bus2298	Cloudy	2	Fine	1	Rainy	1
Bus2226	Bus2552	Rainy	1	Fine	1	Fine	1
Bus2226	Bus2908	Cloudy	2	Rainy	2	Cloudy	2
Bus2250	Bus2334	Rainy	1	Fine	1	Rainy	1
Bus2250	Bus2338	Cloudy	2	Rainy	2	Fine	2
Bus2250	Bus2339	Rainy	2	Rainy	2	Fine	2
Bus2250	Bus2394	Rainy	3	Fine	3	Rainy	2
Bus2250	Bus2880	Rainy	2	Fine	2	Rainy	2
Bus2276	Bus2306	Fine	1	Cloudy	1	Cloudy	1
Bus2276	Bus2396	Rainy	1	Rainy	1	Fine	1
Bus2276	Bus2674	Cloudy	1	Cloudy	1	Rainy	1
Bus2296	Bus2410	Fine	3	Fine	3	Rainy	3
Bus2296	Bus2464	Rainy	1	Cloudy	1	Cloudy	1
Bus2296	Bus2816	Fine	2	Fine	2	Fine	2
Bus2298	Bus2526	Cloudy	2	Fine	2	Fine	2
Bus2298	Bus2908	Rainy	1	Fine	1	Rainy	1
Bus2306	Bus2602	Rainy	2	Rainy	2	Cloudy	1
Bus2308	Bus2394	Cloudy	1	Fine	1	Rainy	1
Bus2308	Bus2608	Cloudy	2	Fine	2	Rainy	2
Bus2326	Bus2412	Rainy	2	Cloudy	2	Fine	2
Bus2334	Bus2952	Rainy	1	Rainy	1	Rainy	1
Bus2338	Bus2468	Rainy	1	Fine	1	Fine	1
Bus2339	Bus2468	Cloudy	2	Cloudy	2	Cloudy	1
Bus2340	Bus2436	Cloudy	3	Cloudy	3	Cloudy	2
Bus2340	Bus2684	Fine	1	Cloudy	2	Fine	1
Bus2342	Bus2552	Rainy	1	Rainy	1	Fine	1
Bus2352	Bus2464	Cloudy	1	Rainy	1	Cloudy	1
Bus2352	Bus2534	Rainy	2	Cloudy	2	Rainy	2
Bus2352	Bus2636	Cloudy	3	Cloudy	3	Fine	3
Bus2394	Bus2594	Fine	1	Rainy	1	Cloudy	1
Bus2394	Bus2638	Cloudy	1	Rainy	1	Fine	1
Bus2410	Bus2526	Fine	2	Cloudy	1	Cloudy	1
Bus2410	Bus2588	Rainy	1	Fine	1	Fine	1
Bus2410	Bus2590	Fine	1	Cloudy	1	Rainy	1
Bus2410	Bus2816	Cloudy	1	Fine	2	Fine	1
Bus2414	Bus2602	Cloudy	2	Cloudy	2	Fine	2
Bus2414	Bus2608	Cloudy	1	Rainy	1	Fine	1
Bus2420	Bus2424	Rainy	1	Cloudy	1	Fine	1

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Bus2420	Bus2652	Rainy	3	Cloudy	2	Rainy	3
Bus2424	Bus2916	Cloudy	1	Rainy	1	Cloudy	1
Bus2436	Bus2740	Fine	1	Fine	1	Fine	1
Bus2436	Bus2752	Cloudy	3	Fine	1	Rainy	2
Bus2436	Bus2954	Cloudy	2	Cloudy	2	Rainy	1
Bus2438	Bus2916	Cloudy	1	Cloudy	1	Cloudy	1
Bus2464	Bus2590	Cloudy	2	Rainy	2	Cloudy	2
Bus2466	Bus2662	Cloudy	1	Cloudy	1	Rainy	1
Bus2466	Bus2752	Rainy	1	Rainy	1	Rainy	1
Bus2467	Bus2662	Rainy	1	Fine	1	Fine	1
Bus2467	Bus2752	Fine	1	Fine	1	Fine	1
Bus2468	Bus2552	Cloudy	2	Cloudy	2	Fine	1
Bus2472	Bus2594	Cloudy	1	Rainy	1	Fine	1
Bus2494	Bus2652	Rainy	2	Cloudy	2	Cloudy	2
Bus2494	Bus2916	Cloudy	1	Fine	1	Fine	1
Bus2510	Bus2511	Cloudy	1	Fine	1	Cloudy	1
Bus2526	Bus2552	Cloudy	2	Rainy	2	Rainy	2
Bus2534	Bus2636	Fine	2	Rainy	3	Rainy	2
Bus2588	Bus2590	Fine	1	Cloudy	1	Cloudy	1
Bus2590	Bus2595	Cloudy	1	Rainy	1	Cloudy	1
Bus2590	Bus2597	Rainy	1	Rainy	1	Rainy	1
Bus2594	Bus2952	Fine	1	Cloudy	1	Rainy	1
Bus2636	Bus2652	Cloudy	2	Rainy	3	Cloudy	2
Bus2636	Bus2880	Cloudy	1	Rainy	1	Fine	1
Bus2652	Bus2880	Rainy	3	Cloudy	2	Rainy	2
Bus2674	Bus2722	Fine	1	Rainy	1	Cloudy	1
Bus2684	Bus2698	Cloudy	1	Rainy	1	Fine	1
Bus2740	Bus2956	Fine	1	Cloudy	1	Fine	1
Bus2752	Bus2956	Rainy	3	Rainy	3	Fine	1

APPENDIX D

LIST OF PUBLICATIONS

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3. Marayati Marsadek, Azah Mohamed and Zulkifli Mohd. Norpiah. 2009. Risk Based Static Security Assessment of Power Systems Considering the Effects of Severity Functions. *The 3rd International Power Engineering and Optimization Conference (PEOCO 2009)*, Shah Alam, Malaysia.
4. Marayati Marsadek, Azah Mohamed & Zulkifi Mohd. Norpiah. 2010. Risk assessment of line overload in a practical power system considering different types of severity functions. *The 9th WSEAS International Conference on APPLICATIONS OF ELECTRICAL ENGINEERING (AEE'10)*.
5. Marayati Marsadek, Azah Mohamed & Zulkifi Mohd. Norpiah. 2010. Assessment and classification of line overload risk in power systems considering different types of severity functions. *WSEAS TRANSACTIONS on POWER SYSTEMS*, 3 (5): 182-191.
6. M Marsadek, A Mohamed, Z M Norpiah. Risk of Static Security of a Power System Using Non-Sequential Monte Carlo Simulation. *Journal of Applied Sciences, 11 (2)*, 2011: 300 – 307.
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8. Marayati Marsadek, Azah Mohamed & Zulkifli Mohd. Nopiah. 2011. Risk-Based Voltage Collapse Assessment Using Generalized Regression Neural Network. *The 3rd International Conference on Electrical Engineering and Informatics*. (Submitted).
9. M. MARSADEK, A. MOHAMED and K. S. YAP. 2011. Risk based static security assessment in a large scale power system using computational intelligent techniques. *International Journal of Electrical Power and Energy Systems*. (Submitted).