Power System Stability Assessment and Enhancement using Computational Intelligence

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To my parents, my brothers, my sisters, my wife
and my children Abd-Elrahman, Maryan and Noran

Abstract

The main objective of the dissertation is to develop a fast and robust tool for assessment of power system stability and design a framework for enhancing system stability. The proposed framework is - based on the investigation of the dynamic behavior of the system - a market based rescheduling strategy that increases the stability margin.

The dissertation specifically puts emphasis on the following approached:

Power System Stability Evaluation: System stability is investigated by simulating a set of critical contingencies to determine whether the disturbances will result in any unsafe operating conditions and extract the necessary information to classify system states. The classification is based on the computation of the critical fault clearing time (CCT) for transient stability assessment (TSA) and the minimum damping of oscillation (MDO) for power system oscillatory stability assessment (OSA). The customary method of power system transient stability analysis including time-domain simulation (TDS) is used to compute the CCT at each critical contingency and Prony analysis as an efficient identification technique to estimate the mode parameters from the actual time response. The use of Prony analysis is to account for the effects of the change in location of the small disturbances as well as the increase in system nonlinearity on oscillating modes.

Fast Power System Stability Assessment Tool: An artificial neural network (ANN) is designed to serve as accurate and fast tool for dynamic stability assessment (DSA). Fast response of ANN allows system operators to take suitable control actions to enhance the system stability and to forestall any possible impending breakup of the system. Two offline trained ANN are designed to map the dynamic behavior by relating the selected input features

and the calculated CCT (as indicator for transient stability) and MDO (as indicator for oscillatory stability). Input features of ANN are selected to characterize the following:

Changes in system topology and power distributions due to outage of major equipment such as transmission line, generation unit or large load

Change in fault location and the severity of the fault

Variation in loading levels and load allocation among market participants

The features are generated for a wide range of loading at each expected system topology. Initial feature sets are pre-selected by engineering judgment based on experience in power system operation. In order to improve the accuracy of ANN to map the power system dynamic behavior, final selection is performed in the following three steps. In the first step, the generators terminal voltage drops immediately after fault are selected features to characterize the severity of the contingency with respect to the generators and to detect the fault location. In the second step, new features based on the inertia constant and the generated power in each area are calculated to characterize the changes in system topology and power flow pattern during normal and abnormal operation. In the third step, a systematic clustering feature selection technique is used to select the most important features that characterize the load levels and the power flow through lines from the mathematical viewpoint. The results prove the suitability of ANN in DSA with a reasonable degree of accuracy.

Dynamic Stability Enhancement: To achieve online dynamic stability enhancement an online market based rescheduling strategy is proposed in the deregulated power systems. In case of power system operation by a centralized pool in vertically integrated electric utilities, generation rescheduling based sensitivity analysis is proposed.

Abstract

In the proposed market for deregulated power systems, the transactions among suppliers and consumers participating in the market are reallocated based on optional power bids to enhance system stability in case the available control actions are insufficient to enhance system stability. All participants are allowed to submit voluntary power bids to increase or decrease their scheduled level with equal chance. These bids represent the offered power quantity and the corresponding price. The goal of the framework is to enhance system stability with minimum additional and opportunity costs arising from the rescheduling.

In case of vertically integrated electric utility, generation rescheduling based sensitivity analysis is used to enhance the system stability. The sensitivity analysis is based on the generators response following the most probable contingency. The generators are split into critical machines with positive sensitivity and non-critical machines with negative sensitivity. The change of the generation level among critical and non-critical machines provides the trajectories for stabilization procedure. The re-allocation of power among generators in each group is calculated based on the generator capacities and inertia constant, which simplifies the optimization procedure and speeds up the iterative to find a feasible solution. The objective is to minimize the increase in the cost due to rescheduling process.

Particle swarm optimization is used as an optimization tool to search for the optimal solution to enhance the system stability with a minimum cost. The handling of all system constraints including stability constraints is achieved using a self-adaptive penalty function. Comparison strategy for selecting the best individuals during the optimization process is proposed where the feasible solutions are ever preferable during selection of local and global best particles.

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Chapter 1
Introduction

1.1 Introduction

The electric power systems have recently grown very fast such as European interconnected power system. The load dispatch centers should continually determine the load planning and dispatching without violating the system constraints to ensure secure and reliable suppliers to all consumers. Utilities try to predict the future energy demand in their areas and develop new generation strategies accordingly to account risks due to extensive interconnection on system stability especially in deregulated electricity markets [1]. Deregulation brings more and more players into energy market, which requires participants acting in an autonomous fashion and all customers equally share the costs and the benefits of existing and regulated generation units. Therefore, in deregulated systems, the available transmission and electrical facilities are highly utilized with large amounts of power transfer through tie-lines where suppliers try to fill as much of the demand as possible using their power plants without constructing new capacities.

Extensive interconnection in such environment alters the stable region of the system and pushes power system to operate closer to their limits, due to greater competition between generation companies and increased demand for large power transactions from producers to consumers. Therefore, the coordination and control functions become more difficult to realize and because of security-related problems introduced by competition [2]. This leads to the appearance of power system oscillations and instabilities during large and small

disturbances. Consequently, the system experiences a number of blackouts due to dynamic instability during credible contingencies where the main reason is the lack of time to take decisive and appropriate control actions. Such system blackouts are the case in 10 August 1996 where a major failure occurrence in the Western System Coordinating Council (WSCC) interconnection system and the U.S.-Canadian blackout of August 2003, which affected approximately 50 million people in eight U.S. States and two Canadian provinces. Therefore, the need for more frequent online dynamic stability assessment and enhancement for reliable operation of power systems is much greater than in the past [3][4].

Reliable operation requires fast tools to monitor system stability that can process a wide range of network connectivity and generation dispatches during normal and abnormal operations. This goal is conducted by an independent system operator (ISO) whose plays the role of a supervisor to procedure supplant market processes on the short frames relevant for protecting system security and reliability. Secure operation is accomplished with the ability of power system to withstand sudden disturbances such as electric short circuits or non-anticipated loss of system components and supply the power to all consumers at satisfactory frequency and voltages. In addition, the system operation must be controlled to stay within acceptable system operating limits such as the ranges of line flows and generators loading rate to maintain operating reliability. When these limits are seriously perturbed the system may suffer from frequency collapse, voltage instability, generators rotor angle instabilities, or system islanding.

1.2 Motivation of the Research

The online monitoring of electric power system dynamics becomes more and more important to evaluate and enhance the performance of system

operation at all levels of loading due to excessive number of possible contingencies. Pursuing system security is the main responsibility of ISO, which must be managed ahead of time by coordinating power transactions in a suitable manner to keep the system security at all operating conditions. This coordination is restricted by the market rules and economic requirements, which increase the risk to lose of synchronism during abnormal conditions due to system instability. Thus, the behavior of the online connected generators should be monitored continuously to keep in synchronism.

The classical analysis of power system stability requires a complete system modeling and is time consuming for large power systems in addition to the dependence of the dynamic behavior on the load conditions and the severity of critical contingencies on the system operations. Therefore, developing real-time computational tools for online monitoring and enhancing of system dynamic stability are the main targets of the research. The thesis focuses on the online dynamic stability assessment (DSA) and enhancement, particularly power system transient stability assessment (TSA) and power system oscillatory stability assessment (OSA). Fast online DSA may provide supervisory input to the ISO for enhancing the system security and relieving the emergency states by specifying the necessary counter-measures according to the acceptable security level. These counter-measures include activation of online controllers such as reactive power compensation switching or network changes such as further generator tripping, load shedding as well as generation scheduling. The proper counter-measures are essential to prevent cascading outage of overloaded electrical equipment, which required an overall online analysis strategy from steady state to dynamic state. These proposed counter-measures should be non-discriminate for all participants and consumers in case of deregulated power system.

1.2 Motivation of the Research

The necessary actions to relieve the effect of contingencies should be prepared in advance and ISO should utilize fast tools for online monitoring of system states to activate the proper control action immediately during abnormal operation. Because of the uncertainty associated with the large-scale power system operation, the prepared control actions may be not enough to anticipate the effect of all critical contingencies on the system transient stability. Similarly, with the continuously changing power flow; it is not possible to design and install power system stabilizers to cover all the expected operating conditions. Therefore, this study suggests using computational intelligence (CI) for fast online DSA and implementing online market for dynamic stability enhancement. CI can be adapted to be a black box for DSA as shown in Figure 1.1 because of its ability to generalize using a very small portion of all possible pattern pairs in the problem space [5]. CI includes methods such as ANN, Decision Trees, Expert Systems and Adaptive Neuro-Fuzzy Interface Systems. ANN as an efficient computational intelligent tool is selected for TSA and OSA in this thesis [6][7]. Efficient use of ANN for DSA requires training of ANN to cover all the expected system conditions that will not be influenced by system topology or loading level. Therefore, proper selection of input features is required to implement a robust tool for accurate estimation of DSA.

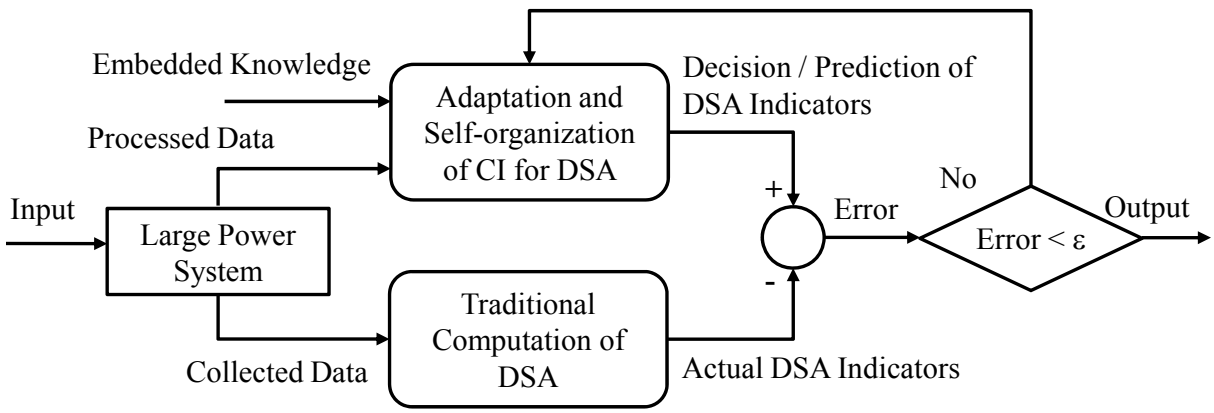

Figure 1.1 Simplified view of computational intelligence adaptation for DSA

The prepared control actions have been used to enhance system stability and in case of insufficient control actions, immediate actions may be required for a secure system operation. For fair and non-discriminated control actions for all participants, this study proposes a new market based strategy to reallocate the energy among participants based on optional voluntary energy offers to enhance system stability. These energy bids describe the offered energy quantities and the corresponding prices to accept changing in scheduled levels.

1.3 Objectives and Contributions of the Thesis

This research focuses on developing fast and robust tools for online dynamic stability assessment and enhancement to meet various needs already existing or emerging from the vulnerability in power systems. Figure 1.2 presents the closed loop control strategy for system stability assessment and enhancement.

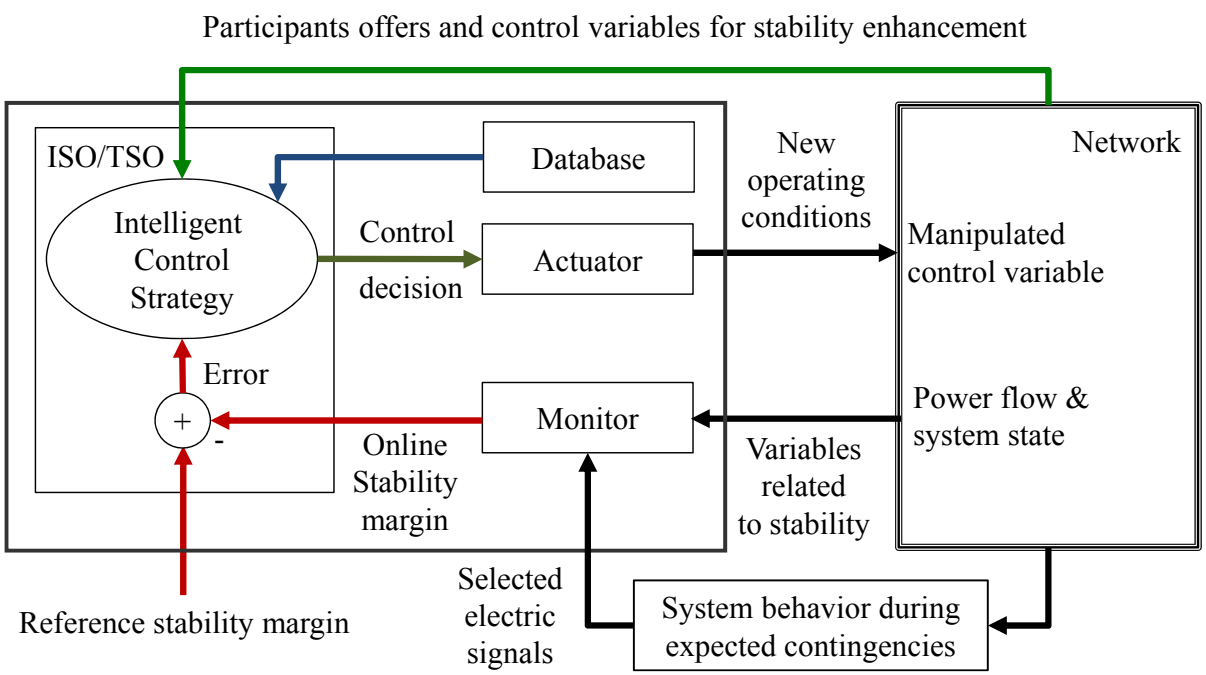

Figure 1.2 Closed loop strategy for stability assessment and enhancement

1.3 Objectives and Contributions of the Thesis

The ISO should monitor the power system state continuously utilizing selected control variables related to system stability and investigating the system behavior during the expected credible contingencies. If the standard stability margin is not satisfied, the proper control decisions should be used to activate the necessary control actions to enhance the power system stability and achieve the standard stability margin. These control actions are based on varying the available online control variables and control of participants transactions.

The system dynamic stability is monitored based on power system transient stability and oscillatory stability. Critical fault clearing time (CCT) is used as indicator for TSA and minimum damping of oscillation (MDO) as indicator for OSA. The values of CCT and MDO at the most credible contingency can be used as dynamic stability indices in typical control centers. The level of dynamic stability can be interpreted from these values, as the values increase, one has an increased opportunity to isolate and clear the effect of the disturbance. This implies that the power system is secure for that particular event. On the other hand, very short values of CCT and MDO are very difficult to deal with during the design and coordination of protective relays and circuit breakers. Generators should have CCT higher than FCT of its protection devices to avoid disconnection due to loss of synchronism or overloading. Which further implies that if the system may encounter such shorter values for a possible disturbance the system is insecure in that operating environment. Therefore, increasing CCT improves the system transient stability.

Time domain simulation (TDS) is an efficient method for CCT calculation but it is not suitable in online application due to time of computation. Instead of TDS, this study suggests ANN to learn the power system dynamic behavior in order to estimate CCT, which provides acceptable results in much faster time.

Similarly, the OSA can be performed by eigenvalues computation based on the linearized power system model when all the detailed information and the required time of computation are available. With increasing the system nonlinearity and the lake of available information, the system oscillatory stability can be investigated using many identification techniques. System identification techniques can be used to obtain the system modal parameters based on a small number of inputs or power system oscillating behavior such as Prony analysis [8]. In this thesis, Prony analysis is used to investigate power system oscillatory stability in order to account for the increase of system nonlinearity and the variety of small disturbances. Identification methods such as Prony analysis need experiences to select the proper location and magnitude of propping signal and the corresponding variables for observing time response of electrical signals. Therefore, Prony analysis is not suitable in online applications to identify the state of large-scale power system. Prony analysis is used to investigate the system oscillatory stability and generate the necessary data to specify system dynamics following small disturbances. Thus, ANN is trained to map the system oscillations and dynamics to estimate MDO for OSA following a set of credible contingencies in online applications.

Online control actions should be used to enhance the power system stability during abnormal operating conditions. In case of available control actions are insufficient to enhance the power system stability, ISO should prepare an intelligent control strategy for enhancing the system stability. In the light of aforementioned prospective description, the followings are investigated as a part of the research.

A) **Assessment of online power system dynamic stability**: Two ANNs are designed to be fast-response tools for DSA to overcome the drawbacks in dynamic simulation of large power system using traditional methods. ANN is

used to estimate CCT as index for TSA. During the generation of input-output patterns, CCT is evaluated based angle stability using TDS to achieve accurate results. CCT measures the proximity of the system to be unstable due to loss of synchronism. Similarly, ANN is designed to estimate the MDO as indicator for OSA regardless the loading condition, system topology and fault location. For an accurate design, features selection process is used to select the most important information to map the system dynamics using engineering and mathematical judgments. Input features are selected in two stages in order to enhance the accuracy of ANN for DSA. In the first stage, initial feature sets are selected based on engineering experience in power system analysis from the viewpoint of stability. In the second stage, the final selection of input features is achieved in three steps. In the first step, the generator terminal voltages are selected as ANN input features to characterize the severity of the contingencies with respected to generators and fault location. In the second step, input features are selected to characterize the system topology changes and changes in power distribution due to disconnection of large electrical equipment such as generators or transmission lines. A new input feature is proposed for each area to characterize these changes based on the power generated from each generating unit and the corresponding inertia constant in each area. In the third step, a systematic feature selection algorithm is used to select the most important features from the mathematical viewpoint. All selected input features are used to implement a single hidden layer feed-forward structure ANN. Back-propagation algorithm is used in the training process. After training process, all data related to the trained ANNs are saved to be used during online DSA and enhancement.

B) **Dynamic stability enhancement via new market strategy**: The main contribution of the thesis is the development of a framework to enhance power system stability in a fair manner during critical operating conditions. ISO may

need to reschedule the power transactions cleared by energy markets, which may be violating the accepted limit of system stability. In deregulated environment, the rescheduling process may be not acceptable from the participants viewpoint because of economic restrictions. The thesis suggests a non-discriminated market strategy to enhance the system dynamics in case of the prepared control actions are not enough for system stabilizing. For fair operation of deregulated power system, participants should not be forced for re-dispatching without equal opportunities to maximize their revenue. In this case, the contracted generators may not accept to change their scheduled output and ask for additional cost to apply the required changes for system stabilization. Hence, it is important to find the basis for minimizing the total cost of power rescheduling to achieve the standard stability limits.

The market model is proposed to achieve continuous dynamic stability enhancement with minimum cost as open access market to all suppliers and consumers participation. In the proposed market, all consumers and suppliers have equally change to participate with power rescheduling offers for surplus. Participants submit voluntary offers describing the willing of change in the scheduled power and the corresponding energy quantities and prices. Market optimization starts with the no cost counter-measures such as Flexible AC Transmission System devices (FACTs) and automatic transformer tap-changers to minimize the total cost. Particle swarm optimization (PSO) is used as optimization tool to guarantee the optimal solution within the offered space of change while all operational constraints and stability constraints are considered using self-adaptive penalty function. Self-adaptive penalty function is used to avoid the use of additional coefficients in order to relate the constraints violation to the original objective function.

1.4 Thesis Organization

Chapter 1 introduced an introduction about motivation and the main objectives of the thesis. The remainder of the thesis is organized as follows: Chapter 2 introduces a general theoretical background of the classification of power system stability and definitions of associated terms. In addition, the chapter presents the general factors affecting power system stability and brief description of the analysis of power system security. it also presents the available preventive measures to avoid system instability and the power system modeling for stability analysis.

Dynamic stability assessment is the main target in chapter 3. The chapter focuses on the analysis techniques and mathematical tools that can be used for dynamic stability assessment. These include a brief discussion of the methods used to assess system transient stability such as direct method based transient energy function and time domain simulation for complete system model. It introduces the application of time domain simulation based on Bisection technique to calculate the critical fault clearing time as index for transient stability. The chapter presents a brief discussion about oscillatory stability assessment using modal analysis and ringdown based Prony analysis methods. Prony analysis is used to estimate the power system minimum damping of oscillations as index for oscillatory stability from the time response of electric signal following small disturbances. In addition, the chapter introduces a brief discussion about the basics of ANN modeling and training. The chapter presents the application of ANN as a computational intelligence tool for DSA to account for the computation time with using traditional methods during online applications. The chapter also deals with the selection process of input features. Features selection process is necessary for implementing ANN to map the

system dynamics for accurate DSA where the proper selection of input features improves the ability of ANN to be fast and robust tools for TSA and OSA.

Dynamic stability enhancement is the main target in chapter 4. The chapter starts with describing the counter-measures for dynamic stability enhancement. The chapter presents the fundamentals of particle swarm optimization as a proposed evolutionary technique that is used as optimization tool to minimize the total cost during dynamic stability enhancement. In addition, it introduces the basic concepts of constrained optimization problem and various penalty techniques that can be used to account the constraints violations during optimization process. In addition, the chapter presents a comparison strategy for selecting the best individuals during optimization process. The chapter explains the dynamic stability enhancement in the vertically integrated electric utility using generation rescheduling based sensitivity analysis of the generator responses during critical contingences. The requirements for power system deregulation, the behavior of participants in deregulated markets and the responsibilities of ISO are discussed. The chapter deals also with the real-time operation of deregulated electricity market for accounting power imbalance and considering dynamic stability enhancement. The market determines power distributions among participants prior to online application of the cleared energy transactions from energy markets to anticipate the expected error in forecasted load and the effects of system congestions. This may include generation rescheduling, load curtailments and ancillary service arrangements. In addition, a proposed framework for continuously checking and enhancing of online dynamic stability is proposed. This framework can be used for dynamic stability enhancement during unpredicted abnormal conditions. In the proposed framework, the cleared schedules from real-time balancing market are adjusted based market-strategy for stability enhancement in case of insufficient prepared control actions during unpredicted abnormal conditions. Therefore, all suppliers

and consumers are allowed to participate in the market with energy offers. These offers should describe the limits of the change in the scheduled power and the corresponding cost functions.

Chapter 5 summarizes the deduced conclusions from the dissertation. The main conclusions from the proposed framework for dynamic stability assessment and enhancement will be highlighted. In addition, the chapter presents a brief list of suggested potential research directions for further study

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Chapter 2

Power System Dynamics and Stability

2.1 Introduction

Power system stability has been recognized as a vital and important issue for a reliable and secure interconnected power system operation as far back as the 1920s [9]. The importance of stability problem associated with power system operation arises from increasing power exchange between the constituent parts of a large interconnected power system. In a free deregulated market, utilities are allowed to participate in the market without mandatory upper or lower limits. Thus, a number of highly publicized blackouts happened in the early years. The blackouts illustrate the necessity of assessing the stability of large power systems and maintaining an adequate level of system security to minimize the risk of major blackouts resulting from cascading outages emanating from a single disturbance. The main requirement of system stability is to keep the synchronous operation of power system with adequate capacity and fast reaction to meet the fluctuations in electric demand and changes in system topology. Successful operation of a power system depends largely on the engineer's ability to provide reliable and uninterrupted service to all loads and supply the required amount of loads by the available facilities [9].

Distance between the current state and a hypothetical state wherein units may lose synchronization evaluated after each state of estimation and after each new power flow. In the evaluation, the concern is the behavior of the power system when it is subjected to transient disturbances. If the oscillatory response of a power system during the transient period following a disturbance is damped within acceptable time and the system can settle in a finite time to a new steady

state, it is considered stable [11]. The depicted Figure 2.1 presents the sequence of operation states to assure a secure and reliable power system operation. As seen in the figure, the system state evaluated continuously to assure reliable and steady state operating condition and necessary actions, which need to be ready to anticipate such abnormal sates. The steady state operating condition of a power system is an operating condition in which all the physical quantities that characterize the system are considered constant for the purpose of analysis [12].

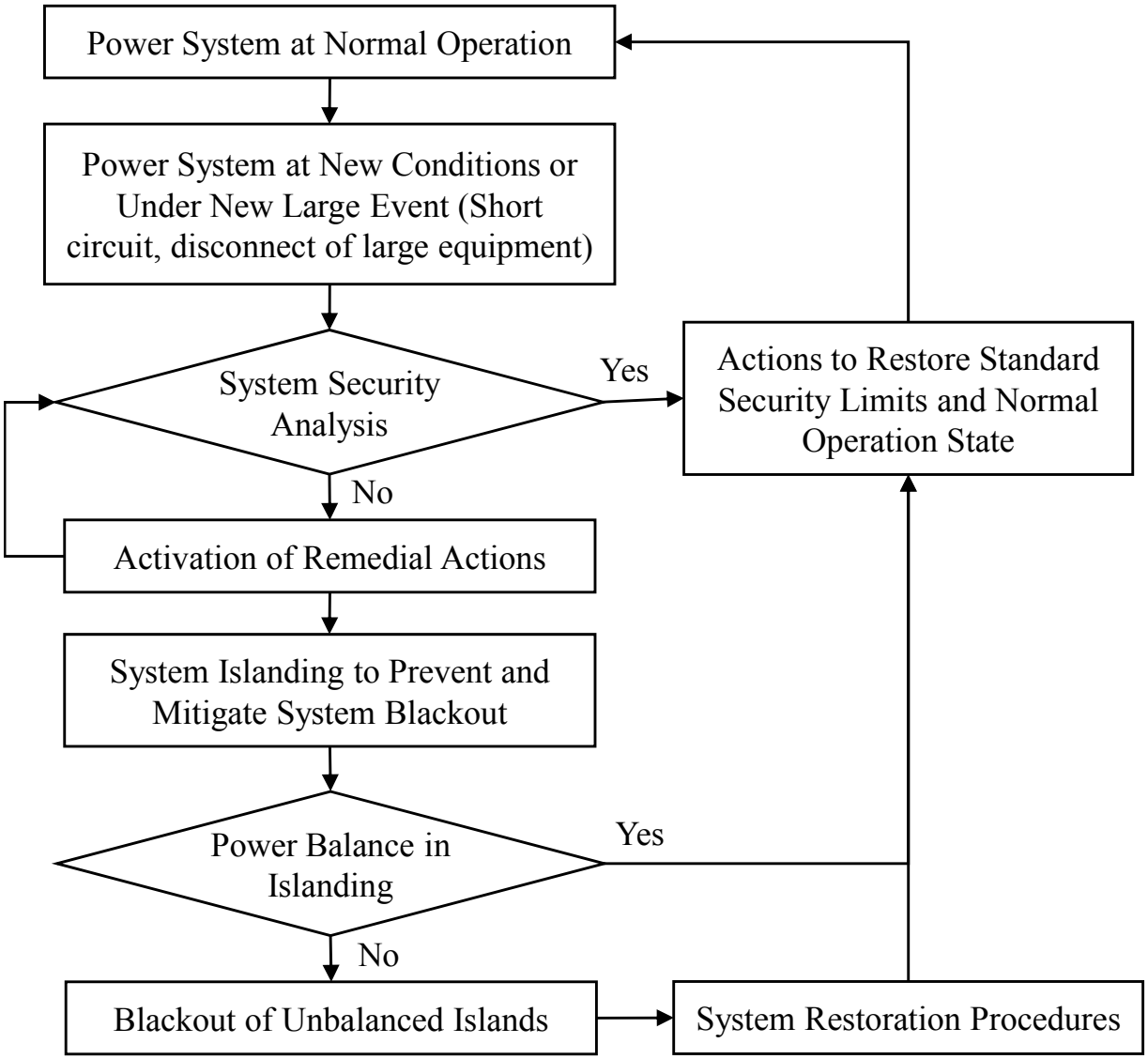

Figure 2.1 Sequence of operation states to assure system security

The instability of power system might be characterized by different ways dependent on the system configuration, the nature of events and the system

modes. This chapter addresses, in general, the state of the art of power system stability and the forthcoming chapters are concerning with our main work which is focused on the power system transient stability and small signal stability.

2.2 Definition and Classification of Power System Stability

Power system stability is the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact [9]. Stability phenomenon is a single problem associated with various forms of instabilities affected on power system due to the high dimensionality and complexity of power system constructions and behaviors. For properly understood of stability, the classification is essential for significant power system stability analysis. Stability classified based on the nature of resulting system instability (voltage instability, frequency instability…), the size of the disturbance (small disturbance, large disturbance) and timeframe of stability (short term, long term). In the other hand, stability broadly classified as steady state stability and dynamic stability. Steady state stability is the ability of the system to transit from one operating point to another under the condition of small load changes [11]. Power system dynamic stability appears in the literature as a class of rotor angle stability to describe whether the system can maintain the stable operation after various disturbances or not. Figure 2.2 shows the classification of power system stability in IEEE/CIGRE joint task force on stability terms and definitions [9].

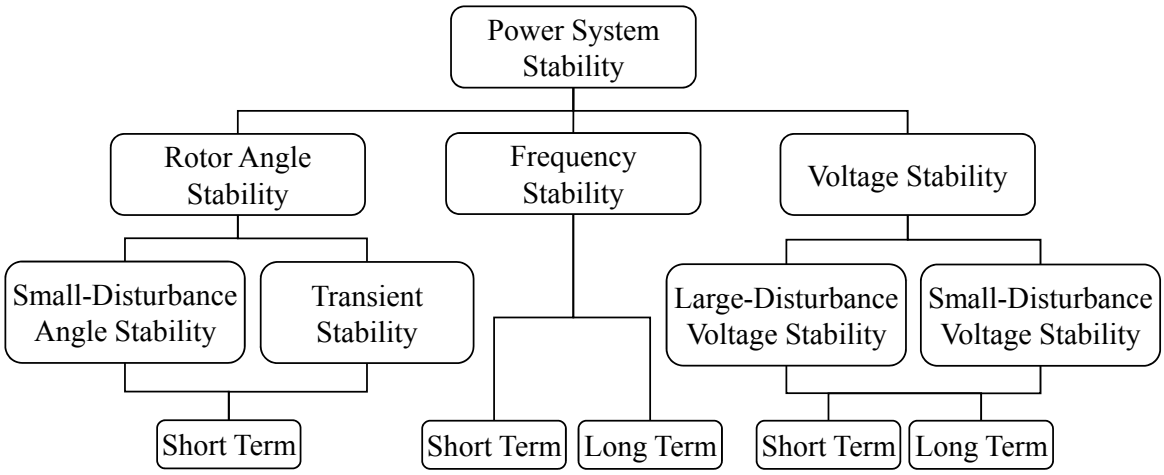

Figure 2.2 Classification of stability based on IEEE/CIGRE joint task force on stability

2.2.1 Rotor Angle Stability

Rotor angle stability is concerned with the ability of interconnected synchronous machines of a power system to remain in synchronism under normal operating conditions and after being subjected to a disturbance [9]. The stability of synchronous machines depends on the ability of restoring the equilibrium between their electromagnetic outputs torques and the mechanical input torques and keeping at synchronize with other machines following a major disturbance such as short circuit. Under steady state conditions, there is equilibrium between the input mechanical torque and the output electromagnetic torque of each generator, and the speed remains constant. If the system is perturbed, this equilibrium is upset and instability may occur in the form of increasing or decreasing angular swings of some generators leading to their loss of synchronism with other generators. The change in electrical torque ΔT_e of a synchronous machine following a perturbation can be resolved into two components as follows [13]:

$$T_e = T_S \, \Delta\delta + T_D \, \Delta\omega \tag{2.1}$$

Where $T_S\,\Delta\delta$ is the component of torque change in phase with the rotor angle perturbation $\Delta\delta$ and it is referred to as synchronizing torque component. T_S is the synchronizing torque coefficient. $T_D\,\Delta\omega$ is the component of torque change in phase with the speed deviation $\Delta\omega$ and it is referred to damping torque component. T_D is the damping torque coefficient.

Stability of each machine in the system depends on the existence of both components. Lack of sufficient synchronizing torque produces instability through aperiodic or non-oscillatory drift in the rotor angle, whereas lack of damping torque results in oscillatory instability causes rotor oscillating with increasing amplitude. Rotor angle stability depends on the initial operating state and the severity of the disturbance on synchronous machines. Commonly, rotor angle stability are classified into small disturbance-rotor angle stability and large disturbance-rotor angle stability for gaining more understanding and insights into the nature and characteristics of stability problem.

2.2.1.1 Small Disturbance Rotor Angle Stability

Small-disturbance rotor angle stability (oscillatory stability) is concerned with the ability of the power system to maintain a steady state operating point when subjected to small disturbances [13]. Oscillations have been recognized as a consequence of parallel operation of alternative current generators which are connected to provide more power capacity and more reliability. Thus electromechanical oscillations are understandable because of the change in kinetic energy of rotating parts (rotor) in electrical machines due to their moment of inertia and the synchronizing torque, which acts to keep the generators in synchronism during disturbances.

Oscillations can also arise in the power system due to any sudden change in a power system such as high power flows over weak tie lines, which can

become heavily loaded if many generators oscillate towards another group at the same time. Fast and powerful voltage regulators or other types of controls may produce oscillations in the network. If the disturbance is small, the synchronizing torque keeps the generators in synchronism with generators relative angles oscillation. These oscillations should decay for small signal stable system operation otherwise; the system is a small signal unstable. Critical oscillatory modes can be triggered by a small disturbance because of the weak interconnection and stress. These oscillations limit the amount of power that can be transferred among system areas at peak load and may lead to power system break-up and outage.

Oscillatory stability problems are usually due to insufficient damping for power system oscillations. The system mode parameters can be investigated using two basic approaches; namely modal analysis of complete state spaces or time response analysis of collected synchronized measurements. The oscillation modes are mainly classified into local and inter-area modes [13].

Local modes are associated with the swinging of units at generating station with respect to the rest of power system at 1.0 to 2.0 Hz. When a generator tied to a power system via a long radial line, it is susceptible to local mode oscillations. Local modes affected by the strength of the transmission system at the plant, the generation level and excitation control system [14]. The oscillation may be removed with a single or dual input power system stabilizer that provides modulation of the voltage reference of the automatic voltage regulator with proper phase and gain compensation circuit [15].

Inter-area modes are associated with the swinging of many machines in one area of an interconnected power system against machines in other areas and have major impact on the global stability of the complete power system. It involves two coherent groups of generators swinging against each other at 0.05-

1.0 Hz. Poorly damped inter-area oscillation affecting every part of interconnected power system and coordinated analysis are required to check the small signal stability of the whole power system. Inter-area modes depend on various reasons such as weak ties between interconnected areas, voltage levels, and the nature of the load.

Additionally, other types of oscillations have been recorded such as intraplant modes, torsional modes and control modes.

Intraplant modes is associated with machines on the same power generation site oscillate against each other at 2-3 Hz depending on the unit ratings and the reactance connecting them. Usually the rest of the system is unaffected because the oscillations manifest themselves within the generation plant.

Torsional modes are associated with the turbine generator shaft system rotational components due to the interaction between generator exciter control and prime mover control, and HVDC controls in the frequency range 10-46 Hz. Usually these modes are excited when a multi-stage turbine generator connected to the grid through a series compensated line. A mechanical torsional mode of the shaft system interacts with the series capacitor at the natural frequency of the electrical network. The shaft resonance appears when network natural frequency equals synchronous frequency minus torsional frequency [16].

Control modes are associated with generating units and other equipments control such as poorly tuned controls of excitation systems, speed governors, FACTs devices controls, HVDC converters. Loads and excitation system can interact through control modes. Transformer tap-changing controls can also interact in a complex manner with nonlinear loads giving rise to voltage oscillations [17].

The minimum damping ratio of oscillation, which is associated with the local and inter-area oscillations is considered as an indicator for oscillatory stability in this thesis. The disturbances should be considered sufficiently small where the linearization of the system equations is permissible for the purpose of modal analysis. In case of inaccurate linearization process, an identification technique is required to identify the system modes based on the time response of electrical signals.

2.2.1.2 Large Disturbance Rotor Angle Stability

Large-disturbance rotor angle stability (transient stability) is concerned with the studying of the ability of power system to maintain synchronization among synchronous machines when subjected to a server transient disturbance e.g. a three-phase short circuit [13]. Transient stability depends on the current operating conditions of the system and the severity of the contingency on connected generators. The angles between each pair of generator rotor angles will change continuously by small amounts as power distribution change. Transient instability phenomenon is usually in the form of uncontrollable significant increase and separation of the relative angles between two or more rotors due to insufficient synchronizing torque [18]. The resulting system response involves large excursions of generator rotor angles and influences by the nonlinear power angle relationship. Small-disturbance rotor angle stability as well as transient stability is categorized as short-term phenomena.

2.2.2 Voltage Stability

Voltage stability refers to the ability of a power system to maintain steady voltages at all buses in the system after being subjected to a disturbance from a given initial operating condition [13]. The voltage deviations need to maintain

within predetermined ranges. A voltage stability problem occurs in heavily stressed systems, which associated with long transmission lines. Voltage stability depends on the active and reactive power balance between load and generation in the entire power system and the ability to maintain/restore this balance during normal and abnormal operation. The main contributor in voltage instability is the increase of reactive power requirements beyond the sustainable capacity of the available reactive power resources when some of the generators hit their field or armature current time-overload capability limits. The other contributor is the extreme voltage drop that occurs when active and reactive power flow through inductive reactance of the transmission network; this limits the capability of the transmission network for power transfer and voltage support.

A typical scenario of voltage instability is unbalance reactive power in the system resulting in extended reactive power transmission over long distances. As long as the load increases, the power transmitted to supply load also increases while bus voltages on transmission line will drop in inductive network. Close to the maximum transmission capability, a small increase of the load implies a great decrease in the voltage level of the network that may lead to cascaded outages (under-voltages protective devices) while instability occurs in the form of a progressive fall of some bus voltages (voltages collapse). Generally, the voltage collapse mainly affected by the large distances between generation and load, under load tap changing transformers performance during low voltage conditions, unfavorable load characteristics, and poor coordination between various control and protective systems. In addition, the system may experience uncontrolled over-voltage instability problem at some buses due to the capacitive behavior of the network and under excitation limiters that preventing generators and synchronous compensators from absorbing excess reactive power in the system. This can arise if the capacitive load of a

synchronous machine is too large. Examples of excessive capacitive loads that can initiate self-excitation are open-ended high voltage lines, shunt capacitors, and filter banks from HVDC stations.

The phenomena of voltage stability can be classified into small disturbance and large disturbance voltage stability. Small-disturbance voltage stability refers to the system's ability to maintain steady voltages when subjected to small perturbations such as incremental changes in system load. A criterion for small-disturbance voltage stability in that, at a given operating condition for every bus at the system, the bus voltage magnitude increases as the reactive power injection at the same bus increased. A system is voltage-unstable if, for at least one bus in the system, the bus voltage magnitude decreases as the reactive power injection at the same bus increased [12]. Large-disturbance voltage stability refers to the power system ability to maintain steady voltages following large system disturbance such as loss of generation, loss of critical lines, system faults, or protection system failures. Investigation of this form of stability requires the examination of the dynamic performance of the system over a time sufficient to capture the interactions of such devices as under load tap changing transformers and generator field current limiters [12].

The voltage stability can be classified in terms of time into short-term stability and long-term voltage stability. Short-term voltage stability involves the dynamics of fast acting load component such as induction motors and electronically connected devices with study period of interest in the order of several seconds. Long-term voltage stability involves the slower acting equipment such as tap-changing transformers and generator current limiters with study period extend several minutes. There are many methods can be used to mitigate voltage instability problem including operation of uneconomic generators to change power flows or provide voltage support during emergencies, using reactive power control and compensation devices, under-

voltage load shedding to avoid voltage collapse or control of network voltage and generator reactive output.

2.2.3 Frequency Stability

Frequency stability refers to the ability of a power system to maintain steady frequency following a severe system upset resulting in a significant imbalance between generation and load [13]. A typical cause for frequency instability is the loss of generation, which results in sudden unbalance between the generation and load. The control schemes of frequency deviation used to recover the system frequency without the need for customer load shedding by instantaneously activating the spinning reserve of the remaining units to supply the load demand in order to raise the frequency. In case of an incident with a large frequency deviation, the primary control (in the first 30 minutes) is activated where the partly loaded or carry spinning reserve units selected to initiate an automatic rapid increase of their outputs within a few seconds. The controllers of all activated generators alter the power delivered by the generators until a balance between power output and consumption is re-established. Spinning reserve to be utilized by the primary control should be uniformly distributed around the system. Then the reserve will come from a variety of locations and the risk of overloading some transmission corridors will be minimized. The frequency stabilization obtained and maintained at a quasi-steady state value, but differs from the frequency set point. The Secondary control, in the portion of the system contains power unbalance, will take over the remaining frequency and power deviation after 15 to 30 seconds to return to the initial frequency and restore the power balance in each control area [19]. Tertiary control is additional to, and slower than, primary and secondary frequency control, which is supervisory with respect to the secondary control that corrects the loading of individual units within an area. Load shedding used

as last option to minimize the risk of further uncontrollable system separation, loss of generation, or system shutdown. Automatic load shedding initiated using under-frequency relays expected to be able to shed the required amount of load during low frequency events. These relays detect the onset of decay in the system frequency and shed appropriate amount of system load until the generations and loads are in balance [19].

2.3 Factors Affected on Power System Stability

Stability of a nonlinear system depends on the type and magnitude of inputs, and the initial state. Power system stability is affected by many factors including the behavior and characteristics of system equipment, system control and protection schemes. The most important factors can be summarized by:

- Pre-and-post-disturbance system state such as the generators loading before the fault and the generator outputs during the fault. The higher the loading before the fault is the more likely to be less stable during faults.
- The duration, location and type of the fault determine the amount of kinetic energy will be gained. Longer fault duration allows generator rotors to gain more kinetic energy during the fault. At certain limit, the gained energy may not be dissipated after the fault clearance. This gained energy may lead to instability.
- Synchronous machine parameters such as the inertia constant H (stored kinetic energy at rated speed per rated power), and the generator terminal voltage. The increase of generators inertia constant tends to reduce the swings of rotor angle and hence improve system stability. The generator bus voltages specify the profile of the power angle curve and hence effects on the delivered power into the entire system.
- Excitation system and governor characteristics of synchronous machines have important role in damping of power oscillations. The automatic

voltage regulator (AVR) senses the terminal voltage and helps to control it by acting within the excitation system. Fast valving for rapidly opening and closing steam valves of the turbine used to control the generators accelerating power during faults.

- Transmission reliability margin greatly effect on stability where a transmission outage may take place due to overloading during system abnormal conditions, which may lead to uncontrolled loss of a sequence of additional network elements
- System relaying and protection have a great importance in system stability. The power system has a finite capacity to absorb such energy and as majority of fault are transient in nature, rapid switching and isolation of unhealthy lines followed by rapid reclosing improves the stability margins. Special protection schemes can be used to split the grid at predetermined points in the network to quickly avoid cascading actions.

2.4 Power System Security Analysis

Power system security describes the ability of a power system to withstand and survive plausible contingencies without interruption of the customers. Security requires detection of dangerous operating conditions and contingencies as well as the associated actions to steer the system away from any such situations. Security analysis can be divided into static and dynamic security. Static security analysis is the ability of the system to supply load without violating operating conditions and load curtailment, which mainly includes the pre- and post-contingency states [20]. Pre-contingency states determine the available transfer capability of transmission links and identify network congestion. Post-contingency states verify the bus voltages and limits of lines power flow.

Dynamic security analysis measures the ability of power system to withstand a defined set of contingencies and survive by the transition to an acceptable steady state condition, which includes methods to evaluate stability and quality of the transition from the pre- to post-contingency state. Dynamic security analysis should be constantly in operation to detect when the security level falls below an adequate safety level to make proper preventive measures for a secure operation.

Figure 2.3 shows an example of such analysis architecture according to CIGRE Report No. 325 [21]. The collected data and database are used to model the system using the identification of the power system configuration and state estimation. After that, the system model validation and security assessment evaluated using a number of computer programs executing voltage stability analysis, small signal analysis and transient stability analysis. Based on the system state, a scientific report describe how close the system is to an insecure state created which should also include information about preventive and corrective action. The tripping of the overloaded equipment can be achieved immediately within the admissible overload duration which detected by overload or distance protection systems and a warning should be given to the dispatchers [21].

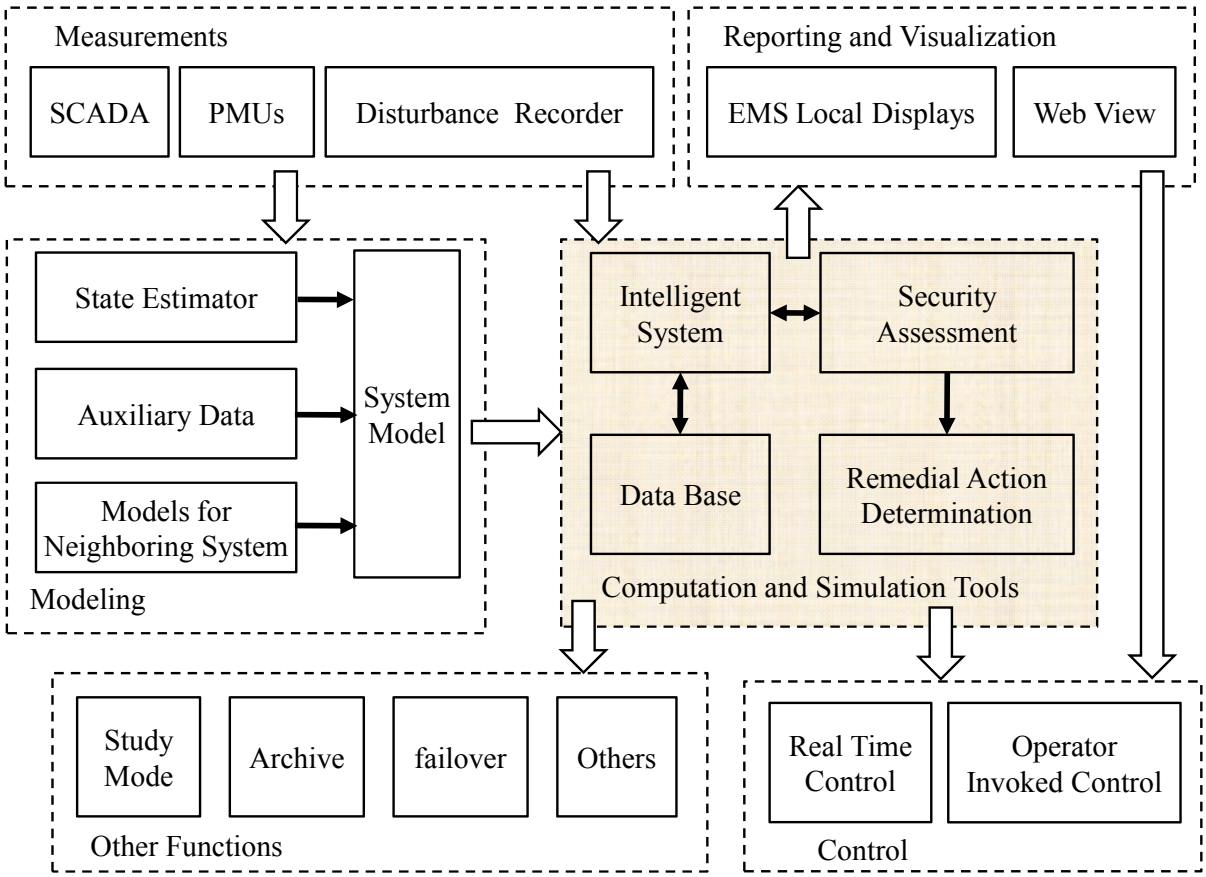

Figure 2.3 Components of dynamic security analysis according to CIGRE Report No. 325

2.4.1 Dynamic Stability Assessment

Dynamic stability assessment deals with the analysis of the system in the transition from the initial to the final operation condition following a disturbance or a changing power demand. A power system is dynamically stable for a particular steady state operating condition and for a particular disturbance if, following that disturbance; it reaches an acceptable steady state operating conditions. An important requirement was the ability to determine the risk of blackout, which can be computed by quantifying the distance between the current state and the steady-state stability limit rather than just characterizing it as stable or unstable. This required a fast and accurate online security assessment tools and special actions to prevent system instability, which

commonly defined as remedial actions. The remedial actions include curative and preventive actions that should be prepared in the operational planning stage. Curative remedial actions should be prepared in advance and immediately activated after any credible contingency or abnormal conditions to relieve system constraints. Preventive remedial actions should be designed in advance at steady state to anticipate the events and restore the security level in case curative remedial actions which are not sufficient to face the expected contingencies.

The security analysis and recommended actions are investigated in the computation block in Figure 2.3, which includes a number of computer programs to execute voltage stability analysis, small-signal stability analysis, transient stability analysis and any other important phenomenon to evaluate the system state. Based on the system state the system operator should design or execute the proper preventive and corrective actions. After occurrence of the contingency, if there is a delay or insufficient of remedial actions to anticipate the new situation, the system falls at risk. Therefore, in a short while the ISO has to coordinate future remedial actions with neighbors to search about convenient remedial action. These actions should be able to secure the system and to be ready for the occurrence of new emergencies, which includes load shedding and generation rescheduling. Beside the remedial actions, the automatic N-1 contingency simulation should be evaluated periodically, at least every 5-15 minutes in real time operation. This highlights the importance of fast DSA tools to evaluate the system dynamics during contingencies.

The term dynamic stability appeared in the literature to denote different aspects of stability related to generator rotor angles [9]. Dynamic stability studies contain a wider range of phenomena by different authors. In this study, dynamic stability concerns the system stability during small disturbance (oscillatory stability) and large disturbance (transient stability). The dynamic

stability studies consist of considering the fluctuations in load and generation, the network reactions following critical disturbances and recommending the appropriate operating measures to avoid undesirable operating modes.

2.5 Preventive Measures to Avoid System Instability

In power system design and preparation stage, a wide number of disturbances have to be assessed by system operators. If the system is found to be unstable (or marginally stable) following any contingency, variety of actions can be taken to improve the system stability. These preventive actions can be classified mainly into Offline and online preventive actions. Offline preventive measures: Improvement of system stability can be achieved by many actions including:

- Organizing the system configuration and maintenances in such that being suitable for the particular operating conditions without overloading during abnormal conditions.
- Reduction of transmission system reactance which can be achieved by adding additional parallel transmission circuits, providing series compensation on existing circuits and by using transformers with lower leakage reactance.
- Activating new generation facilities for reactive power support and voltage control service such as power system stabilizers, FACTs, distributed generation technologies, and rapid thermal units with fast-valving capability and fast acting automatic excitation systems.
- Connecting dynamic breaking resistors at the generator and substation terminals in order to break the acceleration of the rotor of generators during faults. Shunt resistors can be switched in to create an artificial load following a fault, in order to improve the damping of accelerated generators

- Installing efficient protective devices and coordinating between the interconnected system operators for faster fault clearing and initiating proper corrective actions during abnormal conditions.
- Online remedial and preventive measures: The operation of interconnected power system is economically oriented based competitive manner in the most cases. This complicates the ability of Offline preventive measures to keep the power system away from the stability limits. This produces the importance of system operators to use online DSA and operating the power system within these limits. There are many online preventive measures can be used to safeguard and enhance system stability such as:
- Changing the system topology such as tripping of critical generator to ensure that the other generators maintain in synchronism. In addition, generation rescheduling/re-dispatching can be used to reallocate power generation in order to avoid system overloads and relieve constraints.
- Using of high-speed protective schemes such as transmission line protection with single-pole tripping and adaptive reclosing capabilities to minimizes system disturbance. High-speed automatic reclosing system is effective methodology to restore power continuity.
- Effectively use of online transformer tap-changers and phase shifting transformers to control the power flow across transmission system by continuous control of voltage regulator set points and changing the phase using taps.
- Automatic load shedding of interruptible consumers is an effective corrective counter-measure to maintain the frequency at nominal value during abnormal conditions. In the simple implementation, under-frequency relays installed at fixed points and with fixed settings can be made adaptive by adjusting the location and level of shedding in

accordance with power flow and voltage conditions on the transmission network [18].

- Assuring reactive-power generation or absorption control and using special control of HVDC links to control the DC power and maintain generation/load balance in AC networks during disturbances.
- Implementation of high-speed excitation systems to rapidly boosts field voltage in response to disturbances. Increasing of the internal voltage of a generator has the effect of proving transient stability.

In real time application, the system configuration and power distribution are possibly not fully similar to the planned situation studied. Therefore, abnormal operating conditions may require immediate actions by market participants for control their generation/consumption facilities to restore the standard security level. In deregulated electricity market, a market participant who makes a change in scheduled generation, as a recommended action in response to an abnormal condition, may make a request to the ISO/TSO for compensation. Thus, the implementation of online generation rescheduling should be preceded by competitive bidding strategy to cope with any expected contingency.

2.6 Power System Modeling and Stability Analysis

The power system comprises a large number of electrical components. The modern systems have became more complex as they are enhanced with new devices such as Flexible AC Transmission System devices (FACTs) and Distributed Generation technologies. The analysis of power system dynamics have been characterized by complex dynamic behavior due to the modeling complexity and interactions/interrelations among individual components as well as the computational structure for describing modern power systems. Modeling of power system dynamics have been associated with describing each individual

component by algebraic and/or differential set of equations. Combining the individual dynamic models together with the associated algebraic constraints and power flow equations leads to the dynamic model of the whole power system. A nonlinear dynamic system with its control can be described by equation 2.2 and equation 2.3, which should be solved simultaneously in order to investigate the dynamic behavior following a disturbance[12][13].

$$\dot{\mathbf{x}}=\mathbf{f}(\mathbf{x},\mathbf{u}) \tag{2.2}$$

$$\mathbf{y}=\mathbf{g}\ (\mathbf{x},\mathbf{u}) \tag{2.3}$$

Where, **x** is the state vector with n state variables. The state vector represents the dynamic states of generators, loads and other system controllers. **u** is the vector of inputs to the system set which includes the automatic voltage regulator set point and uncontrollable input parameters such as generator power levels variations, and load active and reactive power levels. **y** is the vector of outputs such as phasor angle and magnitude of bus voltages and bus generated reactive power. **f** is the vector of nonlinear functions defining state variables in terms of state and input variables. **g** is the vector of nonlinear functions relating state and input variables to output variables such as power flow equations and system constraints.

The power system stability of nonlinear system described by these equations depends on the type and magnitude of inputs, and the initial state. During the analysis of stability, when the magnitude of voltages and currents satisfy a certain number of constraints, the system is in an equilibrium state at locally stable operating point. The equilibrium points are those points where all the selected state variables derivatives are simultaneously zero, whenever the system is not in equilibrium, the system state will change with time. The conventional TDS has been successfully used for solving these equations in

order to analyze the system dynamic behavior due to its extended modeling capability and the ability to provide accurate system stability predictions. TDS approach simulates the system dynamics in the during-fault and post-fault configurations by solving step-by step integration of equation 2.2 and equation 2.3 in the time domain and computes the time response of the monitored electrical signals. However, TDS is considered as a reference for analyzing of power system dynamics during generating the database.

Chapter 3

Dynamic Stability Assessment

3.1 Introduction

Sudden changes or disturbances in power systems are associated with a number of phenomena with different timeframe involved. In general, the power system stability can be assessed for the most severe fault possible such as three phase faults. Faults at critical locations may cause circuit tripping due to overloading or loss of synchronism of some generating units. Therefore, DSA is important issue in the modern interconnected power system where the disturbances produce power swings and rotor oscillations. During network disturbances, the power generators have to provide immediate support by changing the currently generated power supplied to the grid. The immediate change is restricted by the power system inertia during the initial few hundred milliseconds. Most turbines are unable to yield the fast torque response required to act in such small level in transient stability. Thus dynamic behavior investment and preparing the proper actions that improve system response during contingencies are important aspects during power system operation and control. The ISO coordinates the available control actions to enhance the system behavior during abnormal conditions. The control variables that can be used to enhance the power system stability are discussed in section 2.5.

Generation rescheduling is considered as a practical preventive or remedial control action to improve the system security during any contingency. The stability enhancement utilizing generation rescheduling is to find a generation configuration with the improved system dynamic behavior while satisfying

operational constraints with minimum shift from the economic operation. A fast and robust tool to assess system dynamic behavior is important to prepare the proper online amount of generation rescheduling and necessary actions. The investigation of the dynamic behavior requires extensive mathematical formulation and calculations due to the existence of a large number of different models and the associated nonlinearity. The objective of these calculations is to find the conditions that will exist in the power system just after a sudden change such as opening of a transmission line or occurrence of anticipated contingencies.

3.2 Transient Stability Assessment

Transient stability analysis concerns with the system's ability to reach an acceptable steady state operating conditions following a large disturbance. Transient stability associated with a large disturbance such as loss of generators, sudden change in loads, network significant changes or three phase short circuit faults. A large disturbance is a disturbance for which the equations describing the system dynamics cannot be linearized for the purpose of analysis. This disturbance causes as imbalance between the mechanical input power to each generator and its electrical output power. Then, the generator rotors start to swing with respected to each other. There are three approaches for transient stability assessment [13]:

Direct methods such as transient energy function that is based on Lyapunov theory to compute the critical kinetic energy. The system is considered in a stable state if the kinetic energy accumulated at the instant of fault clearance can be absorbed by the electrical components of the system.

Time-domain-simulation techniques can be used to investigate the dynamic stability for the selected set of contingencies and to convert the resulting

behavior into index for transient stability assessment. TDS can deal with a very detailed model of the power system, which improves the accuracy of TSA.

Automatic learning techniques have been used to assess transient stability in the real time applications in order to reduce the computation time. The well-known families of these approaches include decision tree, and ANN [22]. A good and adequate database is certainly the crucial point for automatic learning methods. The main advantage of these methods is that they are computationally fast.

3.2.1 Transient Stability Assessment by Direct Method

The direct methods determine the stability without explicit solving the system differential equations using transient energy for assessment of transient stability [12]. Transient energy function (TEF) methods are formulated based on Lyapunov theorems for establishing asymptotic stability and regions of attraction for equilibrium [23]. TEF describes the total system transient energy that is gained by the system during the fault-on period, which describes the system state during post-disturbance operation. When the gained kinetic energy is converted into potential energy, the system may be considered in transiently stable state. The transient energy function V, which describes the total system transient energy for the post-disturbances is defined as:

$$\begin{aligned} V = & \sum_{i=1}^{N_g} \frac{M_i \omega_i^2}{2} - \sum_{i=1}^{N_g} p_{mi}(\theta_i - \theta_i^s) \\ & - \sum_{i=1}^{N_{g-1}} \sum_{j=i+1}^{N_g} (C_{ij}(\cos\theta_{ij} - \cos\theta_{ij}^s) - \int_{\theta_i^s+\theta_j^s}^{\theta_i+\theta_j} D_{ij} \cos\theta_{ij} d(\theta_i + \theta_j)) \end{aligned} \tag{3.1}$$

where M_i and p_{mi} are the per unit moment of inertia and the mechanical input power of generator i respectively. ω_i and θ_i^s are the angular velocity of

generator i and the angle of bus voltage at post-disturbance. C_{ij} and D_{ij} are depending on the real and imaginary components of the admittance matrix and the generator voltages.

In equation 3.1, the first term is called the kinetic energy, which is a function of generator speeds. The sum of terms 2, 3, and 4 is called the potential energy, which is a function of generator angles. The quantity V measures the amount of transient energy which is injected into the system by the fault. The critical energy V_{cr} measures the energy-absorbing capability of the post-fault system. The system is stable if V is less than V_{cr} [12]. The transient energy margin is defined as $(V_{cr} - V)$ and is used as a measure of the system relative stability.

The availability of a qualitative measure of the degree of stability or instability in terms of the energy margin makes the direct methods an attractive tool for a wide range of problems [24]. There are some difficulties associated with the application of TEF in recent power system. These difficulties include the impossibility of an efficient TEF for detailed multi-machine system and the uncertainty of determination of the correct energy margin to classify system to be sufficiently stable. There are several works for modifying the TEF to improve these limitations such as Pseudo-Lyapunov approaches, which combine TDS and TEF for online transient stability assessment. These approaches take advantage of the superior ability of TDS in detailed system modeling and the qualitative measure provided by TEF to derive preventive and corrective control actions [12]. The main disadvantage is the proper energy margin suggestion for a stable system operation. TDS runs up to the instant of fault clearing to obtain the angles and speeds of all generators, which are used to calculate the total system energy at the fault clearing time. By comparing the calculated value with the

critical system energy, the system state of stability can be determined [25]. The transient stability assessment procedure simply involves the following steps:

Step1: Calculation of the critical energy V_{cr}

Step2: Calculation of the total system energy at the instant of fault clearing V

Step3: Calculation of stability index (V_{cr} - V), the system is stable if the stability index is positive.

The calculation of the boundary of the region of stability for a large power system is the most difficult step in applying TEF method. If the boundary can be determined, TEF gives a margin of stability rather than just the stable/unstable result.

3.2.2 Time Domain Simulation

Time domain simulation deals simultaneously with the system differential equations and algebraic equations to simulate the dynamic behavior of the power system under fault. These equations describe the performance of system equipment and the associated control systems. The simulation period split into pre-fault, during fault and post-fault with different network configuration to investigate the ability of the system to withstand the disturbance under consideration.

TDS starts with solving the load flow problem to initialize the pre-disturbance state. The solved load flow gives the data corresponding to the pre-disturbance state. The post-disturbance dynamic behavior of electrical signals is determined by systematic numerical integration of differential equations, which are modeled the power system. At each time step of simulation, the time derivative of each state variable is calculated. From the present state variables and their corresponding rates of changes, the state variables at the next time step

can be calculated by using the integration techniques [12]. Consequently, the algebraic variables are updated by using the algebraic equations. At the instant of disturbance, the appropriate data must be modified. Then, the process repeated until the time of interest reached. The swing curves represent the evolution of rotor angle of each machine known at the end of each time step. These curves further compared with each other in order to determine whether the rotor angular difference of any two machines exceeds the predefined accepted limit. The iterative process will stop if the system is unstable based on a specified limit otherwise the calculations are pursued for the maximum simulation time.

The stable cases are much more time consuming than the unstable ones. The angular difference rather than absolute angles is often a better choice to distinguish between stable and unstable system state since it is easily to observe the relative motion of rotor between the machines [12]. If any angular difference becomes larger than a predefined limit, the system is considered under transient instability encountering. The corresponding synchronous generator may loss synchronizing with other machines in the system and may be isolated by the protection system. The corresponding fault clearing time is considered as CCT, which associated with that contingency. The isolation of faulted element is accomplished by protective rely to activate circuit breaker interruption.

The CCT depends on the system configuration and the loading level at the instant of fault occurrence. The most accurate way to assess the transient stability power system is the systematic TDS. TDS is used to accommodate for the complexity of system modeling and stability conditions by observing its electromechanical angular and voltage swings during the simulation time. To reach this aim, Power System Dynamic (PSD) simulation software based upon TDS method is presented and applied at all system operating points during

contingencies in order to calculate the CCT in this dissertation [26]. Figure 3.1 presents the main structural components and their interrelations that functionally are implemented in the PSD software environment.

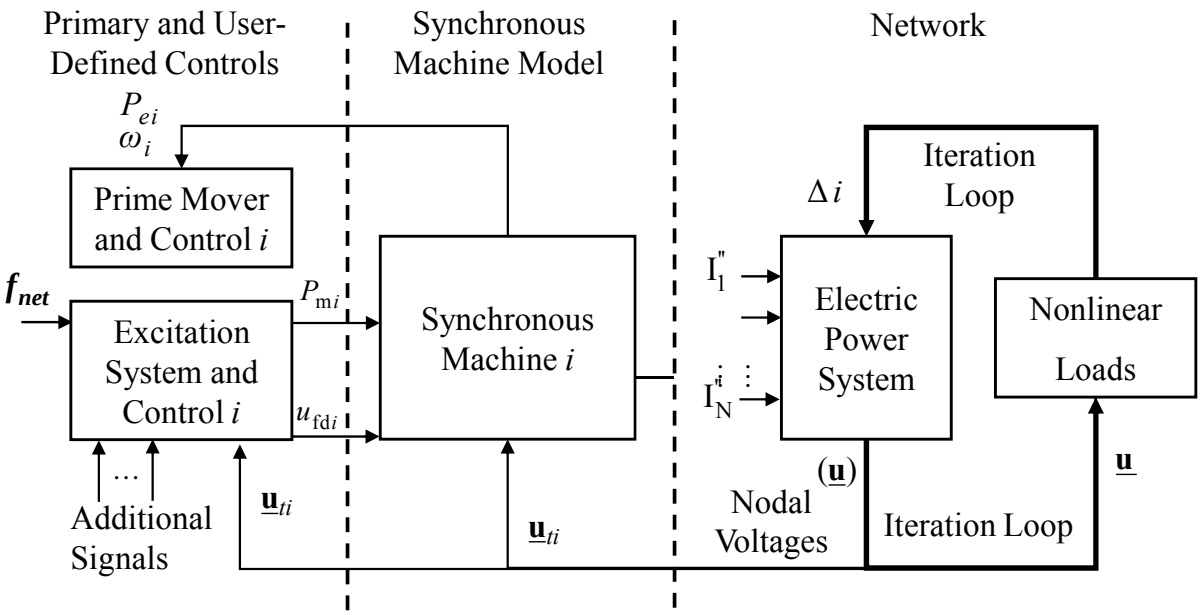

Figure 3.1 Nonlinear modeling and simulation of large power system in PSD software

A brief explanation of the PSD is presented In the following section [27]. The block in the middle of Figure 3.1 is used to describe the dynamics of synchronous machines. Their overall dynamics involve the full scale of energy storing elements from mechanical masses to electric and magnetic fields. All synchronous machines are driven by prime movers, normally turbines and under direct primary controls. Synchronous machines provide virtually all power generations and have major influence on the overall dynamic performance of power systems due to their characteristics. A reduced 5th order model, where stator transient dynamics (stator flux linkage derivatives) are neglected, is used for all synchronous machines in this study. The model consists of a set of differential and a set of algebraic equations. Input variables to the models are the complex terminal voltage $\underline{u}_{ti}$, the mechanical turbine power P_{mi} and the

excitation voltage $u_{\mathrm{fd}i}$. Moreover, the injected currents into the network that depend on the corresponding state variables of the synchronous machines are used as inputs to the algebraic network equations.

The shown nodal voltages at the bottom of the right side are computed by solving the algebraic network equations of the nodal admittance matrix. Moreover, the nonlinear voltage dependent loads can be incorporated in the system where the solutions to update the injection currents might be carried out iteratively. The blocks in the left of Figure 3.1 represent the voltage and governor controllers. The block of governor control contains, in addition to the direct primary control of the turbine torque (i.e., the governor mechanism), the mechanical dynamics of the equipment, such as the turbine or boiler that tie to the system dynamically through the governor control valve. Similarly, the voltage control block typically includes voltage regulators and exciters; and their dynamics depend on the nature of the feedback control arrangement and the nature of the source of DC voltage $u_{\mathrm{fd}i}$. Moreover, the user-defined controller structures can be easily incorporated either through voltage or governor controller sides and such options give greater flexibility in analysis and simulation studies.

3.2.2.1 Critical Fault Clearing Time

The critical fault clearing time is defined as the longest duration of a fault that does not lead to any generator loss of synchronism in the system or any other inadmissible repercussion for the system such that the power system is transiently stable. During large disturbances such as a three-phase short circuit, the protection system senses the presence of fault and the corresponding relays initiate the tripping of the nearest circuit breakers to isolate the fault. The time duration from the instant the disturbance occurs until the circuit breakers isolate

the fault is termed by fault clearing time (FCT). Therefore, any generator shall have a CCT higher than FCT of the protection devices installed in the transmission system to avoid a loss of the connected generators. The loss of the connected generators may induce unacceptable consequences for the whole system following contingencies. The total fault clearing time consists of the combination of operating time of the main protection system; signaling time, rely time and breaker interrupting time. Normally, the three phase short circuit faults close to the generator transformer terminals is the worst fault position. Therefore, the corresponding CCT has been used as index to monitor the power system transient stability level during faults in many literatures and is used in this study. As the value of CCT increases, the system has an increased opportunity to isolate and clear the disturbance using the protective relays and circuit breakers. Thus if the CCT value is less than the operating time of the circuit breaker for the corresponding electric component experiencing the fault, then the system is not considered transiently stable. The accepted limit of CCT is different from system to other but the common value is around 150 milliseconds, which is used in this dissertation as the limit for transient stability of the system. The CCT is much more beneficial than the power limits which can be investigated using TEF. TSA using CCT is characterized by the ability to screen and rank a set of contingencies to select the most sever ones beside specifying stability scenarios as stable or unstable state.

3.2.2.2 CCT Evaluation using TDS by Bisection Technique

Analyzing many contingencies have to be done iteratively in short period to evaluate system states. The contingency selection criterion is required to determine in advance the set of credible contingencies that are severe for the system operation. Either in online or Offline, computation of CCT may be excessive and time consuming. PSD tool, which introduced in section 3.2.2, is

used to estimate the CCT in order to specify a quantified index for transient stability assessment. CCT is normally calculated by uniformly increase the fault clearing time until the system instability. In order to shortage the computation time, Bisection technique is used to find the CCT for each fault in order to avoid the repetitive time-consuming with step increase fault duration [28]. Figure 3.2 presents the flow chart of the Bisection technique, which can be used to estimate the CCT for each contingency. The technique starts with initial FCT and searches for the boundaries, which includes the CCT. As shown in Figure 3.2, an initial fault clearing time (FCT $= t_0$) is assumed where the time boundaries are initially assumed within ($t_0 \pm \sigma$). If the CCT is found between these time boundaries, the Bisection technique can be applied to estimate the CCT, otherwise these time boundaries should be changed until the system is stable at one boundary and unstable at the other boundary to clarify that CCT found between the two limits. Then, the dynamic response of the system is evaluated at mid-point (t_{mid}) between higher and lower limits. If the system is stable, the lower limit (t_1) is replaced by mean value (t_{mid}). Otherwise, the higher value (t_2) is replaced by mean value (t_{mid}) in the next calculation. The sectioning process continues until the acceptance tolerance, ε between the limits is satisfied. Then the CCT selected to be the higher limit. The total time of computation depends on various parameters. The chosen parameter σ should be large enough to restrict the number of simulations. In addition, this value can be adaptive during the simulation from one contingency to another to reduce the total simulation time.

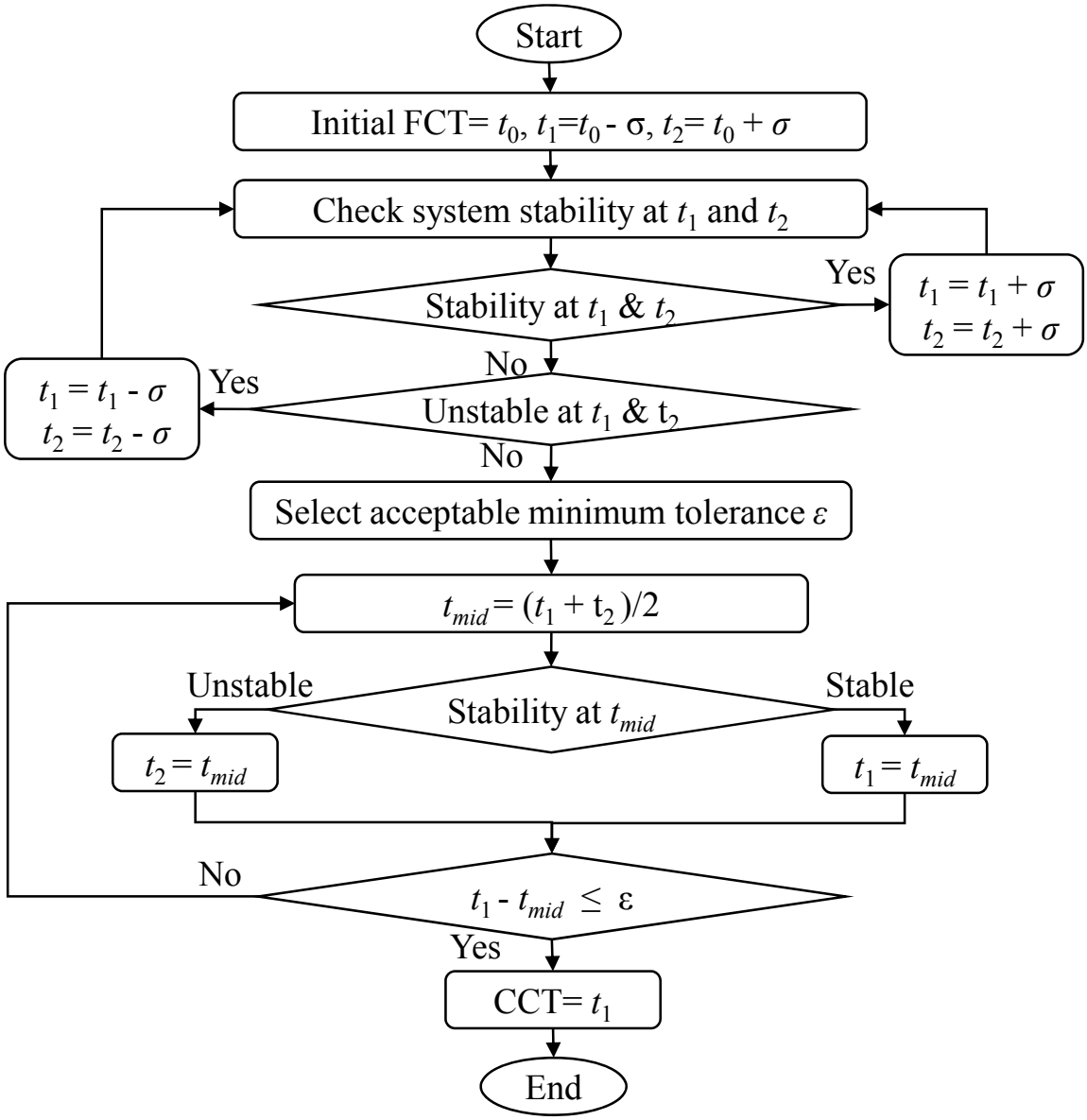

Figure 3.2 Estimation of CCT using TDS by Bisection technique

The parameter ε should be taken quite small to be sure that the stable simulation is close enough to the last unstable one. The choice of initial FCT depends on the particular application sought and the experience of system performance during faults. This process should be repeated for each selected contingency to calculate the corresponding CCT value. After screening the selected set of contingencies, the contingencies can be ranked based on CCT values and the worst contingency with the lowest CCT is selected as the most

sever contingency. The corresponding CCT specifies the distance at this particular operating point from transient stability boundary.

The application of the Bisection technique reduces the required computation time to calculate the CCT using TDS. TDS provides the opportunity to consider the detailed power system modeling and all expected scenarios. It provides detailed time response of the electrical signals following faults with high degree of accuracy. The total time required to calculate the credible degree of a contingency set still very high to screen the system states during online applications. Online TSA based computational intelligence has been proposed to overcome the drawbacks of traditional methods. ANN as an efficient computational intelligence is used to assess the power system stability in this study. ANN is trained offline using pre-analyzed input-output patterns to be applied in online applications. The design of ANN to assess the power system transient stability will be discussed in section 3.4.

3.3 Oscillatory Stability Assessment

Oscillations are due to natural modes of the system and therefore cannot be eliminated. Damping of transient oscillations is becoming an important issue of great concern, with the trend to include damping techniques as a part of a dynamic stability analysis. Oscillatory stability as defined is the ability of the power system to maintain synchronism when subjected to a small-disturbance. Instability may result due to rotor oscillations with increasing amplitude in cases of lack of sufficient damping torque [12]. Various techniques have been used to investigate problematic system oscillation to analysis and mitigate the effect of oscillation on power system operation [29]. The main three techniques that can be used to assess the power system oscillatory stability are:

- Time-domain-simulation can be used to investigate the simple cases of

oscillations but it is time consuming and often difficult to interpret the results to separate the modes in a large systems [30].

- Identification techniques are widely used to analyze the oscillatory modes in power system based on the recorded electrical signals, which can be obtained from system measurements or transient stability simulation [31]. In these methods the parameters of the exponentially modulated sinusoidal signals of the measurements can be obtained and used to identify oscillatory stability [32][33].
- Modal analysis is a technique has been used to analysis the oscillatory modes based on the mode parameters. These parameters can be obtained after the system differential equations have been linearized around the current operating point [12].

3.3.1 Linearization

The power system dynamic behavior is governed by equations 2.2 and 2.3. Consistent with power system dynamic theory, to investigate the small signal stability at one operating point accomplished with small motions. It is assumed that the power system subjected to a small-disturbance enough to linearize the general nonlinear dynamic model of equation 2.2 and 2.3 around the operating point. The operating point with initial state vector $\mathbf{x}_0$ is assumed an equilibrium point with input vector $\mathbf{u}_0$ and the derivatives of state vector matrix $\mathbf{x}_0$ are simultaneously zero. As the perturbations ($\Delta\mathbf{x}$, $\Delta\mathbf{u}$) are assumed to be small, the nonlinear functions can be expressed in terms of Taylor's series expression. By using only the first order terms, the approximation for the ith state variable x_i leads to the following equations with r as the number of inputs [12]:

$$\dot{x}_i = \dot{x}_{i0} + \Delta\dot{x}_i = f_i\left[\left(\mathbf{x}_0 + \Delta\mathbf{x}\right), \left(\mathbf{u}_0 + \Delta\mathbf{u}\right)\right] \tag{3.2}$$

$$\dot{x}_i = f_i\left(\mathbf{x}_0, \mathbf{u}_0\right) + \left(\frac{\partial f_i}{\partial x_1}\cdot\Delta x_1 + \cdots \frac{\partial f_i}{\partial x_n}\cdot\Delta x_n\right) + \left(\frac{\partial f_i}{\partial u_1}\cdot\Delta u_1 + \cdots \frac{\partial f_i}{\partial u_r}\cdot\Delta u_r\right) \quad (3.3)$$

$$\Delta\dot{x}_i = \left(\frac{\partial f_i}{\partial x_1}\cdot\Delta x_1 + \cdots \frac{\partial f_i}{\partial x_n}\cdot\Delta x_n\right) + \left(\frac{\partial f_i}{\partial u_1}\cdot\Delta u_1 + \cdots \frac{\partial f_i}{\partial u_r}\cdot\Delta u_r\right) \quad (3.4)$$

Similarly, the linearization for i^{th} output by using equation 2.3 can lead to:

$$\Delta\dot{y}_i = \left(\frac{\partial g_i}{\partial x_1}\cdot\Delta x_1 + \cdots \frac{\partial g_i}{\partial x_n}\cdot\Delta x_n\right) + \left(\frac{\partial g_i}{\partial u_1}\cdot\Delta u_1 + \cdots \frac{\partial g_i}{\partial u_r}\cdot\Delta u_r\right) \quad (3.5)$$

It is easy to show that, equation 3.4 and equation 3.5 are linear approximations of nonlinear equations 2.2 and 2.3 for small changes in state variables, output and control signals. The underlying assumption is that small motions of the power system can be described by a set of ordinary differential equations of the form:

$$\Delta\dot{\mathbf{x}} = \mathbf{A}\ \Delta\mathbf{x} + \mathbf{B}\ \Delta\mathbf{u} \quad (3.6)$$

$$\Delta\mathbf{y} = \mathbf{C}\ \Delta\mathbf{x} + \mathbf{D}\ \Delta\mathbf{u} \quad (3.7)$$

Where **A**, **B**, **C**, **D** are the matrices of derivatives of the functions **f** and **g** with respect to **x** and **u** and evaluated at the equilibrium point about which the small perturbation is being analyzed.

$$\mathbf{A} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \cdots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \cdots & \frac{\partial f_n}{\partial x_n} \end{bmatrix} \quad \mathbf{B} = \begin{bmatrix} \frac{\partial f_1}{\partial u_1} & \cdots & \frac{\partial f_1}{\partial u_r} \\ \vdots & \cdots & \vdots \\ \frac{\partial f_n}{\partial u_1} & \cdots & \frac{\partial f_n}{\partial u_r} \end{bmatrix} \quad (3.8)$$

$$\mathbf{C}=\begin{bmatrix} \frac{\partial g_1}{\partial x_1} & \cdots & \frac{\partial g_1}{\partial x_n} \\ \vdots & \cdots & \vdots \\ \frac{\partial g_m}{\partial x_1} & \cdots & \frac{\partial g_m}{\partial x_n} \end{bmatrix} \quad \mathbf{D}=\begin{bmatrix} \frac{\partial g_1}{\partial u_1} & \cdots & \frac{\partial g_1}{\partial u_r} \\ \vdots & \cdots & \vdots \\ \frac{\partial g_m}{\partial u_1} & \cdots & \frac{\partial g_m}{\partial u_r} \end{bmatrix}$$

The matrix **A** is the state or system matrix, **B** is the control or input matrix, **C** is the output matrix, and **D** is the feed-forward matrix, which defines the proportion of input that appears directly in the output. The dynamic response of the state variables and outputs depends on the initial conditions and the control variables. From the stability viewpoint, the state matrix **A** is the most important which determines the poles of the equations represent of change in state and output variables.

3.3.2 OSA by using Eigen-analysis Methods

Eigen-analysis methods are widely used to perform small-signal stability studies. The dynamic behavior of a system in response to small-perturbations can be determined by investigating the eigenvalues and eigenvectors obtained by solving the characteristic equation of the (n x n) system matrix with (n x 1) non-trivial vector:

$$\mathbf{A}\boldsymbol{\Phi}=\lambda\,\boldsymbol{\Phi} \tag{3.9}$$

$$\left(\mathbf{A}-\lambda\mathbf{I}\right)\boldsymbol{\Phi}=0 \tag{3.10}$$

$$\det.\left(\mathbf{A}-\lambda\mathbf{I}\right)=0 \tag{3.11}$$

The estimation of the mode parameters (eigenvalues and eigenvectors) corresponding to equation 3.11 yields model information about the system which can be used to predict possible unstable behavior of power system

following a disturbance. The location of the eigenvalues is used to investigate the system performance. The system eigenvectors are used to estimate the relative participation of the respective states in the disturbance modes.

3.3.2.1 System Mode Eigenvalues

The eigenvalues of the state matrix **A** specify the natural modes of system response, which provide valuable information regarding the stability characteristics of the power system. The n eigenvalues of the state matrix can be computed by solving the characteristic equation 3.13 of **A** which may be real or complex in the form:

$$\lambda = \sigma \pm j\omega \tag{3.12}$$

The real part σ represents the damping of the corresponding mode. The system is asymptotically stable with damped oscillation when the real part of the eigenvalue is negative (a damped oscillation) and a positive real eigenvalue represents aperiodic instability where the oscillation has an increased amplitude. If the state matrix is real, complex eigenvalues always occur in conjugate pairs. Each pair corresponds to an oscillatory mode. The critical eigenvalues are characterized by being complex and are located near the imaginary axis of the complex plane. The frequency of the oscillation in Hz and the damping ratio (ξ) are given by the following relationships:

$$f = \frac{\omega}{2\pi} \tag{3.13}$$

$$\xi = \frac{-\sigma}{\sqrt{\sigma^2 + \omega^2}} \tag{3.14}$$

The damping ratio determines the decaying rate of the amplitude of oscillation. The time constant of decaying the amplitude of oscillation is $1/|\sigma|$. Where the oscillatory modes have a wide range of frequencies, the use of damping ratio rather than the time constant of decay is considered more appropriate for expressing the degree of damping. The minimum acceptable damping ratio is system dependent and based on operating experience and/or sensitivity studies. It is typically used in the range from 0.03 to 0.05 as a minimum acceptable damping ratio to consider the system transiently stable. Therefore, the damping ratio has been considered as a good indicator for small signal stability and will be used in this thesis with acceptable limit of 0.04 damping ratio.

3.3.2.2 Eigenvectors and Participation Factors

After computing the eigenvalues λ of the state matrix **A**, for any eigenvalue λ_i, the n-column vector **Φ** that satisfies Equation 3.11 is called the right eigenvector of **A** which are associated with the eigenvalue λ_i. Similarly, the so-called left eigenvector, which are associated with this eigenvalue, satisfies a similar equation as follows:

Right eigenvector: $$\mathbf{A}\,\mathbf{\Phi}_i = \lambda_i \mathbf{\Phi}_i, \mathbf{\Phi} = \left[\mathbf{\Phi}_1^{\mathrm{T}}\ \mathbf{\Phi}_2^{\mathrm{T}} \cdots\ \mathbf{\Phi}_n^{\mathrm{T}}\right] \tag{3.15}$$

Left eigenvector: $$\mathbf{\Psi}_i\,\mathbf{A} = \lambda_i\,\mathbf{\Psi}_i, \mathbf{\Psi} = \left[\mathbf{\Psi}_1^{\mathrm{T}}\ \mathbf{\Psi}_2^{\mathrm{T}} \cdots \mathbf{\Psi}_n^{\mathrm{T}}\right]^{\mathrm{T}} \tag{3.16}$$

A participation matrix (**P**) is the sensitivity of the eigenvalues to a change of the diagonal elements of the state matrix that relates the state variables and the system modes of oscillation. Performing the Eigen-analysis will indicate the presence of poorly damped modes. The corresponding participation factors give inside about the characteristic and the source of the problem. These parameters

assist to develop the necessary mitigation measures. When the participation factors are normalized, they provide a straightforward measure of the percent of impact and relative participation of each state variable on a particular mode. The participation factor p_{ki} that can be obtained by multiplying the elements of the left eigenvectors Ψ_{ik} and right eigenvectors corresponding to each eigenvalue Φ_{ki} is expressed as follows:

$$P_{ki} = \frac{\partial \lambda_i}{\partial a_{kk}} = \Psi_{ik}\ \Phi_{ki} \tag{3.17}$$

$$\mathbf{p}_i = \left[p_{1i}\ \ p_{2i} \cdots\ p_{ni} \right]^{\mathrm{T}} \tag{3.18}$$

$$\mathbf{P} = \left[\mathbf{p}_1\ \ \mathbf{p}_2 \cdots\ \mathbf{p}_n \right] \tag{3.19}$$

If, for any mode, the corresponding participation factor of the generator speed is zero, we can imply that adding damping to that generator will have no effect on improving this mode of oscillation. If the participation factor is real and positive, adding damping to that generator will increase the damping of the mode. If the participation factor is real and negative, adding damping to that generator will reduce the damping of the mode [30].

Modal analysis extracts the system modes from the system state matrix, which does not consider the effect of disturbance magnitude and location on the system oscillation. Power systems are continually excited by random inputs with high-order independence. Because of this stochastic nature of these inputs, it is difficult to estimate exactly the modal properties of the system. Thus performing the ringdown analysis on time response of the electrical signals can be used to account for the effects of system nonlinearity and small disturbances on the power system oscillations.

3.3.3 Ringdown Analysis

The time response signals which can be obtained by measuring or simulation may be analyzed by means of signal processing techniques to obtain useful information that can be used to capture the dynamic response of a power system. A proper identification technique and probing signal are required to analyze the dynamic response accurately. In the ringdown analysis, the system may be excited by a large perturbations, such as sever short circuit or tripping of large component, resulting a transient response that can be observed and distinguished from ambient noises. These signals can be analyzed by any efficient identification technique such as Prony analysis or Matrix Pencil methods to extract the oscillation modes contents.

Prony analysis has been widely applied to estimate small-signal dynamic properties, develop equivalent linear models, and tune power system controllers such as power system stabilizers from measured or simulated data [34][35]. Prony analysis is used to extract the valuable information from a uniformly sampled signal and to build a series of damped complex exponentials or sinusoids. A proposed time varying function should be fitted the sampled waveform that represents the dynamic system behavior in order to extract the model contents. The problem is to minimize the error between the actual time varying data and the proposed function [34]. A brief explanation of the Prony analysis methodology and application in the mode contents estimation is presented in the following section.

3.3.3.1 Basis of Prony Analysis

Prony analysis is a method of fitting a linear combination of exponential terms $\hat{y}(t)$ to a uniformly sampled record $y(t)$. Each exponential component

with a different frequency is viewed as a unique mode of the original signal. Figure 3.3 interprets the mode frequency, damping, amplitude and phase. Suppose that after power system subjected to an instant disturbance and there are no subsequent disturbances to the system, the system will ringdown with a free motion with zero input according to a differential equation of the form:

$$\dot{\mathbf{x}}(t) = \mathbf{A}\,\mathbf{x}(t),\ \mathbf{y}(t) = \mathbf{C}\,\mathbf{x}(t) \tag{3.20}$$

While ignoring noise content and assuming non-repeated poles, Then the solution for any state variable and output can be expressed as a function of the eigenvalues, right eigenvectors and left eigenvectors of n x n matrix **A** as follows [35]:

$$x(t) = \sum_{i=1}^{n} (\Psi_i^{\mathrm{T}}\, x_0)\, \Phi_i\, \mathrm{e}^{\lambda_i t} = \sum_{i=1}^{n} R_i\, x_0\, e^{\lambda_i t} \tag{3.21}$$

R_i is the residue matrix, x_0 is the initial value and n is the total number of components in **x** matrix. Consider that the signal component of a measured signal $y(t)$ is equally sampled in time. The objective is to identify the parameters of a finite sum of L damped cosines with minimum error to model the output. Each exponential component with a different frequency is viewed as a unique mode of the original signal $y(t)$.

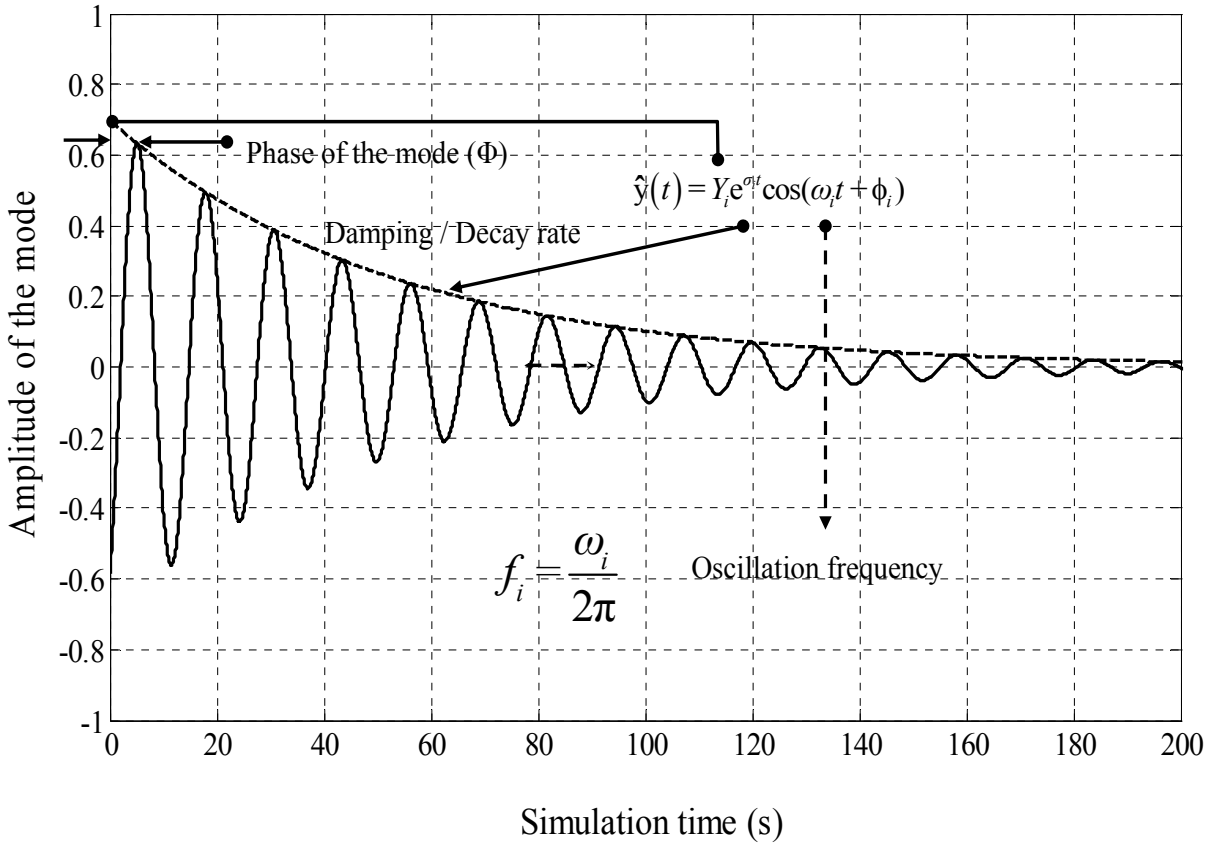

Figure 3.3 Interpretation of Modal Frequency, Damping, Amplitude and Phase

$$\hat{y}(t) = \sum_{i=1}^{L} Y_{mi}\ e^{\sigma_i t}\cos(2\pi f_i t + \theta_i) \tag{3.22}$$

Where Y_{mi} and θ_i are the magnitude and phase of component i at angular frequency $\omega = 2\pi f_i$ which is derived from influence of the initial conditions. The damping factor σ_i and the frequency f_i are corresponding to the eigenvalue λ_i of the state matrix.

The objective is to estimate real parameters ($\sigma_i, f_i, Y_{mi}, \theta_i$ $with\ i\ = 1 \ldots L$) from m samples of the time series $\hat{y}(t)$ that produces $\hat{y}(t) = \mathrm{y}(t)$ for all integer number k. If we let t=kT, where T is the constant sample period of m observed samples of $\mathrm{y}(t)$. The equation can be converted into discrete-time form as:

$$\hat{y}\left(k\mathrm{T}\right)=\sum_{i=1}^{L}B_i z_i^k,\ \ z_i=\mathrm{e}^{\lambda_i \mathrm{T}} \qquad k=0,1,2\ldots m\text{-}1 \tag{3.23}$$

Where $B_i = \frac{Y_{mi}}{2}e^{j\theta_i}$ is an output residue corresponding to the mode $\lambda_i = \sigma_i + j\omega_i$. If z_i is found then eigenvalues λ_i can be calculated. The system eigenvalues can be found from the discrete modes by:

$$\lambda_i = \frac{\ln(z_i)}{\mathrm{T}} \tag{3.24}$$

Prony analysis consists of three steps. In the first step, the coefficients of a nonlinear prediction model are calculated. The linear prediction model is built to fit the equally sampled data record with length m as shown in (3.25). Normally, the length m should be at least three times larger than the proposed order L.

$$\hat{y}\left(k\mathrm{T}\right)=a_1\hat{y}((k-1)\mathrm{T})+\cdots+a_L\hat{y}((k-L)\mathrm{T}) \tag{3.25}$$

Estimation of the linear prediction model coefficients a_L is crucial for the derivation of the frequency, damping, magnitude, and phase angle of a signal. To estimate these coefficients accurately, many methods can be used to solve the obtained series of equations. A matrix representation of the signal at various sample times can be formed by sequentially writing the linear prediction of $\hat{y}(k\mathrm{T})$ repetitively. By inverting the matrix representation, the linear coefficients a_L can be derived from (3.28).

$$\begin{bmatrix} \mathrm{y}(L) \\ \mathrm{y}(L+1) \\ \vdots \\ \mathrm{y}(m-1) \end{bmatrix} = \begin{bmatrix} \mathrm{y}(L-1) & \mathrm{y}(L-2) & \cdots & \mathrm{y}(0) \\ \mathrm{y}(L) & \mathrm{y}(L-1) & \cdots & \mathrm{y}(1) \\ \vdots & \vdots & \vdots & \cdots \\ \mathrm{y}(m-2) & \mathrm{y}(m-3) & \cdots & \mathrm{y}(m-L-1) \end{bmatrix} \begin{bmatrix} \mathrm{a}_1 \\ \mathrm{a}_2 \\ \vdots \\ \mathrm{a}_L \end{bmatrix} \tag{3.26}$$

The obtained system of equations can be solved by the least squares method to find the L unknown coefficients a_L. In the second step, the roots z_L of the Lth order polynomial can be found by solving the system characteristic equation:

$$z^L - \left(a_1 z^{L\text{-}1} + a_2 z^{L\text{-}2} + \cdots + a_L z^0\right) = 0 \tag{3.27}$$

The eigenvalues are then calculated by substitution the roots z_i in equation 3.24. The last step in Prony analysis is the solution of (3.23) in matrix form to calculate the output residues that produce $\hat{y}(t) = y(t)$ for all data points. This achieved by substituting at all m samples and constructing the following relationship:

$$\begin{bmatrix} y(0) \\ y(1) \\ \vdots \\ y(m-1) \end{bmatrix} = \begin{bmatrix} z_1^0 & z_2^0 & \cdots & z_L^0 \\ z_1^1 & z_2^1 & \cdots & z_L^1 \\ \vdots & \vdots & \vdots & \cdots \\ z_1^{m-1} & z_2^{m-1} & \cdots & z_L^{m-1} \end{bmatrix} \begin{bmatrix} B_1 \\ B_2 \\ \vdots \\ B_L \end{bmatrix} \tag{3.28}$$

The magnitude and phase angle calculated from the output residues. The estimating waveform $\hat{y}(t)$ is then calculated from equation (3.24). The quality of reconstructed signal then evaluated using appropriate measure such as signal to noise ratio. The greatest advantage of Prony analysis is its ability to identify the damping factor of each mode in the signal. Due to this advantage, power system oscillatory stability can be identified accurately.

3.3.3.2 Tuning of Prony Analysis Parameters

The Prony analysis parameters should be adjusted to achieve the most accurate results at different situations. The major problems in applying Prony analysis to estimate the modal parameters are that the true order of the fitted model and change of the results with change in system disturbance. If the order

of the system is unknown, proposed values should be used to calculate the roots of the system characteristic equation. The poles corresponding to high frequencies, which are known not to be present in power system, are discarded. The results can be improved by using the technique of shifting time windows and by selecting the suitable small disturbance to clearly able to identify the modes of oscillations. The selection of sampling time and the data length in an analysis window depends on the simulation time step and the estimated frequency range. High signal to noise ratio (SNR) between the actual data and estimated waveform is needed to get accurate results. Moreover, signals should be chosen for analysis in which the modes of interest are clearly observable. The definition of SNR given as follows:

$$\mathrm{SNR} = 20 \log \frac{\left\| \hat{y} - y \right\|}{\left\| y \right\|} \tag{3.29}$$

Prony analysis can produce inaccurate system mode estimates if high nonlinear characteristics are included in the analysis records. This lead to omit the initial data points following a system disturbance. It should only be used with response data that appears to be limited random fluctuations which is often the tail end of a signal record [34].

3.3.4 Estimation of Power System Minimum Damping

The investigation of oscillatory stability of power system focuses on a small number of dominant eigenvalues, which affect on the system operation specially the associated ones with inter-area oscillations and local-area oscillations. The instability, which is associated with system oscillation, is mainly due to the shortage in the system damping torque. Thus, MDO is considered as indicator for small signal stability assessment. In this study, the mode with damping ratio

below 4% is considered to have insufficient damping during the corresponding operating point as shown in Figure 3.4. Therefore, a change in the power flow is required for eigenvalues shifting to improve system small signal stability.

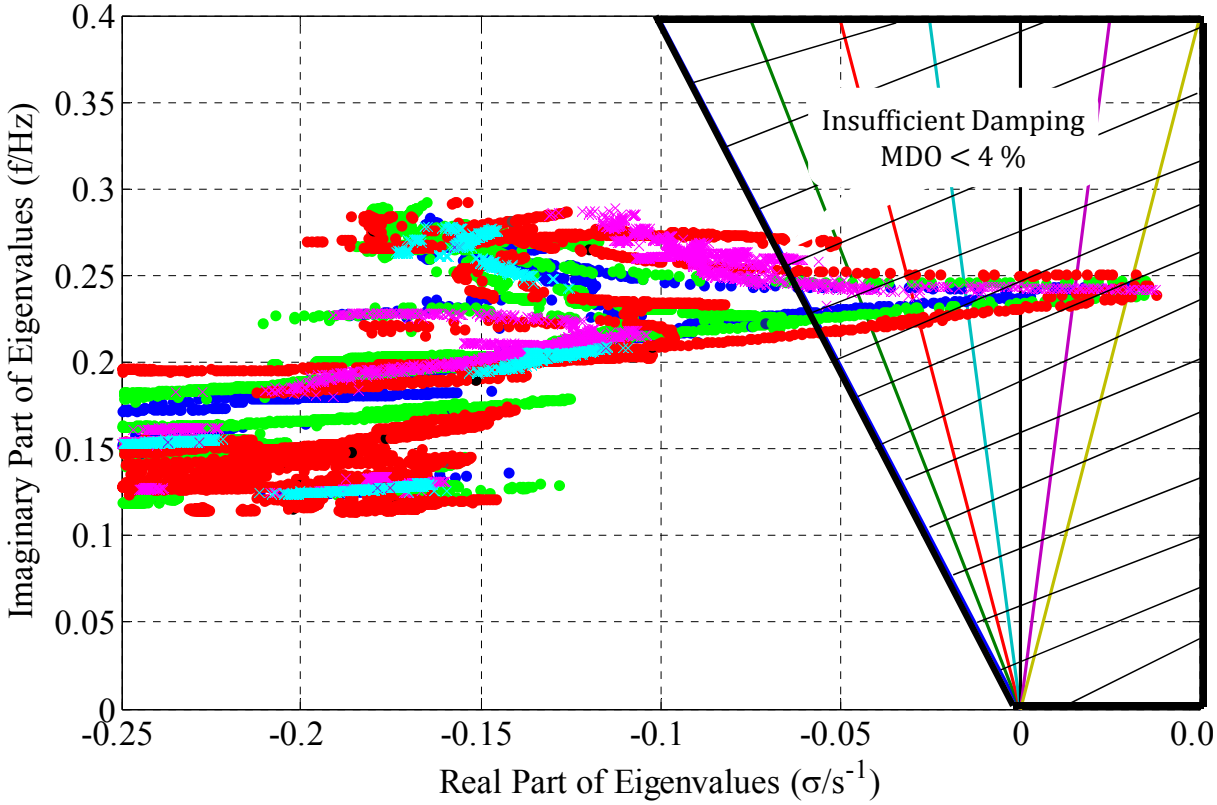

Figure 3.4 Eigenvalues for different operating conditions

At a given operating scenario, the damping coefficients corresponding to the set of dominant eigenvalues are calculated by applying a selected set of contingencies. The lowest minimum damping coefficient is called MDO and is used as indicator for OSA. In this thesis, Prony analysis is applied to the generators active power as signals. The generators active power seem to be the most sensitive in determination of system damping, where system oscillation is mainly due to a power imbalance between the swinging generators. The use of Prony analysis is to account for the effect of high nonlinearity of the system during small disturbances. Dynamic system identification toolbox (DSI) is used to identify system oscillations and damping following injection of the probing

signals [35][36]. In order to improve the system mode identification significantly, a probing signal with a proper duration should be injected at certain locations. Three-phase short circuit is applied at pre-selected fault locations with different fault durations to investigate the system response.

The MDO is calculated by the Modal analysis using PSD software environment after linearized the power system state equations at the current operating point and is used as a reference value during tuning of the Prony analysis parameters. Figure 3.5 shows the estimated MDO by using DSI toolbox at different contingencies and fault durations applied in the 16-machine Power Stability Test system (PST16) [37]. This test system is designed to investigate the different types of stability phenomena. The target is to check the effect of fault duration on the modes identification by using Prony analysis from the time response of signals of the faulted system. As seen in Figure 3.5 the deviations of the calculated MDO using Prony analysis are minimum and the values remain close to the reference value for a fault of 1.0 millisecond duration at pre-selected fault locations. Thus, a three-phase short circuit with 1.0 millisecond duration is considered as enough small step faults to estimate the MDO as index for OSA. Figure 3.6 presents the comparison between the estimated percentages of MDO by using Prony analysis relative to the calculated percentages of MDO which are calculated by using modal analysis. These results are obtained with using a 1.0-millisecond three-phase fault as a small contingency, which is applied at bus A1 in area A at different operating points.

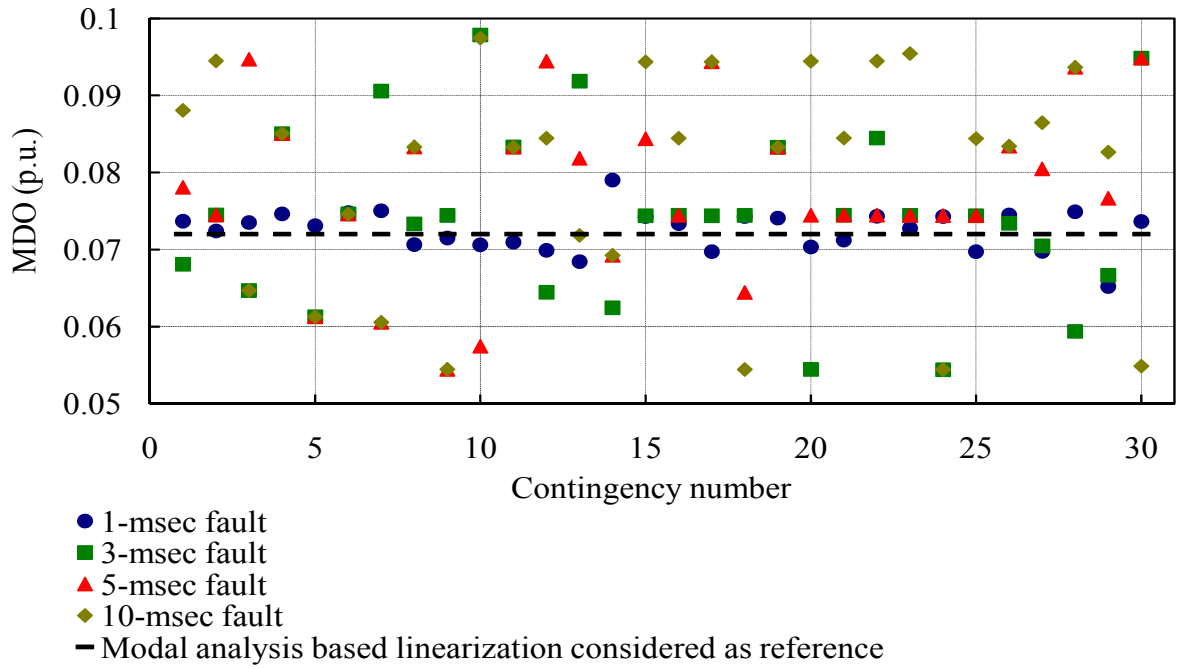

Figure 3.5 MDO at different fault locations and different durations

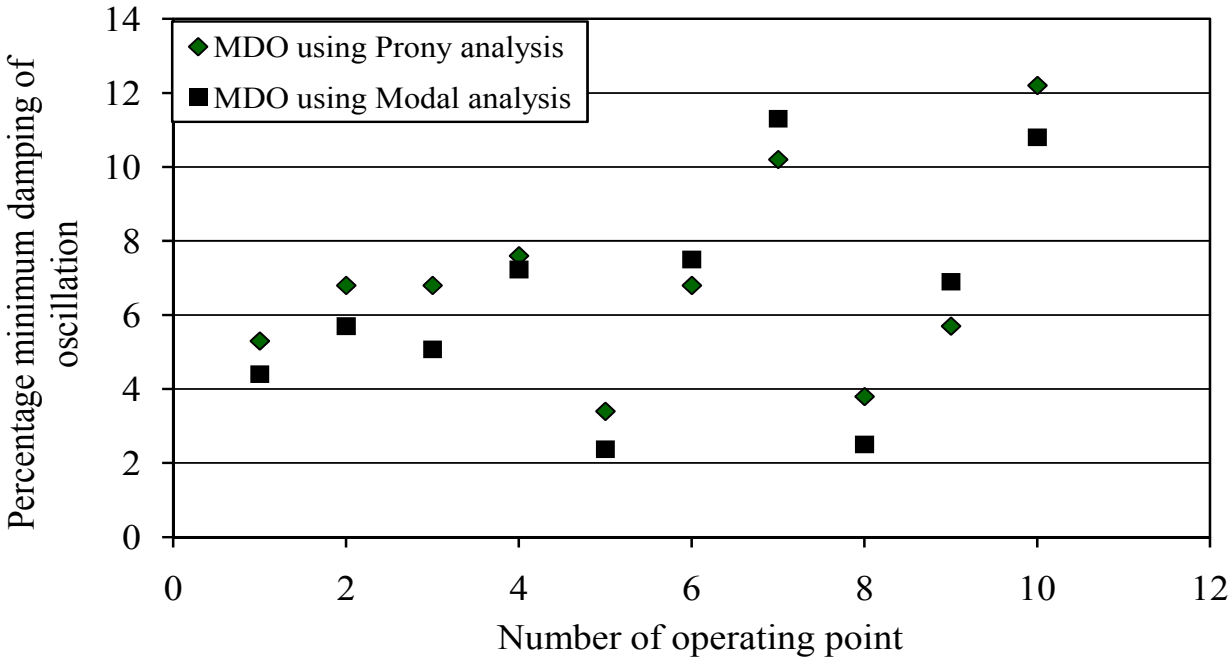

Figure 3.6 MDO evaluated by Prony analysis relative to modal analysis

Figure 3.7 shows generator active power deviations due to following a small disturbance at the bus B6 in area B on PST16 after removing the initial transient response. The figure clarifies the existence of oscillations between groups of generators. Table 3.1 presents dominant modes and associated

frequencies and damping ratios by applying the Prony analysis using the DSI toolbox. Figure 3.8 presents comparison between the actual system data and the identified system data using DSI. The observed inter-area oscillation modes with 0.208 and 0.8759 Hz frequency and approximately 25.82% and 7.48% damping ratios respectively are typical characterized. These modes can be observed as shown in Figure 3.9, which compares the magnitude and phase of the transfer functions of the actual identified systems. Inter-area oscillation between area B and area C can be characterized from the time response in Figure 3.7.

Table 3.1 The dominant modes by applying Prony analysis

Mode	1	2	3	4	5	6	7
Frequency (Hz)	0.2080	1.7154	0.8759	1.231	1.335	1.413	1.8061
Damping ratio (p.u.)	0.2582	0.1824	0.0748	0.0804	0.1129	0.0918	0.1014

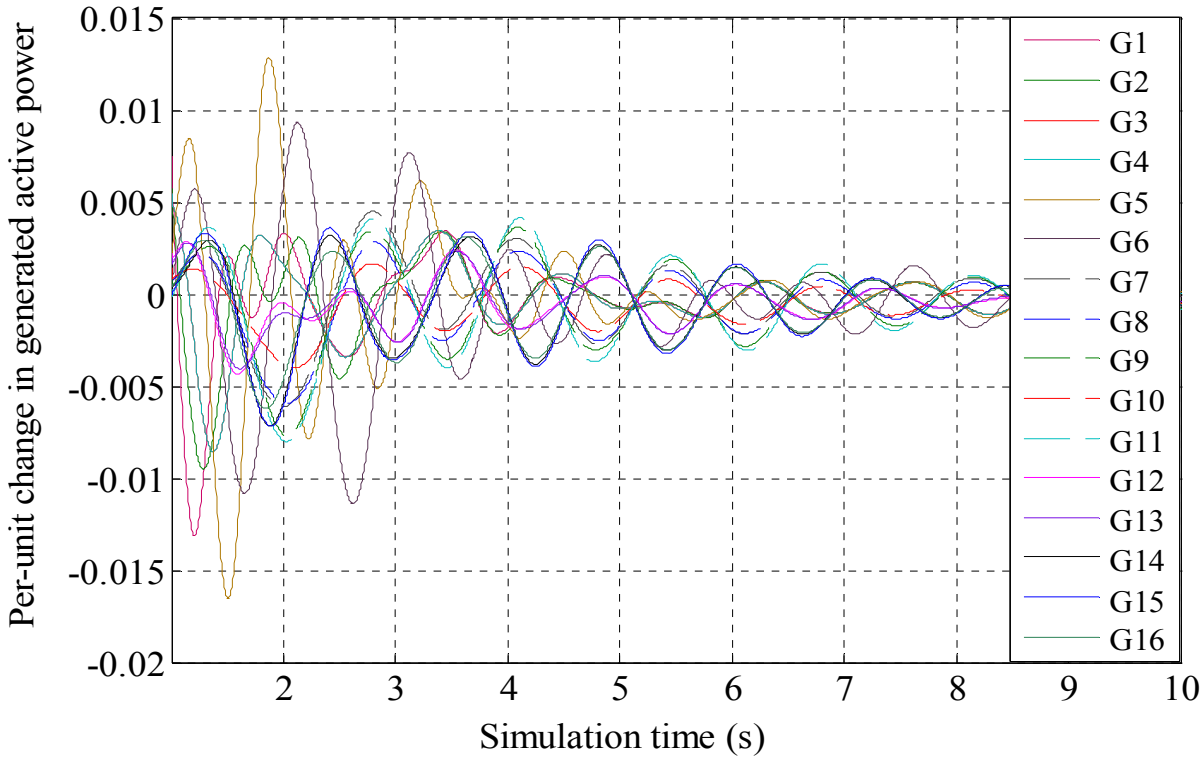

Figure 3.7 Time response of generators to 1.0-millisecond short circuit fault

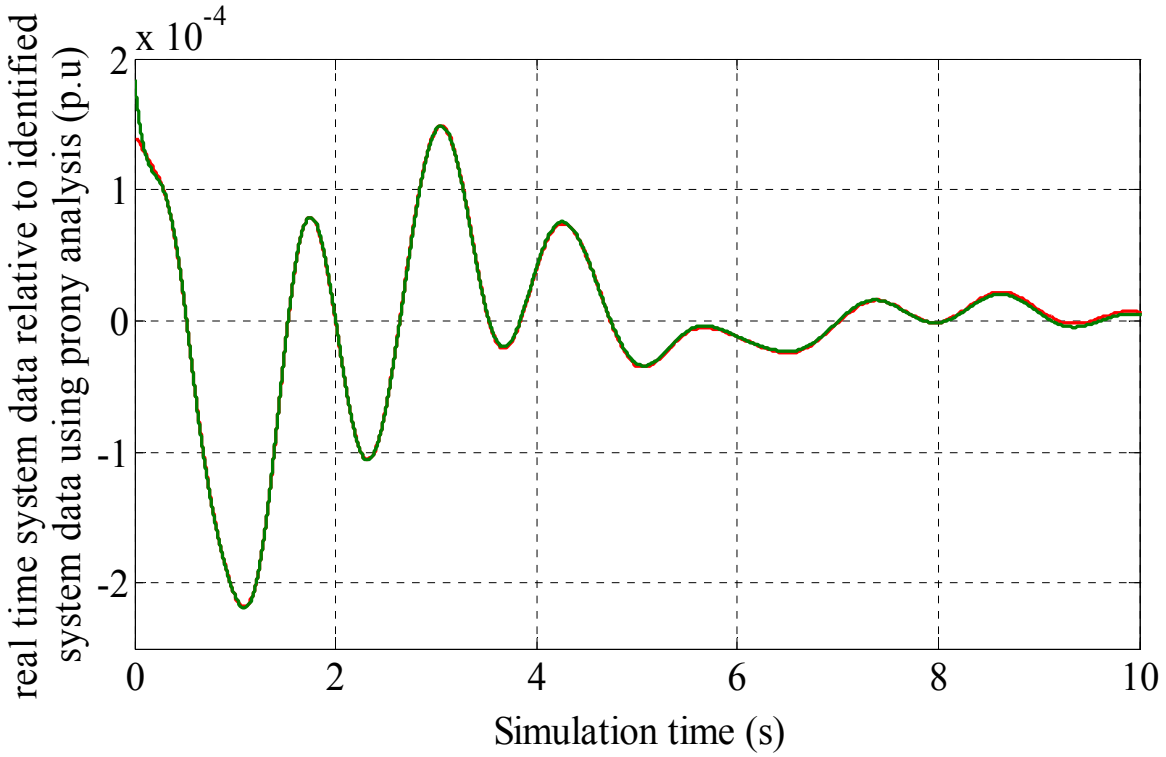

Figure 3.8 Power deviations relative to identified data using Prony analysis

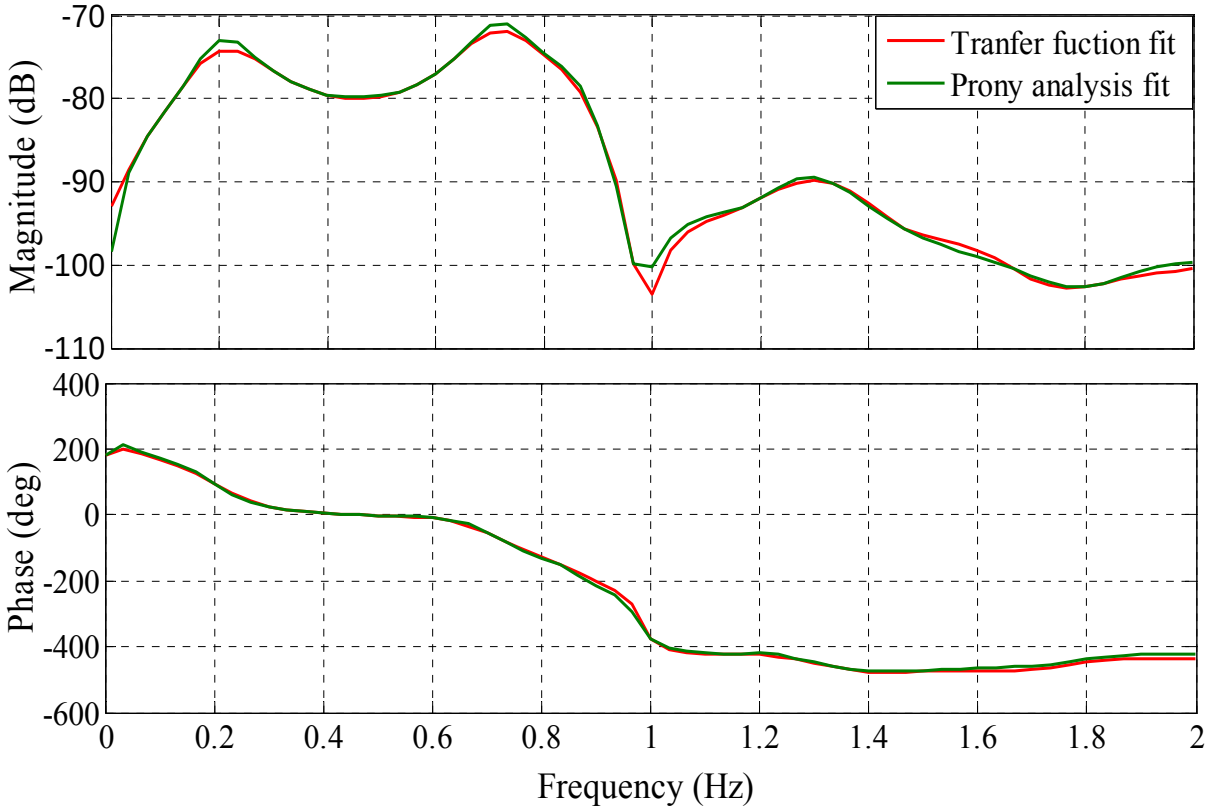

Figure 3.9 Signal spectrum and model response using Prony analysis

3.4 Dynamic Stability Assessment using ANN

Power system dynamic model is composed of linear and nonlinear equations, which involves many discrete and continuous state variables with sophisticated models. TDS provides an accurate calculation of TSA involving repeatedly solving large, sparse, time varying nonlinear state space differential equations of power networks over thousands of time steps. These iterative calculations cannot be applied in the online applications. Similarly, DSI based Prony analysis is an efficient method for estimating the damping of oscillations following power system disturbances as oscillatory stability index but it is time consuming in input data preparation. For accurate estimation of the system modes, proper choice of the number of sample points and the sampling ratio for proper signal to noise ratio are needed [32]. Thus, it is not suitable for online applications.

Fast and accurate Online DSA provides the system operators with much more information about the system states and the distance to blackouts in order to activate proper actions during abnormal conditions. In the operation of deregulated power system, more advanced methods are needed for online DSA to achieve fair competition among participants. Since the computational intelligent methods such as ANN are learned based on training patterns, it have been shown a good performance in many power system applications. ANN bases pattern recognition learning technique is successfully used for online monitoring of power system dynamics to overcome the required computation time and mathematical complexity requirements. ANN has the capability of capturing essential functional relationships among the data.

This capability is valuable when such relationships are not a priori known or are very difficult to describe mathematically such as the dynamic behavior of

large power system during disturbances. Therefore, the use of robust ANN is highly recommended for fast online DSA based on its adaptive nature by learning with examples rather using input-output relationships. ANNs are able to provide continuous margins with estimating of CCT and MDO as indicators of the distance from the dynamic stability boundaries [38] [39]. Offline trained ANN is used as a black box to predict the CCT and MDO based on the current operating point as indicator for TSA and OSA. The next sections present the basic architecture and design of ANN for DSA. The selection of the proper input features for ANN is necessary to improve the accuracy of ANN for accurate estimation of the system dynamic behavior.

3.4.1 Architecture and Training of ANN

The main features of ANN are the ability of learning from the extracted data from the system where associative data can be recalled at retrieval mode. In addition, its inherent parallel architecture allows for fast computation especially when dealing with large-scale networks. Without loss of generality, ANN can be considered as a nonlinear black box model structures to be modeled by conventional parameters estimation. ANN as an intelligent black box can be used to map the inputs directly to the outputs regardless the complexity, which is associated with the relation between inputs and outputs values. The accuracy and the best architecture of ANN depend on the problem to be solved and the selected input features. Therefore, ANN has to be trained by using suitable input-output patterns for good generalization of the entire application.

There is a variety of ANN models that are expanded with more neurons in hidden layers to increase the capability to store the information. Multilayer feed-forward network with back-propagation technique is receiving the most attention in power system applications and is used in this study [40]. The connections

between neurons are weighted by factors, w as shown in Figure 3.10 and the corresponding neuron output function is presented in equation 3.30. There are many activation functions, which can be used in the construction of ANN. Four commonly used activation functions to compute the output values are linear, ramp, step and sigmoid functions. Among them, the sigmoid function, which is presented in equation 3.31, is widely used to model the nonlinear processing specially in the multilayer artificial networks that are trained using the back-propagation algorithm. Most activation functions give outputs within the intervals [0, 1] or [-1, 1]. The patterns are normalized within the same range to maximize the capability of generalization.

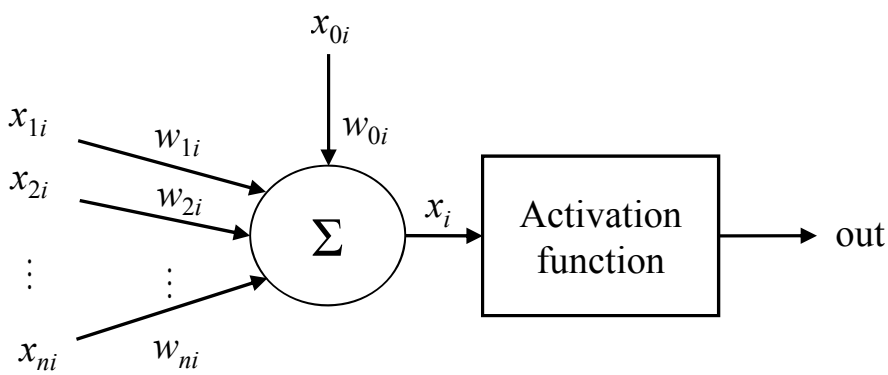

Figure 3.10 Single processing unit structure of an ANN

$$\text{out}(x_i) = f\left(\sum_{j=1}^{n} x_{ji} \cdot w_{ji} + x_{0i} \cdot w_{0i}\right) \tag{3.30}$$

$$f(x_i) = \frac{1}{1 + \mathrm{e}^{-x_i}} \tag{3.31}$$

The number of the neurons in the input layer and output layer depends on how many selected input features and target values respectively. The number of hidden layers and the number of neurons in each hidden layer depend on the complexity of the entire problem to be solved. In most cases, these numbers are determined in trial and error technique. After the ANN has been restructured, it

needs to be trained. The training is the process of determining and storing the appropriate weights and biases representing the relation between the inputs and outputs. The process of learning can take place in supervisory mode (when the back-propagation networks are used) or in unsupervised mode (when the recurrent networks / Kohonen networks are used). The training algorithm should provide ANN the ability of generalization and properly classifies data, which has not been seen before and gives the correct output. Thus, the input-output patterns are merged, shuffled and normalized to avoid memorization problems during the training process. The normalized data then divided into training, testing and validation subsets beside a set for testing as unforeseen data. It modifies the synaptic weights by a learning process to achieve the desired response. Training the network involves feeding the network with a set of input signals and the corresponding desired response. The network then tries to learn from the examples by constructing an input-output-mapping The training of ANN by back-propagation involves three stages:

- The feed forward of the input training patterns
- The calculation and back-propagation of the associated error, which are calculated using the equation 3.32
- The adjustment of the weights and biases by gradient descent method as given in the equation 3.33 [41]

During the forward pass, the input vector is applied to the input nodes of the network. This signal propagates through the network layer by layer and finally produces an actual output. In this forward pass stage, the synaptic weights are not modified and they remain constant. Once actual output is obtained, it is compared with the target output and an error signal is obtained. This error signal is then propagated-back into the network in the opposite direction. During this stage, the synaptic weights are adjusted in such a way that

the actual response moves closer to the target response. The process is maintained until average squared error over the entire training set converges to sufficiently small value. For a given training set, back-propagation learning may thus proceed in one of the two basic ways; sequential mode and batch mode. In sequential mode of operation weights updating is preformed after the presentation of each training pairs. In batch mode of back-propagation learning, weights updating is preformed after the presentation of all the training data that constitute an epoch. If there is N_d training data pairs x and y with M targets, the total error to be minimized, E_t, and the steepest descent of updating the weights can be written as:

$$E_{\mathrm{t}}(w) = \frac{1}{2N_d} \sum_{k=1}^{N_d} \sum_{m=1}^{M} y_k^m - \hat{y}_k^m(y_k^m, w)^2 \tag{3.32}$$

$$w_{ij} \leftarrow \left(w_{ij} - \eta \frac{\partial E_{\mathrm{t}}}{\partial w_{ij}} \right) \tag{3.33}$$

Where, η is a learning rate. The minimization of error can be obtained by gradient methods or stochastic optimization where detail can be found in [42][43]. After training, the trained network is tested with presenting of new patterns to the network that has not used during training. The results of the testing show that whether the trained ANN is able to perform with a reasonable accurate output to new input patterns. If the testing is successful then all information about the trained ANN is saved to be used through the online applications.

3.4.2 ANN Modeling for DSA

The schematic diagram of main steps in ANN modeling for DSA is shown in Figure 3.11. To synthesize the system states at different operating conditions,

the data should be collected to characterize the changes in load levels, changes in fault location, and changes in power system topologies during normal and abnormal conditions. During the generation of data, which is used during training process, the information is arranged as initial features sets. The initial input features should be reduced in length (dimension of patterns) and width (number of features) to be suitable for ANN training within acceptable accuracy. Finally, ANN designed and trained to map the entire input-output patterns. Feature selection is the most important step in designing ANN to be a robust tool for DSA.

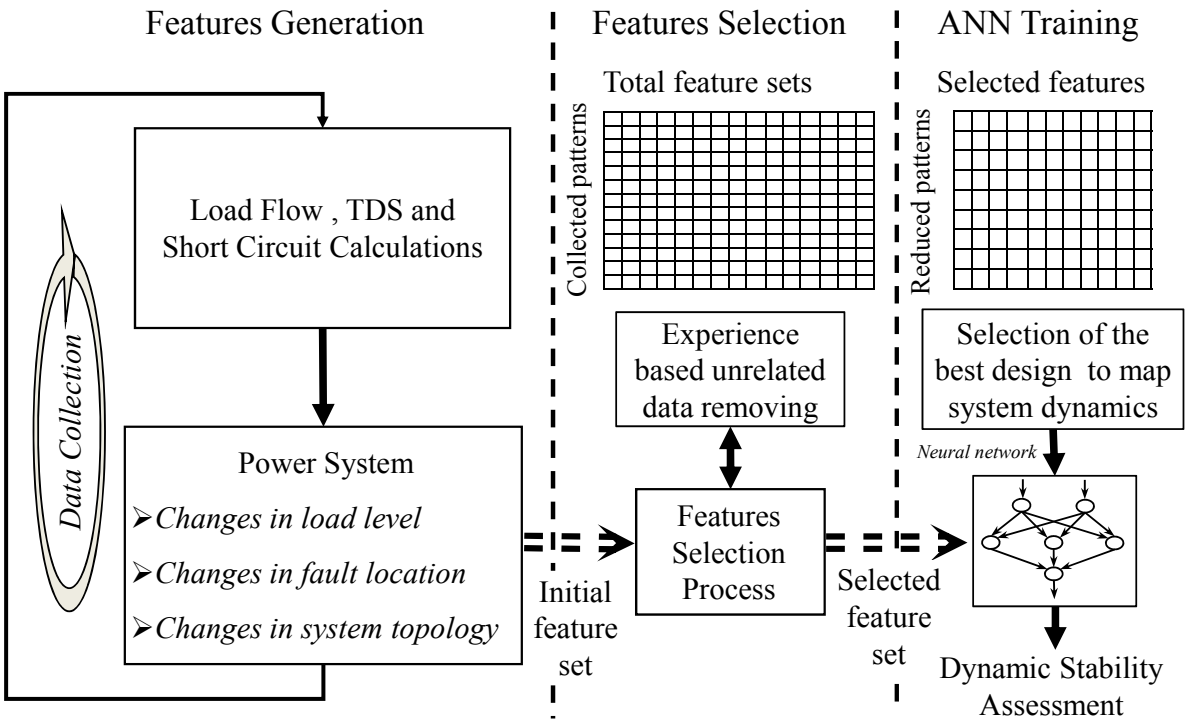

Figure 3.11 Main steps in ANN modeling for dynamic stability assessment

The selected input features should be easily accessible, accommodate different system configuration changes and should characterize appropriately a variety of power operating conditions. These input features should be able to synthesize the dynamic behavior during expected faults at variety of operating conditions. Due to the high nonlinearity and complexity of system modeling,

features selection cannot be performed according to engineering judgment or physical knowledge only. It should be selected also based on the standard mathematical dependency and correlation among features.

3.4.2.1 Features Generation

A large number of input-output patterns are generated either from historical stored data or by perturbing both real and reactive loads randomly in a wide range of loading levels. This study uses the PST 16-Machine Test System for stability analysis in Appendix A.1. To generate training data for the ANN training, different load flow scenarios under varying operating conditions are considered. In this study, input-output patterns are generated by randomly varying the active and reactive power demand at all load buses by using equation 3.34 and equation 3.35 in the range from 50% to 130% of their base case operating point. The data collection is repeated at each expected system topology, which is assumed to be occurred by disconnecting transmission lines and/or generators. Nine expected system topologies are considered during preparing input-output patterns. Table 3.2 and Table 3.3 list the considered disconnections of generators and transmission lines.

$$P_l(k) = P_l^0(k) \cdot \Delta L(k) + 2 \cdot \Delta P(k)\left[0.5 - \varepsilon_p^k\right] \tag{3.34}$$

$$Q_l(k) = Q_l^0(k) \cdot \Delta L(k) + 2 \cdot \Delta Q(k)\left[0.5 - \varepsilon_q^k\right] \tag{3.35}$$

Where P_l and Q_l are the base load case. ΔL is the required loading ratio. ΔP and ΔQ are the expected random variation of load. ε_p and ε_q are random numbers between 0 and 1.

During data collection, initial input feature sets are selected based on the knowledge of the network. These feature sets are selected to characterize the

system from the viewpoint of stability and operation conditions. This includes a set of operating conditions where the generation in one area is increased while the generation in another area is decreased in order to achieve the real power exchanges. This leads to stress in the tie lines connecting areas, which may lead to inter-area oscillations. However, since power plants in the network are modeled by connecting a particular number of generator units, the number of connected units can be adapted to the generation conditions and load levels.

Table 3.2 Disconnected transmission lines during topology changes

Topology number	1	2	3	4	5
Terminal of disconnected transmission lines	Base case	A5b/A6	B13/B14	B13/B14 B4/B9	C4/C7

Table 3.3 Disconnected generators during topology changes

Topology number	6	7	8	9
Names of disconnected generators	G1-G2	G7-G8	G13	G1-G2-G7-G8-G13

Each operating point is adjusted by using the optimal power flow to determine the power distribution where system constraints and limits should be satisfied for all selected dispatched operating points. All generators in the system are assumed to share in the increase in system loading with controlled generator terminal voltage. During data collection, the credible contingency is selected to be a three-phase-to-ground short circuit faults. The faults are considered to release by self-clearance without change in the specified system topology. To reduce the dimension of the input-output patterns, the credible contingencies are selected based on the CCT to have a maximum value of 500 milliseconds as shown in Figure 3.12. Thus at all expected system topology if the CCT values at

certain location always greater than 500 milliseconds, the contingency at this location will not be considered as critical contingency and the corresponding data will be omitted. Twenty-one contingencies, which are distributed in all system areas, were selected and applied at each operating point during data collection.

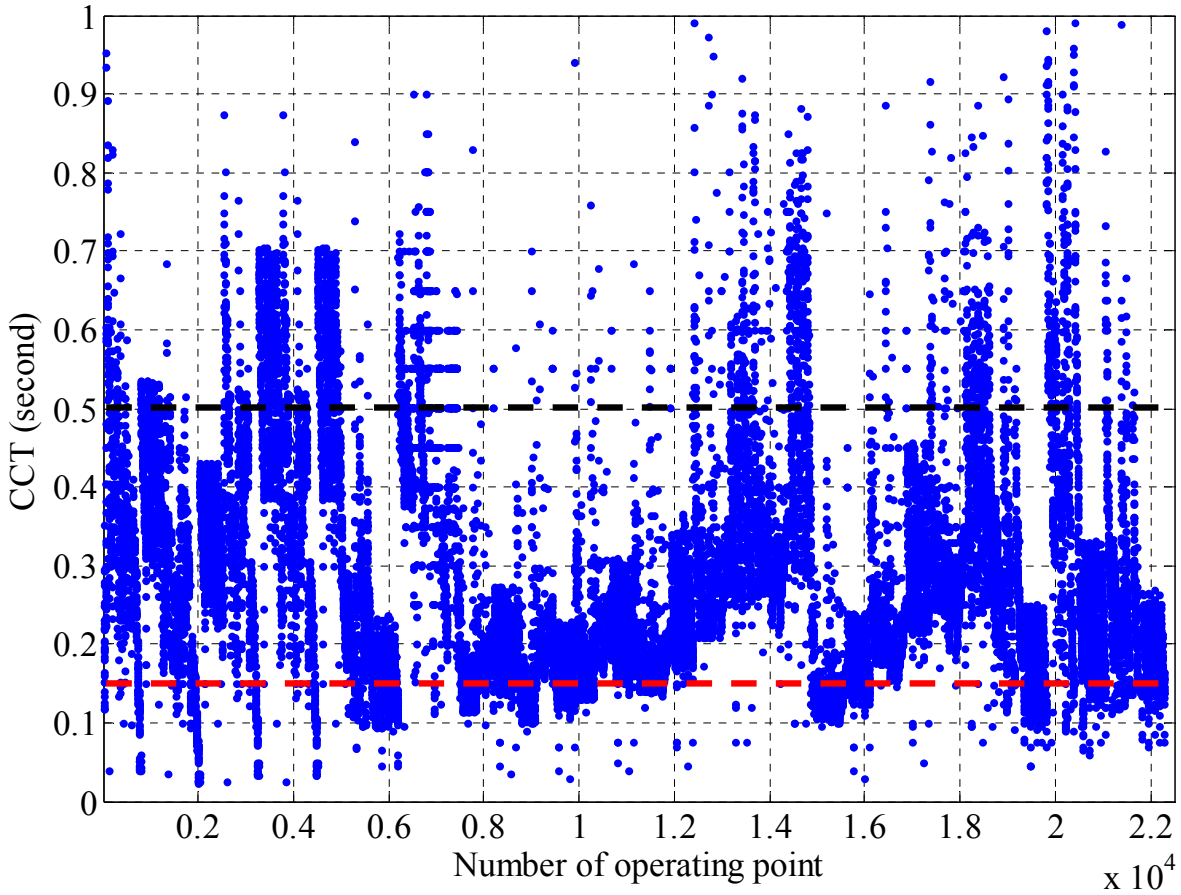

Figure 3.12 The selected limits for CCT during data collection and preparation

For each operating point, PSD software is used to get all the required data during the simulation. the corresponding CCT for these predefined set of critical contingencies are computed by using the Bisection technique described in section 3.2.2.2. The estimation of the MDO at each operating scenario is calculated by using DSI toolbox as discussed before in section 3.3.4.

3.4.2.2 Selection of ANN Input Features

Features selection process should be used to identify the optimal combination of features, which contain valuable information that efficiently represents all system data and generates input patterns of ANN. With increasing the size of the modern power systems, the number of features, which can be considered, is substantially increased. So that the assignment of specifying the system quantities, which can be chosen as input features is a difficult task. The features selection process is important to minimize the required training time, the memory requirements and is an important key to the success of ANN applications for effectively map the desired output and the selected features with acceptable accuracy. Therefore, the input features are selected in two stages to enhance the accuracy of selection as shown in Figure 3.13.

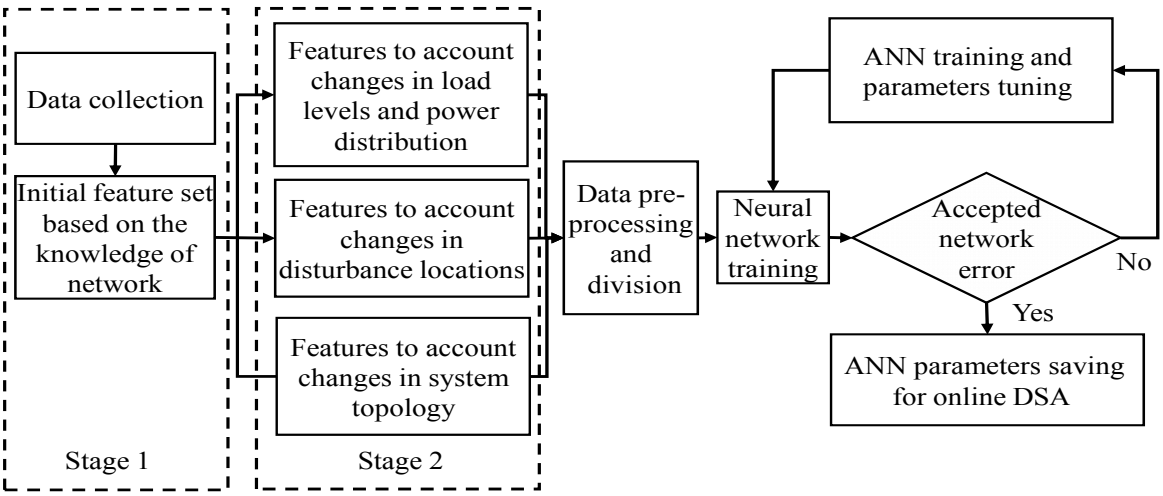

Figure 3.13 Features selection stages and the ANN training procedure

First stage: Knowledge based network features selection

In the first stage, initial feature sets are selected by engineering judgment based on their field experiences and the required target to be estimated. These features should be adequately characterizing all expected operating states of the

system from dynamic stability point of view, particularly in this study the power system transient stability and oscillatory stability considering system topology changes. However, the preferred features are the generators related features and the power distribution related features. The proposed initial selected features from the PST16 test system are listed as follows in Table 3.4.

Table 3.4 Pre-selected features from the PST 16-Machine Test System

#	Features Description	Number Features
1	Total active and reactive generation in each Area	6
2	Individual generator active and reactive power	32
3	Voltage magnitude and angle of each bus	132
4	Transformers tap changers	28
5	Active and reactive power demand at each load bus	100
6	Active and reactive power on transmission lines	106
7	Active and reactive power on transformers	56

Second stage: Final selection of input features

The second stage of the features selection process is used to find the final input features from the pre-selected initial feature sets. The final features are selected in three steps in order to improve the accuracy of ANN for TSA and OSA. These steps are used to specify which features can be used to characterize the severity of the contingencies on generators, the changes in power distribution and system topology

First step: Features are selected to characterize the severity of the contingencies with respect to the dynamic behavior of generators and to detect the fault locations. The power flow perturbation during faults produces immediately change in the generator terminal voltages. As seen in Figure 3.14, when a three-phase fault occurs at bus A1 in area A of PST 16-machine Test

System, the nearest generators from the fault location get more response as an indication of the distance of these generators from the fault location. This also will help to predict the critical generators during each contingency. According to the author's field experience, the generators terminal voltage drop immediately after a single step fault integration are the most important features for DSA by ANN and therefore preferred as ANN selected input features. These features can be estimated very fast e.g. by using simple short circuit calculation.

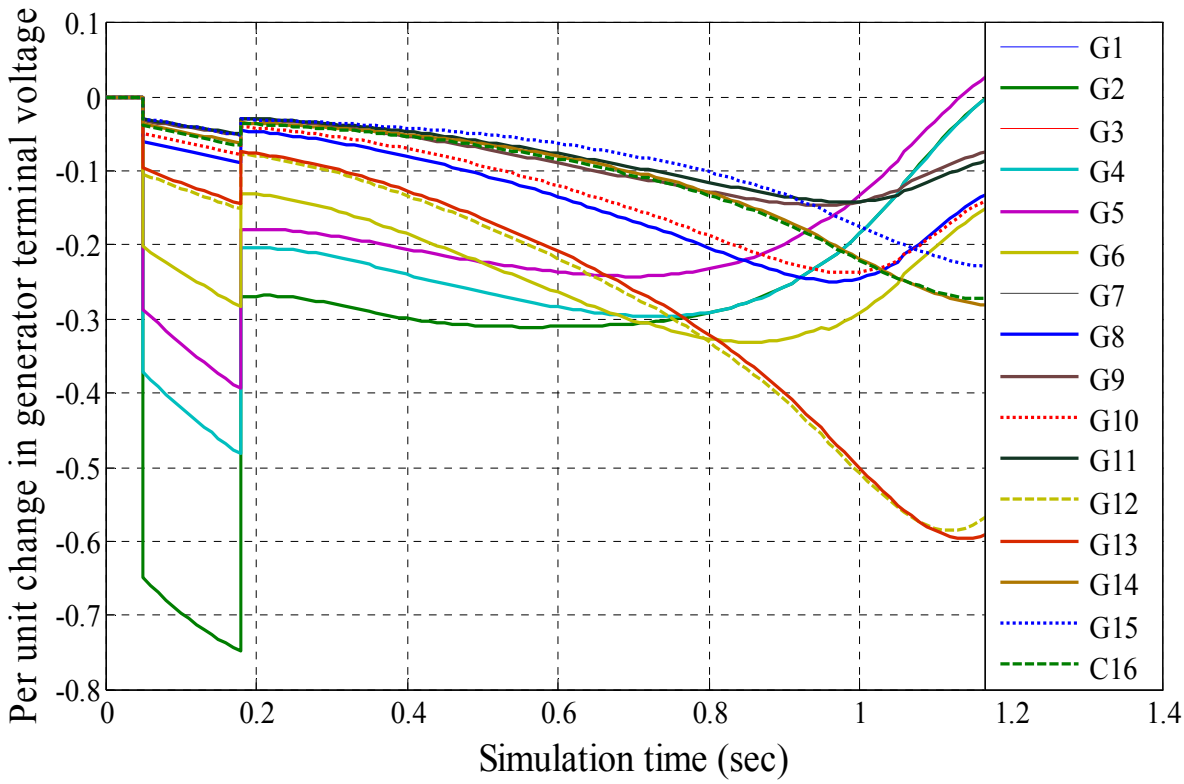

Figure 3.14 Voltage drops at different generator terminals after a single step fault

Second step: Features are selected to characterize the changes in system topology and power distribution during normal and abnormal operation. Area Power Generation Distribution Factor (APGDF), which is calculated by using equation 3.36, is computed for each area and used as recommended ANN input feature. This feature is used to characterize the change in generation in different

areas arising from the disturbance such as disconnection of generators or transmission lines. As shown in Figure 3.15, when the generator GA3 is disconnected by circuit breaker CB1, the power generated from it goes to zero which the installed capacity still available. This leads to decreasing the factors corresponding to Area A as indicator for change in power distribution. Similarly, when the transmission line number 1 is disconnected due to faults, load 1 will be supplied from Area B. therefore, the generated power from Area A is decreased and its factor decreases. At the same time, the power generated from Area B should increase and hence its factor increases. These changes in the power distribution factors can be used as indicator for system topology changes.

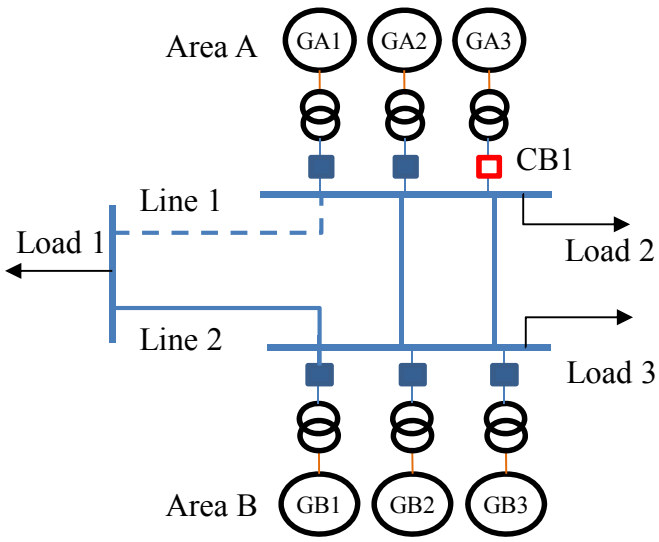

Figure 3.15 A small network to explain the disconnection of equipment

This factor depends on the sum of the generated power times the corresponding inertia constant in each area in relation to the sum of the installed capacity of the connected generator times the corresponding inertia constant in each area. This factor also characterizes the effect of generators inertia effects on the power system stability.

$$\mathrm{APGDF}_k = \frac{\sum_{i=1}^{N_k} H_i \, P_{gi}}{\sum_{i=1}^{N_k} H_i \, S_{gi}} \tag{3.36}$$

Where H_i is the inertia constant of generator i. P_{gi} and S_{gi} are the generated active power and the total capacity of generator i. N_k is the number of generators in Area k.

Third step: Beside the aforementioned selected input features, a systematic feature selection based clustering algorithm can be used to select the most important features which can be used to characterize the change in load levels and power flow through lines from the mathematical view point. Cluster analysis is the assignment of a set of observations into subsets (called clusters) so that the observations in the same cluster are similar in some mathematical senses [44]. The basic tool for hierarchical clustering is a measure of the dissimilarity of one item relative to the other items. There are several ways to define dissimilarity, the most popular being Euclidean distance and Manhattan city-block distance.

Cluster analysis using k-means

One of the most well-known and widely used crisp clustering algorithms is the k-means clustering algorithm [45]. A major advantage of the k-means algorithm is its computational simplicity, which makes it an attractive candidate for a variety of applications. In this study, the k-means based Euclidean distance clustering algorithm, is used to select the most important features. This algorithm has been used to group the system features into a certain number of groups (clusters) such that the features in the same cluster have similar characteristics. Then one feature from each cluster is picked out as a selected input feature based on the distance from the cluster-centroid and field

experiences. The grouping is done by iteratively reassigning items to clusters to minimize the sum of squares of distances between features and the corresponding cluster centroid. The algorithm starts either by assigning items to one of k predetermined clusters and then computing the k cluster centroids or by pre-specifying the k cluster centroids. The pre-specified centroids may be randomly selected items. Before data processing by k-means clustering algorithm, they could be normalized. Normalization is a transformation of each feature in the data set so that their values lie within similar ranges. Data can be transferred either to the range [0, 1] or [-1, 1], or normalized to obtain a zero mean and unit variance, which is the most applicable way according to literature as described in the next equations [46].

$$\overline{x}_k = \frac{1}{N_d}\sum_{i=1}^{N_d} x_{ik} \qquad k = 1,2\cdots l \tag{3.37}$$

$$\sigma_k^2 = \frac{1}{N_d - 1}\sum_{i=1}^{N_d}(x_{ik} - \overline{x}_k)^2 \tag{3.38}$$

$$x_{ikn} = \frac{x_{ik} - \overline{x}_k}{\sigma_k} \tag{3.39}$$

Where N_d is the length of the available data of the kth feature. $\overline{x}_k$ and x_{ikn} are the average value and the normalized data point. The main steps of the k-means clustering algorithm can be summarized as follows [44]:

Step 1: Define the desired number of clusters, K, and the input data space $\mathcal{L} = \{x_i \quad i = 1,2,\cdots,n\}$

Step 2: Randomly selection of a centroid for each cluster and calculate the distance between each item and the selected centroids and assign the items into the clusters based on the distance from the centroids.

$$d_i(x_{Ci}, x) = \sqrt{\sum_{j=1}^{D} (x_{cij} - x_j)^2} \quad D \text{ is the dimension of the data space} \tag{3.40}$$

Step 3: Compute the new location of the centroid of k cluster which includes m items using average coordinating, x_{Ck}^{new}.

$$x_{Ck}^{new}(x_1, x_2, ..., x_D) = \left(\frac{\sum_{i=1}^{m} x_{1i}}{m}, \frac{\sum_{i=1}^{m} x_{2i}}{m}, ..., \frac{\sum_{i=1}^{m} x_{Di}}{m}\right) \qquad k = 1 \ldots \mathrm{K} \tag{3.41}$$

Step 4: Compute the distance of each item to its current cluster centroid and the target is to minimize the distortion or the squared-Euclidean distance.

$$E = \sum_{k=1}^{k} \sum_{c(i)=1}^{n} (x_i - x_{ci})^{\mathrm{T}} (x_i - x_{ci}) \tag{3.42}$$

Where x_c is the kth cluster centroid and $c(i)$ is the cluster containing x_i.

Step 5: Reassign each item to its nearest cluster centroid so that E is reduced in magnitude and update the cluster centroids after each reassignment.

Step 6: Repeat steps 3 to 5 until no further reassignment of items takes place to minimize the squared-Euclidean distance, E.

The selected feature can be selected as the nearest one to the centroid or related ones. After selecting one feature from each cluster, all the selected features are combined together and represent input pattern for ANN training. The output values are simply the DSA indicators. These indicators are the CCT and MDO corresponding to the pre-selected critical contingencies at each operating point of all expected system topologies. From the practical applicability of features selection, the final number of features to be selected

depends strongly on the performance of the modeled ANN. Thus, in order to enhance the accuracy of ANN, different number of features should be investigated and the best one depends on the ANN performance during the training and testing process.

3.4.3 DSA by using ANN

As the aforementioned, the TDS is the usual methods used for TSA and modal analysis or ringdown analysis is the usual methods, which can be used for OSA as discuss before. In real-time application, the activation or the design of the proper corrective and preventive actions depends on the online system state of security. The measure for the system state should be fast and accurate enough to enable ISO to decide the proper actions based on pre-specified stability boundary. This section deals with the developing of ANN as a fast tool for DSA. In this study, the decision boundary for the system to be considered transiently stable is 150 milliseconds. Similarly, the limit to consider the system has sufficient and insufficient damping ratio is set at 4%. When the CCT at each of the pre-selected set of critical contingencies is greater than 150 milliseconds, the system is considered transient stable. As well as when there are no damping coefficients below 4 % with proposed injected signals, the operating point is considered to have sufficient damping.

To improve the accuracy of estimation, two different ANN are implemented to relate the selected input features and the corresponding CCT and MDO as targets, which represent TSA and OSA respectively. A variable number of input features and ANN architecture are used during training to enhance the ANN accuracy. The final selected features and the modeling of ANN is determined to have minimum training and testing errors of estimation.

A single hidden layer, operating a sigmoid activation function, feed-forward structure based on back-propagation training network is implemented to relate the input-output patterns [47]. The number of input neurons depends on the total number of selected input features. The number of output neurons is equal to one for CCT or MDO estimation. There is a number of rules-of-thumb to obtain the best number of nodes in the hidden layer where the appropriate number of neurons is important for ANN accuracy [48][49]. As example of the rules-of-thumb, it should never be more than twice as large as the input layer nodes and it should be between the average and the sum of the nodes in the input and output layers. The number of input features and nodes in the hidden layer are slightly increased to achieve ANN modeling which provides a good performance during training and testing processes.

3.4.3.1 Performance Evaluation of ANN

The performance of the developed neural networks for stability assessment is evaluated by calculating the root mean square error (RMSE), the relative estimation error (E), average estimation error (AE), standard deviation (σ) of the relative estimation error, Pearson correlation coefficients (PCC) and mean absolute percentage error (MAPE) between the estimated values and the computed values. The correlation coefficient determines the extent to which the values of two variables are "proportional" to each other. The definitions are given by the following relationships:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N_d}\sum_{k=1}^{N_d}\left(y_k - \tilde{y}_k\right)^2} \tag{3.43}$$

$$\mathrm{E}_k = \frac{y_k - \tilde{y}_k}{y_k} \tag{3.44}$$

$$\mathrm{AE} = \frac{1}{N_d}\sum_{k=1}^{N_d}\mathrm{E}_k \tag{3.45}$$

$$\sigma = \sqrt{\frac{1}{N_d}\sum_{k=1}^{N_d}(\mathrm{E}_k - \mathrm{AE})} \tag{3.46}$$

$$\mathrm{PCC} = \frac{N_d\sum_{k=1}^{N_d} y_k\,\tilde{y}_k - \sum_{k=1}^{N_d} y_k \sum_{k=1}^{N_d}\tilde{y}_k}{\sqrt{N_d\sum_{k=1}^{N_d} y_k^2 - \left(\sum_{k=1}^{N_d} y_k\right)^2}\sqrt{N_d\sum_{k=1}^{N_d}\tilde{y}_k^2 - \left(\sum_{k=1}^{N_d}\tilde{y}_k\right)^2}} \tag{3.47}$$

$$\mathrm{MAPE} = \frac{1}{N_d}\sum_{k=1}^{N_d}\left|\mathrm{E}_k\right| \tag{3.48}$$

Where, y is the target value. ỹ is the estimated value by using ANN. N_d is the number of input patterns.

3.4.3.2 Transient Stability Assessment using ANN

K-means algorithm is used to select the proper features from the initial selected set starting from five to forty input features. These features are combined with the experimental selected generators terminal voltage drop immediately after the contingency by short circuit calculation and the corresponding APGDF factor for each area to form the input pattern. The selected input features and targets are arranged to form the input-output patterns for ANN training and testing. All the input-output patterns are deemed equally significant and are scaled to remove the effect of large values and to avoid saturation problem.

The data is divided into training (60%), testing (15%) and validation (15%) subsets beside a set for testing as unforeseen data (10%). MATLAB-toolbox is used as a computing tool to implement the ANN for TSA. Among all algorithms

available in the MATLAB toolbox, back-propagation training algorithm of Levenberg-Marquardt optimization, which is based on the weights and the biases updating, is selected because of it provides a fast convergence and a better performance.

ANN is implemented for each selected set of features with a variable number of hidden neurons in order to select the proper features and the corresponding number of hidden neurons. The suitability of the ANN for TSA is investigated by using input-output patterns corresponding to a single contingency. A contingency at Bus C9 in area C with 1100 operating points in all selected system topologies, which are described in Table 3.2 and Table 3.3 are used in ANN modeling. Thousand data points are used in the training process and the remaining hundred data points are used in testing as unforeseen cases. The best number of features for minimum RMSE and high PCC is 42 selected input features with 37 neurons in the hidden layer. The selected ANN input features are listed in Table 3.5. Figure 3.16 presents the linear regression between the target CCT, which is calculated by using TDS and the estimated CCT by using ANN during training process. The results clarify the ability of ANN to estimate the CCT with an acceptable degree of accuracy. The percentage relative estimation error for six hundred selected input-output patterns after training process shown in Figure 3.17. Most of the estimation errors during the training process are less than 5%, which are acceptable for online stability assessment.

Table 3.5 Selected input features for the single contingency case

Name of Features	Selected Features	Number
Terminal voltage drop	Generators terminal voltage drop of after a step fault	16
Total power in each area	ΣPA - ΣPC - ΣQC	3
Generator power	PG2 - QG2 - PG5 - QG6 - QG9 - QG11	6
Magnitude of bus voltage	VA4 - VB9 - VC6 - VC11	4
Load power	PA2 - PA7 - QB1 - QB2 - QB4 - QB9 - PC7 - PC14 - QC5 - QC6	10
Tie-line power	PA5b / B1 - PB6 / C17 - QB6 / C17	3

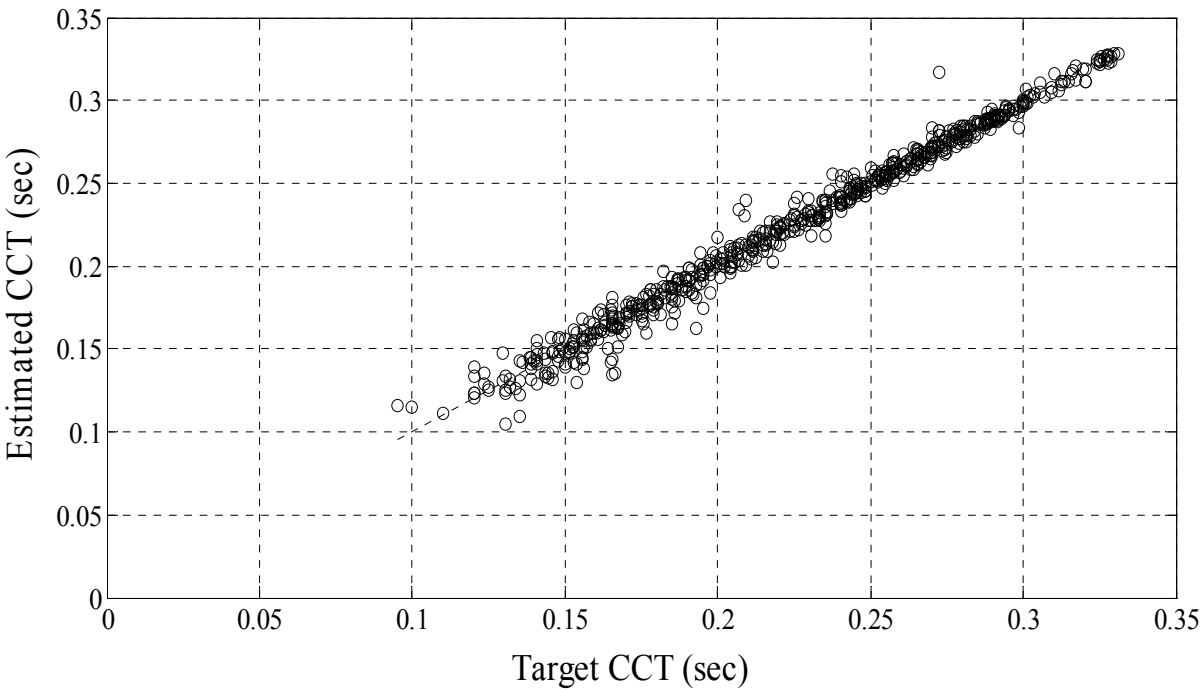

Figure 3.16 The plot regression between CCT calculated by TDS and ANN

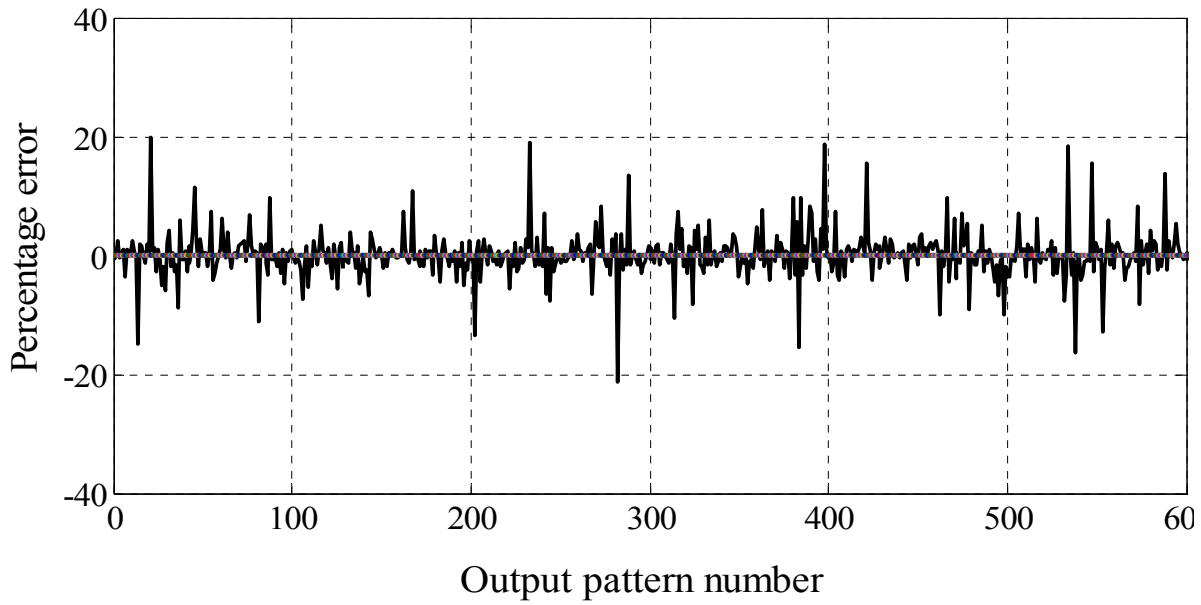

Figure 3.17 Percentage error between target and estimated CCT during training

The trained ANN is tested by using the remaining unforeseen operating points to check the ability of trained ANN to deal with new input patterns. Figure 3.18 presents the target CCT, which is calculated by using TDS relative to the estimated CCT by using the trained ANN for the remaining hundred unforeseen operating points.

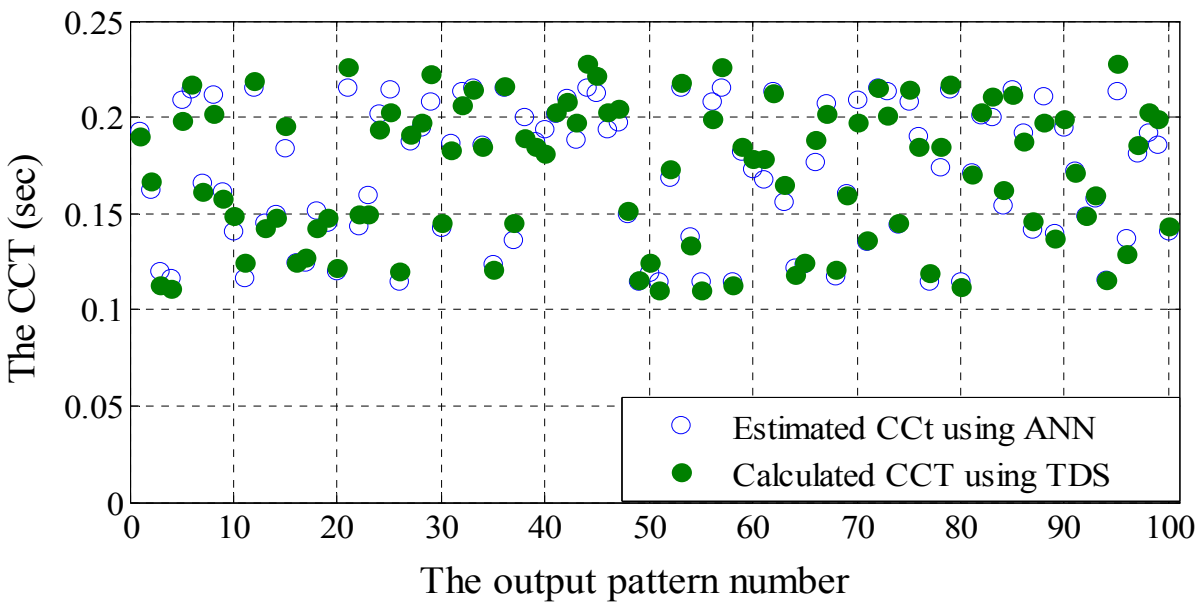

Figure 3.18 The estimated CCT and the target CCT during testing process

Figure 3.19 explains that the trained ANN estimates the CCT for the unforeseen operating points with high accuracy. Table 3.6 presents the performance indicators of the trained ANN. As presented in the table, the low standard deviation, together with the very small average estimation error, leads to the conclusion that ANN is accurate enough for monitoring of the system transient stability when trained based on multi system topologies.

Table 3.6 Performance of ANN during a single contingency test case

E_{max} (%)	E_{min} (%)	AE (%)	σ (%)	PCC (p.u.)	MAPE (%)
17.9	-19.3	0.12	3.79	0.964	5.15

All input-output patterns, which are collected by applying the selected twenty contingencies, are used to select the proper input features and the number of neurons in the hidden layer in order to develop a general ANN for CCT estimation for TSA. The remaining contingency is used for testing process as unforeseen input-output set. During the training process, there are some operating points are observed to have a high estimation error because these points are away from the harmony of the input-output patterns. To solve this problem a number of operating points are created around each of these operating points to improve the accuracy of ANN to estimate the CCT in this operating space. In the other hand the completely remove of these operating point can improve the estimation error but this will affect on the ability of ANN to estimate CCT at this regions.

The proper input features and the corresponding number of neurons in the hidden layer are selected by using iterative process with increasing the number

of neurons for each case. In this process, the input features and the number of neurons in the hidden layer are changed iteratively until the minimum estimation error during training process is achieved. Figure 3.19 shows the RMSE between the CCT, which is calculated by using TDS, and the CCT, which is estimated by using the trained ANN during design process of ANN with varying the number of neurons in the hidden layer. From the figure, we can realize that the best number of input features for minimum RMSE is 46 features with 55 neurons in the hidden layer. The corresponding RMSE is 18.02 milliseconds. The selected input features for minimum RMSE during the training process are presented in Table 3.7. Table 3.8 presents the performance of trained ANN during the training process.

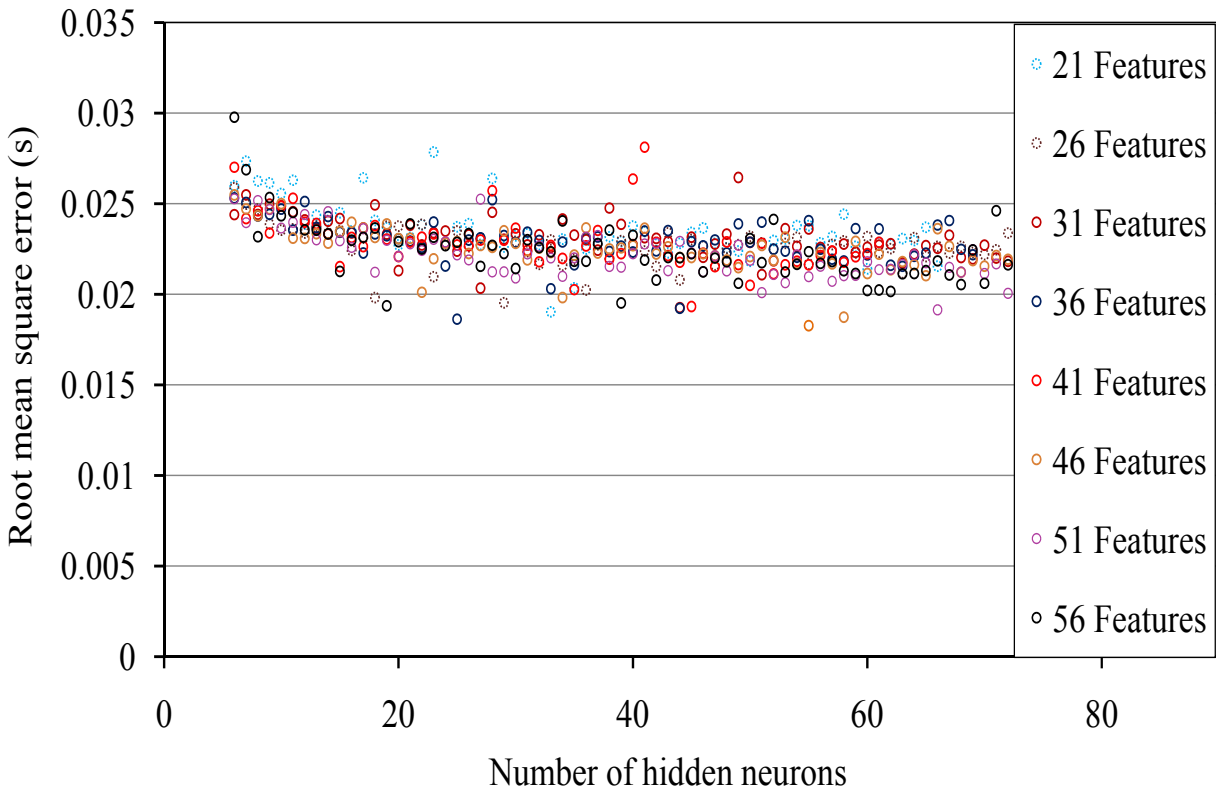

Figure 3.19 RMSE with variable ANN architecture and input features

Table 3.7 Selected input features in multi-contingency case

Name of Features	Selected Features	Number
Terminal voltage drop	Generators terminal voltage drop after step fault	16
Total power in each Area	ΣPA - ΣPB - ΣQC	3
Generator power	QG3 - QG6 - PG8 - PG9 - QC13 - PG14	6
Magnitude of bus voltage	VA4 - VA7 - VB7 - VC6 - VC8	5
Transformer taps	T24 - T22 - T9	3
Loads power	PA2 - PA7 - PB3 - PC4 - PC7 - PC14 - QB1 - QB2 - QC12 - QC18	10
Tie-line power	PA5b/B1 - PB6/C17 - QB6/C17	3

Table 3.8 Performance of ANN during training in multi-contingency case

E_{max} (%)	E_{min} (%)	AE (%)	σ (%)	PCC (p.u.)	MAPE (%)
16.47	-17.12	-0.1343	4.088	0.954	3.12

The high correlation coefficient between the estimated CCT by using ANN and the desired CCT, which is calculated by using TDS, indicates that the ANN has modeled the application problem very well. Therefore, TSA can be estimated by using ANN with a reasonable degree of accuracy. After training, all input-output patterns of the remaining contingency is used for testing the performance of the trained ANN to monitor the uncovered operating points during the training process. Figure 3.20 depicts the target CCT, which calculated by using TDS, and the estimated CCT by using the trained ANN for randomly selected one hundred unforeseen operating points after training process. Figure 3.21 presents the linear plot regression between the target CCT and the estimated CCT of unforeseen operating points during testing process.

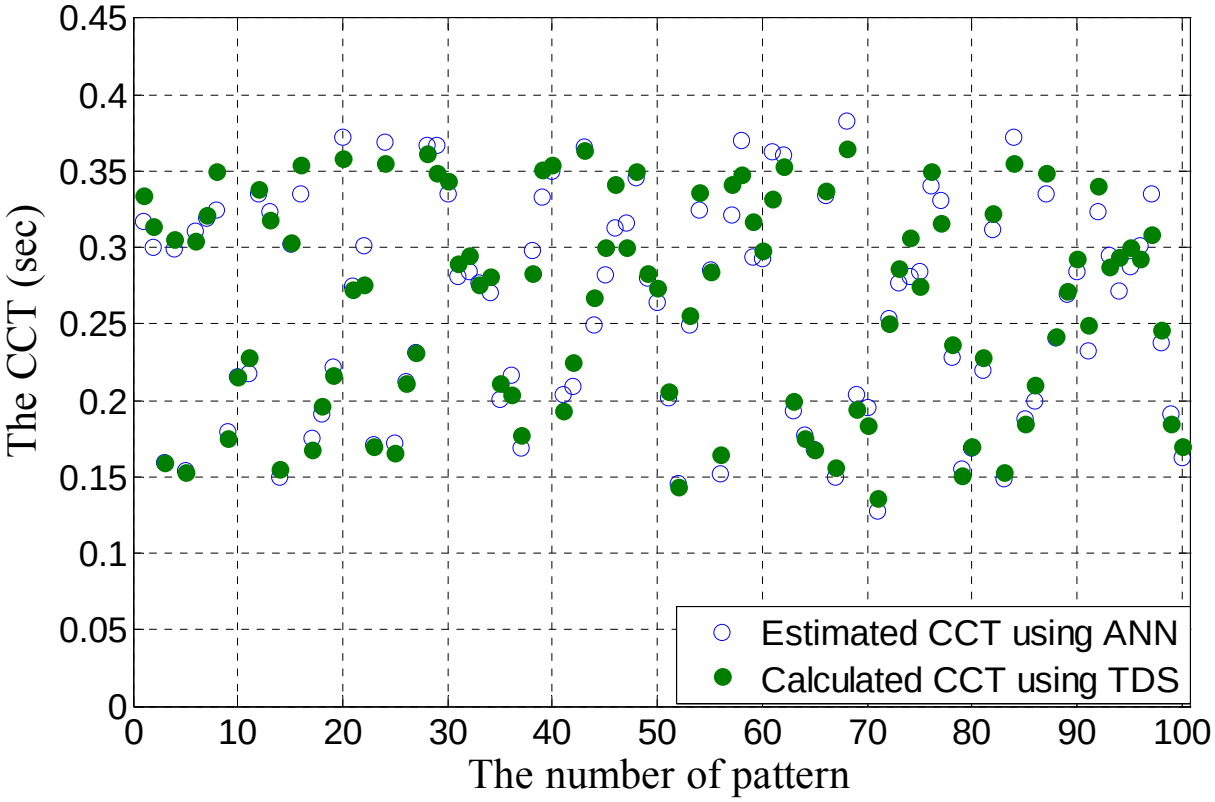

Figure 3.20 The estimated CCT relative to the target CCT during testing process

Table 3.9 presents the evaluated performance coefficients during the testing process of the trained ANN with the unforeseen operating points during the training process. The evaluation of ANN performance includes the RMSE of 14.06 milliseconds and the standard deviation is 5.98% with average relative error -0.13 %. The calculated performance is considered within acceptable limits. Therefore, once trained, the ANN is able to estimate the CCT as index for TSA of all the critical contingencies under any load condition almost instantaneously.

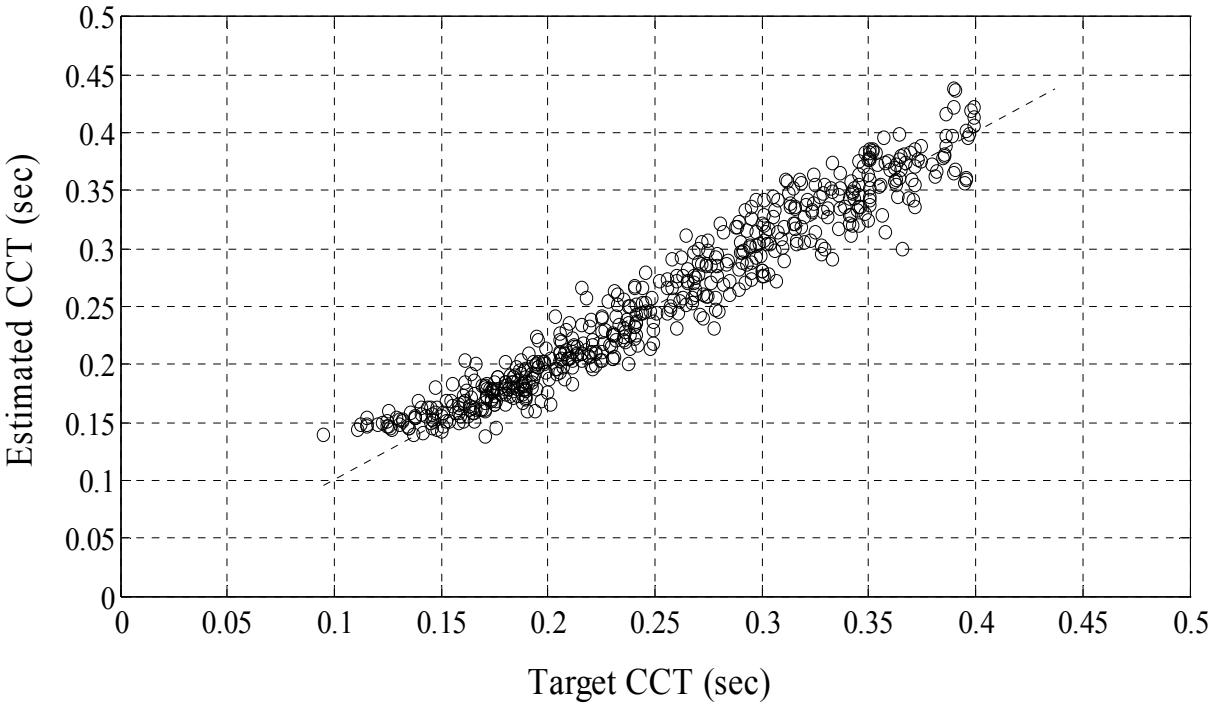

Figure 3.21 The plot regression between targets CCT and to estimated CCT.

Table 3.9 Performance evaluation of trained ANN during testing stage

E_{max} (%)	E_{min} (%)	AE (%)	σ (%)	PCC (p.u.)	MAPE (%)
19.40	-21.58	-0.13	5.98	0.9452	4.60

This fast estimation and relatively acceptable accuracy is useful in the online power system applications, which enable the ISO to execute the required actions to improve the system transient stability. The ability of ANN for TSA considering system topology changes and change in power distributions are evaluated by using randomly selected operating points in each configuration, which are presented in Table 3.2 and Table 3.3. Figure 3.22 presents a randomly selected three operating points for each case study during testing with unforeseen set of input-output patterns.

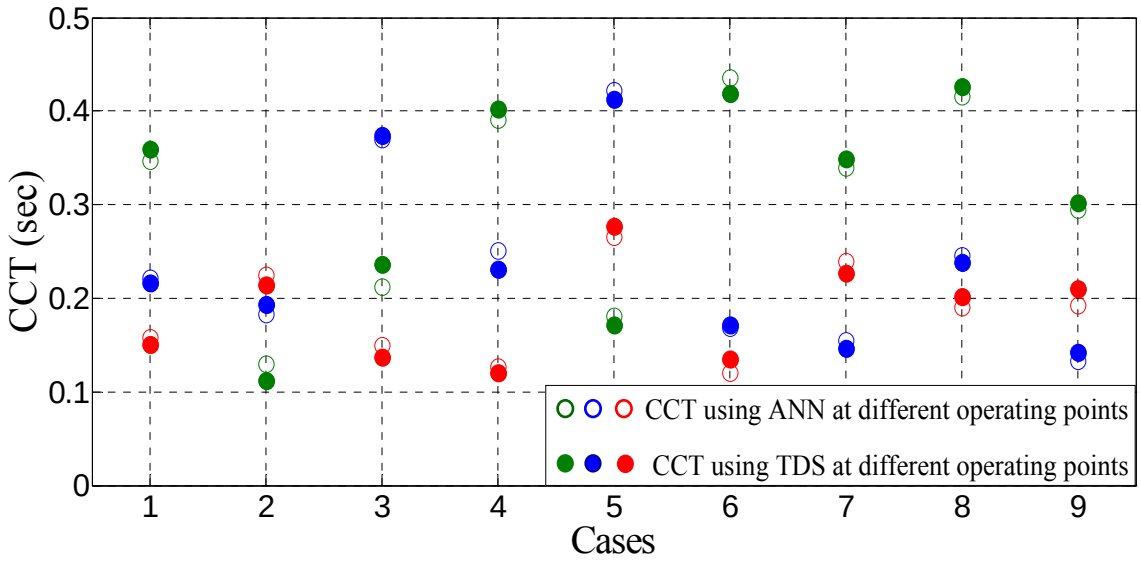

Figure 3.22 Estimated CCT by using ANN relative to the calculated CCT by using TDS

3.4.3.3 Oscillatory Stability Assessment by using ANN

The described procedure in the previous section to design ANN for TSA, is used to model ANN for OSA. A single hidden layer feed-forward structure ANN, which is trained with Levenberg-Marquardt back-propagation, is used for OSA. The trained ANN is used to map the relation between the selected input features representing system dynamic behavior and the MDO calculated by DSI at each operating point as index for OSA. All the collected data are formed as input-output patterns to be used in the training and testing processes. Similarly, variable numbers of selected input features are used to train ANN with variable number of hidden neurons to select the best ANN architecture for accurate estimation. The number of neurons in the hidden layer is selected to minimize the RMSE between the target MDO, which is calculated by using DSI toolbox and the estimated values of MDO by using the trained ANN. The final selected features are listed in Table 3.10. The total selected features are 43 and the ANN designed with 45 hidden neurons. Table 3.11 lists the performance evaluations during testing of the trained ANN with the unforeseen data points.

Table 3.10 Selected input features for OSA using ANN

Name of Features	Selected Features for TSA & OSA	Number
Terminal voltage drop	Generators terminal voltage drop after step fault	16
Area power generation distribution factor	APGDF for each Area	3
Generator power	Qg3 - Qg6 - Pg8 - Pg9 - Qg13 - Pg14	6
Magnitude of bus voltage	VA4 - VB7 - VC6 - VC8	4
Transformer taps	T24 - T22 - T9	3
Tie-line power	PA5b/B1 - PB6/C17 - QB6/C17	3
Loads power	PA2 - PA7 - PB3 - PC7 - PC14 - QB1 - QB2 - QC12	8

Table 3.11 Performance evaluation of the trained ANN during the testing for OSA

Emax (%)	Emin (%)	AE (%)	σ (%)	PCC (p.u.)	MAPE (%)
16.4	-18.9	-0.352	4.96	0.968	4.21

Figure 3.23 shows the target MDO, which is estimated by using DSI based Prony analysis toolbox relative to the estimated values using the trained ANN at randomly selected 50 unforeseen operating points to test the ability of ANN for OSA.

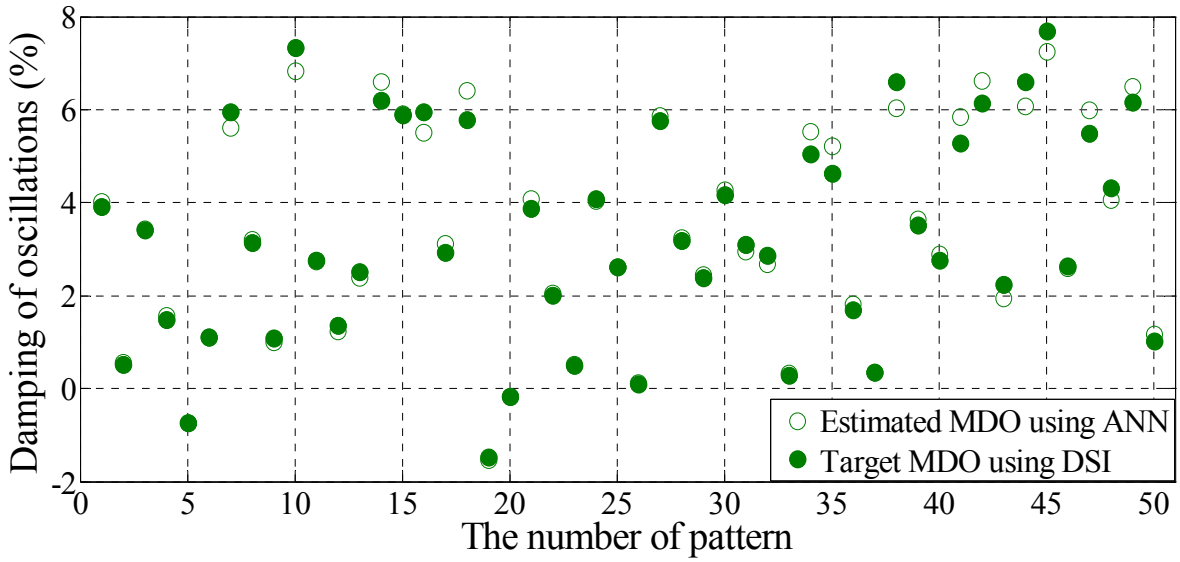

Figure 3.23 Estimated MDO by using ANN relative to the evaluated MDO by using DSI

The maximum percentage estimation error during testing process with unforeseen operating points is 5.7%. The results provide the suitability of ANN in OSA with a reasonable degree of accuracy. The performance evaluation of the trained ANN by using a randomly selected three operating point for each selected topology cases in Table 3.2 and Table 3.3 are presented in Figure 3.24.

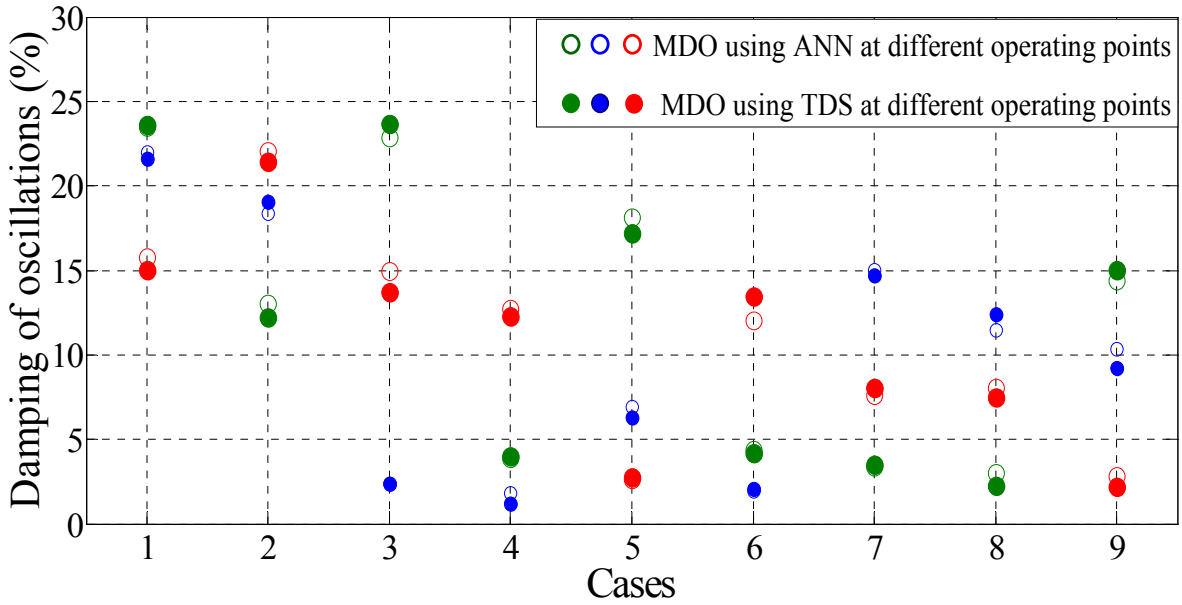

Figure 3.24 MDO estimated by ANN relative to estimated values by DSI

The trained ANNs for TSA and OSA and the corresponding mathematical calculations should be saved. During online power system operation, the selected input features should be collected at each scenario where the trained ANN is used in order to estimate system states. The fast estimation of system state facilitates the activation and the design the proper corrective or preventive actions during abnormal conditions.

Chapter 4

Dynamic Stability Enhancement

4.1 Introduction

In the previous chapter, we introduced, discussed, and emphasized on issue of developing the fast tool for dynamic stability assessment in large interconnected power systems. These tools allow the ISO to achieve better performance analysis and determine the various capabilities of the power system in an online or Offline mode. In the efficient power system operation, to supply the required amount of active and reactive power at constant frequency and with a stable voltage level continually, system stability assessment and enhancement is required. In the case of critical situations, the ISO and TSO need to know how to prevent the system from collapse. Therefore, control actions are required to activate proper counter-measures, which have a stability improving impact on the power system.

This chapter presents a framework to determine the best counter measures for online power system dynamic stability enhancement in case the cleared transactions from energy market violate the standard stability levels. The objective is to solve the online transient and oscillatory stability constrained economic power dispatch problem using a mixture of a modified particle swarm optimization and artificial neural network. Self-adaptive penalty function is used to account all system constraints including dynamic stability constraints. Therefore, a balance between the power generation and the load demand ought to be achieved without overloading the equipment, without violating the voltage

lower and upper limits, and without inducing dynamic instabilities or voltage collapse.

4.2 Counter Measures for Dynamic Stability Enhancement

The common phenomenon which is associated with system instability are the system voltage collapsing due to the lack of voltage regulation abilities, growing oscillations on the system due to the lake of damping torque, and transient rotor angle instabilities which may lead to loss of synchronism. If the system is going into emergency, an immediate emergency control activates corresponding corrective counter-measures to relieve the emergency state. The preventive counter-measures suppose that the pre-defined credible contingency set and the associated phenomena with corresponding control are given a priori. Preventive control tries to change the operating conditions so that these constraints are satisfied for all contingencies. This highlights the importance of the appropriate design for control actions and the associated counter-measures corresponding to each state. In the deregulated power systems, ISO may have a variety of counter-measures to enhance system stability but any action should be fair for all participants. Therefore, the ability of ISO to control the power distribution and to force them to prepare many counter-measures during abnormal conditions is limit.

There are many of the modern power electronic based transmission technologies can be used to enhance system dynamic performance such as high-voltage direct current (HVDC) lines and FACTs systems. FACTs are used to increase the power transfer capability across transmission corridors and feed the system with reactive power at the load centers, which provide direct control of power flow over designated transmission routes. HVDC is used to connect two systems while acts as a barrier to prevent the propagation of system oscillations

and control the active and reactive power at its converters as a special category of FACTs. These can also include distributed generation and control devices such as generation re-scheduling, phase shifter transformers, and transformers with tap-changers through the high-voltage winding of transformers (for less current flow). Furthermore, the systematic use of interruptible load can be used to handle the system stability issue in online operation. Interruptible load schemes offer the consumers a chance to reduce the rate of reliability with reduction in its energy costs. Therefore, consumers choose to have an interruptible load contracts to reduce its demand in case of peak load or abnormal system operation which helps to maintain the standard reliability level [50].

Ancillary services are considered as preventive measures to ensure a reliable operation. In the deregulated power systems, ISO has to purchase the adequate ancillary services in a separate market to regulate the area control error (Automatic generation control) during normal load fluctuations and quick-start generation capacity during abnormal operation to mandated reliability criteria. The ancillary services include many categories, which include:

- Frequency control services, which are used to restore the normal frequency following any mismatch in the load-generation balance, which referred as secondary frequency control.
- Operating reserve (spinning and non-spinning) which is used to increase the generation in order to account for the outage of any generator. This aims to ensure the power balance, which refers generation-side operating reserve services.
- Reactive power and voltage control services, which are needed to support system voltages to be maintained within acceptable limits.

In case of insufficient prepared actions during online operation to enhance system stability, immediate actions are required to avoid system breakdowns commonly unplanned generation rescheduling and load shedding can be used. To obtain fair actions, generations rescheduling and load shedding are selected based on market strategy in this study. The market is implemented based on participant's offers where the main target is to minimize the payments to enhance system stability. In case of vertically integrated electric utility, the generation rescheduling and shifting from economic dispatch should be minimized to reduce the increase of the cost of power generation. Particle swarm optimization (PSO) as an evolutionary algorithm is used as optimization tool to obtain the optimal solution to enhance system stability with minimum payments.

4.3 Evolutionary Algorithm Techniques

The Evolutionary Algorithm (EA) is a generic population-based meta-heuristic optimization technique that uses biology-inspired mechanisms. The population-based methods invoke a set of many solutions at the end of the iteration. The individuals compete in a virtual environment to reach the global optima. EAs do not need to differentiate cost function and constraints and make only few assumptions about the underlying fitness landscape and therefore perform consistently well in many problem categories.

4.3.1 Swarm Intelligent Techniques

Swarm intelligence considered as a branch of artificial intelligence, which consists of a group of agents cooperating with certain behavioral pattern to achieve a certain goal. There are many swarm intelligent models include particle swarm optimization, ant-colony optimization and bacterial foraging. These models are used to undertake distributed optimization problems, which

successfully applied on many power system applications. In this study, PSO is selected to be applied for dynamic stability enhancement based energy market optimization. PSO model has several advantages such as the search mechanism is robust and efficient in maintaining diversity and is able to arrive at the global optimization solution with a high probability. The algorithm is easy to realize with only a few adjustable parameters, is fast converging, and can be conducted with parallel computation [51].

4.3.2 Adaptive Particle Swarm Optimization

PSO is a population based stochastic optimization technique which is developed by Dr. Eberhart and Dr. Kennedy in 1995, and is inspired by social behavior of birds flocking or fish schooling that solves continuous and discrete optimizing problem of a large domain [52]. PSO learns from the scenario and uses it to solve the optimization problems while each individual shares the information with its neighbors. The particle is attracted towards the best position currently experienced by other particles that form its local neighborhoods and/or towards the best position found by any particle in the swarm so far. The individuals fly through the search space with velocities, which are adjusted dynamically according to their historical behaviors. Therefore, the particles have the tendency to fly towards the better and better search area over the course of search process until reach a stopping criterion.

Each individual, called particle, x_i, within the swarm is represented by a vector in multidimensional search space, which represents a potential solution of the entered problem and updates its position by adding the updated velocity, v_i. The updated velocity of each particle influenced by the current velocity in addition to two terms based on the memorized best position it has explored and the global best position explored by the swarm in the feasible search space. The

PSO is modified by introducing the inertia weight, crossover operation, and/or constriction factor to enhance the convergence capability [53]-[55]. The original PSO formulae define each particle, i as potential solution with to a problem in D-dimensional space with a memory of its previous best position x_{ibest} and velocity vector of the swarm v_i, which can be represented as:

$$\mathbf{x}_i^{\mathrm{T}} = [x_{i1}, x_{i2}, \quad \cdots \quad , x_{iD}] \tag{4.1}$$

$$\mathbf{x}_{ibest}^{\mathrm{T}} = [x_{1best}, x_{2best}, \quad \cdots \quad , x_{nbest}] \tag{4.2}$$

$$\mathbf{v}_i^{\mathrm{T}} = [v_{i1}, v_{i2}, \quad \cdots \quad , v_{iD}] \tag{4.3}$$

Particles' velocities can be clamped to a maximum velocity, which serves as a constraint to control the global explosion speed of particles. It limits the maximum step change of the particle position, which adjusts the moving speed of the whole population in the hyperspace. After specifying the local and global best values, the equations used to update the velocity and position of each particle can be represented as:

$$\mathbf{v}_i(k+1) = w\,\mathbf{v}_i(k) + \mathrm{c}_1\mathrm{r}_1\left(\mathbf{x}_{ilbest}(k) - \mathbf{x}_i(k)\right) + \mathrm{c}_2\mathrm{r}_2\left(\mathbf{x}_{gbest}(k) - \mathbf{x}_i(k)\right) \tag{4.4}$$

$$\mathbf{x}_i(k+1) = \mathbf{x}_i(k) + \chi\,\mathbf{v}_i(k+1) \tag{4.5}$$

Where w is the inertia weight, which specifies the effect of previous velocity vector on the new vector and can be represented as:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \tag{4.6}$$

The constriction factor χ, which used to limit the velocity and improve the convergence can be represented as:

$$\chi = \frac{2}{\left|2-\phi-\sqrt{\phi^2-4\ \phi}\right|}, \text{ where}: \phi = c_1 + c_2,\ \phi > 4 \tag{4.7}$$

Where c_1 and c_2 are positive individual and sociality acceleration coefficients, which control the influence of cognitive and social terms on the particle's velocity. r_1 and r_2 are two random values in the range (0, 1) which are used to get the randomness of the search. $iter_{max}$ and $iter$ are the maximum number of iterations and current number of iteration. x_{ilbest} is the recorded local best position for the particle i. x_{gbest} is the recorded global best position for the whole swarm in the explored area. During the optimization if any variable exceed its upper or lower bound, the value of the variable is set to the violated limit, which called set to limit approach. The performance of each particle is evaluated by using the objective function. The standard procedure of PSO algorithm is presented in Figure 4.1, which can be easily implemented with few coding lines as follows:

Step1. Initialize the inertia weight, constriction factor, and other necessary parameters.

Step2. Initial population and corresponding velocity vectors are generated randomly within the hypercube of feasible space.

Step3. Evaluate the fitness function for each individual using its current position considering constraints violations.

Step4. Specify the best position for each individual by comparing the current performance with its previous best performance.

Step5. Specify the global best position for the swarm by comparing the best performance of each individual with the previous global best performance of the swarm.

Step6. Update the velocity and position of the individuals according to equations 4.4 and 4.5.

Step7. If the convergence is obtained or the stopping criterion is met, then stop and return the best solution and the corresponding fitness value, otherwise go back to Step 3.

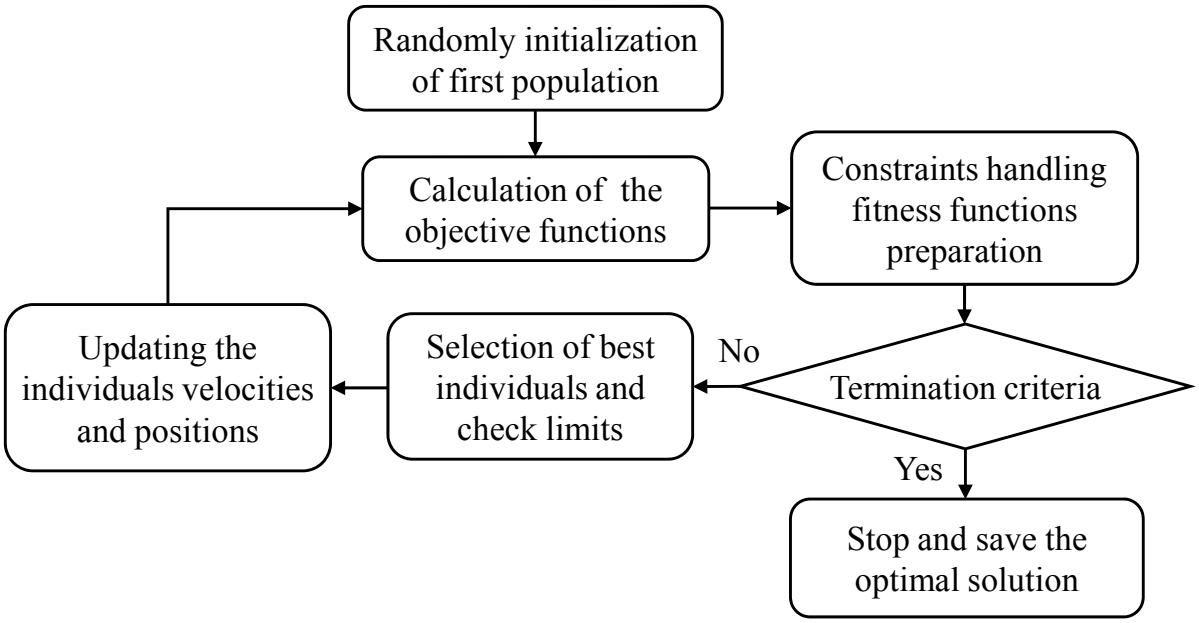

Figure 4.1 The basic steps of standard PSO algorithms

The control variables could be continuous and discrete; the continuous variables initialized with uniformly distributed pseudorandom numbers and kept within limits during iterative process. In the case of discrete variables, an additional operator needed to account for the distinct nature of these variables. A rounding operator was included to ensure that each discrete variable is rounded to its nearest decimal integer value that represents the physical operating of a given variable during the process. The PSO successfully applied to solve complex global optimization problems in many areas such as reactive power dispatch, optimal power flow, and controller parameter estimation. PSO has the following key features compared with the conventional optimization algorithms [56].

- The optimization procedure is measured by a fitness function directly instead of mathematical operations gradient or Hessian and special property like differentiability or convexity.
- PSO is a population-based technique, thus the final solution is free from the effect of the initial solution and the existence of the memorizing strategy to store the previous history of the individuals improves the optimization process.
- The random distribution of the individuals over the search space provides a good probability for PSO to escape local optimal solution and catch the global optimal solution.
- The code of PSO is simple in operation and convenient application and easily programmed with basic mathematical and logic operations.

The PSO terminates when the pre-specified number of iterations or function evaluations has been performed or when no improvement of best solution has been achieved during a specified number of iterations. Thus, the optimization process stopped when a specified tolerance value pertaining to the fitness function is obtained.

4.3.3 Constraints Handling

Most of the practical optimization problems have linear and/or nonlinear constraints, which should be satisfied at the final solution. Difficulty in satisfying constraints will increase with the number of constraints, the type of constraints (continuous or discrete) and the criticality of the constraint in terms of absolute satisfaction. Traditional mathematical programming has many difficulties to solve many constraints optimization problems with non-differentiable objective functions (and perhaps even non-differential constraints) or with disjoint feasible regions [57]. PSO gives the opportunity to construct a

single fitness value from the objective function and constraints. Constraint-handling approaches tend to incorporate information about infeasibility (or distance to the feasible region) into the fitness function in order to guide the search. The fitness value should reflect the degree of feasibility and the distance between the particle and the global optimal solution. The general constrained optimization problem formulated as:

$$\text{Minimize: } f(\mathbf{x}), \quad \mathbf{x}^{\mathrm{T}} = [x_1, x_2, \quad \cdots \quad , x_n] \tag{4.8}$$

$$\text{Subject to: } \begin{array}{l} h_i(\mathbf{x}) = 0,\ i = 1,2,\cdots,I \ \text{ Equality constraints} \\ g_j(\mathbf{x}) \le 0, j = 1,2,\cdots,J \ \text{ Inequality constraints} \end{array} \tag{4.9}$$

Where $f(\mathbf{x})$ is a scalar value objective function, $h_i(\mathbf{x})$ and $g_j(\mathbf{x})$ is constraints functions, and $\mathbf{x}$ is a vector of variable to solve the problem might include lower and upper bounds. The most methods transform the equality constraints into inequality constraints by using a very small acceptable tolerance $\boldsymbol{\varepsilon}$ to aid the finding of a feasible solution during little number of iterations.

$$|h_i(\mathbf{x})| - \varepsilon \le 0 \qquad i = 1,2,\cdots,\mathrm{I} \tag{4.10}$$

Penalty technique is the most commonly used method for constraints handling in the area of evolutionary computation [58]. Death penalty (rejection strategy) method also can be used to deal with infeasible solutions where individuals that violate any one of the constraints are completely rejected and no more operations are used to extracted information from those infeasible individuals where the removed individuals are replaced by randomly generated feasible ones [59]. This method used with convex search area and wide feasible regions with respected to the whole search area to get the ability to initiate new feasible solutions. There are many penalty functions, which commonly used to

modify objective functions to account the constraints violation in fitness function formulation to improve the search strategy.

4.3.3.1 Penalty Techniques

A penalizing strategy replaces constrained problem by unconstrained problem while its solution ideally converge to the solution of the original constrained problem. The unconstrained problems are formed by adding new terms to the objective function, which is called constrained fitness function that contains a penalty term as a measure of constraints violation as in (4.29).

$$\varphi(\mathbf{x}) = \varphi_f(\mathbf{x}) + p(\mathbf{x}) \tag{4.11}$$

Where $p(\mathbf{x}) = 0$ if $\mathbf{x}$ is feasible and $p(\mathbf{x}) > 0$ if $\mathbf{x}$ is infeasible solution for minimization process. $\varphi(\mathbf{x})$ is the constrained fitness function and $\varphi_f(\mathbf{x})$ is the modified objective function.

The big challenge is how to formulate the penalty function, which relates the constraints violation to the original objective function. A simple method to penalize infeasible solutions is to apply a constant (static) penalty to those solutions that violate feasibility in any way similar to the popular Lagrangian relaxation method. The constraint violations increase the fitness function in the case of minimization or decrease the fitness function in the case of maximization problem. A general formulation is as follows for a minimization problem:

$$\varphi(\mathbf{x}) = \varphi_f(\mathbf{x}) + \sum_{i \in \mathrm{I}} \gamma_i h_i^+(\mathbf{x}) + \sum_{j \in \mathrm{J}} \gamma_j \left| g_j^+(\mathbf{x}) \right| \tag{4.12}$$

h_i^+ and g_j^+ are the magnitude of the violation of equality and inequality constraints. The main drawback of the static penalties is introducing new

coefficients corresponding to each constraint, which are problem-dependent and effect on the quality of solution and speed of convergence. Also with integrating the fitness function with different categories of constraints, it is very difficult to adapt the proper penalty coefficient each constraint. The dynamic penalty function developed to avoid drawbacks associated with static penalizing. The idea of a dynamic penalty approach is to use the iterative progress to influence the computation of the penalty factor of each individual. The researcher suggest many methods to specify these coefficient such as distance-based static penalty function or unique static penalty function with multiple violation levels established for each constraint [57]. The dynamic penalty can adjusted according to the degree of violation of constraints and during progress in evolutionary process. One form of the dynamic penalty introduced in [60] where the penalty function is constructed with multiplication of two components, the first is variable penalty factor and the second is quantification of the violation of the constraints. Joines and houck [61] proposed a dynamic penalty function in which the penalty increases during the progress through generations.

Dynamic penalty functions share the same problem of specifying several parameters with static penalty functions in addition the optimization process will fail to get a feasible solution if the feasible region is far away from the initial estimation or may converge to a local optimum. To address this concerning issue, adaptive penalty functions have been suggested where information gathered from the search space will be used to control the amount of penalty added to infeasible individuals [62]-[64].

4.3.3.2 Self-Adaptive Penalty Functions

One of the most recent constraint handling approaches is based on a self-adaptive penalty function that required no user specified constants to explore all

the entire search space where the penalty adapts according to the performance of the swarm. Birul Tessema and Gary G. Yen [65] propose a self-adaptive penalty scheme for constrained optimization problems. Among many-tested constraints handling approaches, the proposed scheme is free of parameter tuning, and guaranteed to find a solution for every tested problem during the preparation of the software used for optimization in this study. Therefore, this approach effectively modified and implemented to account the power system constraints during the optimization using PSO throughout this study. In this algorithm, the information collected from the infeasible solution effectively used in tracing the optimum. The algorithm considers all the individuals are important, but at different stages and under different situations throughout the search process. When the current population is far away from feasible region, the individuals with low constraints violation will help to force the population to find feasible individuals. On the other hand, if the swarm has many feasible solutions, the search should be concentrated to find the optimum solution. In this case, individual with low objective value are more important than individual with low violation of constraints. Thus, the proposed algorithm evaluates the fitness value based on the feasibility of the current population. Based on the existence of feasible individuals, the calculation of fitness values can be categorized into three cases as follows:

Case A: Normalized fitness functions using (4.13) are calculated and used to represent the swarm if all individuals in the current population are feasible. Then individuals are compared based on their normalized fitness value alone.

$$\varphi(\mathbf{x}) = \varphi_{fn}(\mathbf{x}) = \frac{f(\mathbf{x}) - f_{min}(\mathbf{x})}{f_{max}(\mathbf{x}) - f_{min}(\mathbf{x})} \tag{4.13}$$

Case B: When all individuals in the current population are infeasible, the average constraints violation of each individual in equation 4.14 were used to formulate the fitness value during evaluation, this will force the particles to find feasible individual before searching on the optimum using objective function by reducing the constraints violation.

$$\varphi(\mathbf{x}) = viol(\mathbf{x}) = \frac{1}{\mathrm{I}+\mathrm{J}} \sum_{m=1}^{I+J} \frac{C_m}{C_{m,\max}} \tag{4.14}$$

$$\text{where}: C_m = \begin{cases} |g_m(\mathbf{x})| & m = 1, \cdots\cdots, I \\ |h_m(\mathbf{x})| - \varepsilon & m = I+1, \cdots, I+J \end{cases} \tag{4.15}$$

Case C: If there are feasible and infeasible individuals in the population, a modified fitness value is calculated to account the distance between individual and feasible region as well as constraints violation as given in 4.15. Individual with both low fitness value and low constraints violation will be considered better fit than individuals that have high fitness value or high constraint violation or both. If two individuals have equal fitness values, According to the penalty function, if the ratio of the feasible individuals r_f in the current population is small, then the individual closer to the feasible space will be considered better. Otherwise, the individual with lower normalized fitness value will be better.

$$\varphi(\mathbf{x}) = \sqrt{\varphi_{fn}(\mathbf{x})^2 + viol(\mathbf{x})^2} + (1 - r_{\mathrm{f}}) \cdot viol(\mathbf{x}) + r_f \cdot \varphi_{fn}(\mathbf{x}) \tag{4.16}$$

The main feature of this method is that the infeasibility measure has the properties that it increases in value adaptively with both the number of active constraints, the magnitude of each constraints and the number of feasible individuals in the population. In addition, it is observed during the application that this algorithm is capable of finding feasible solution within small number of

iterations. A comparison strategy for selection of best individuals when updating the positions of the particles during PSO application is introduced to enhance the optimization process and to avoid the effect of normalization process of the fitness function during updating the position and velocities of the population.

4.3.3.3 Comparison Strategy for Selecting Best Individuals in PSO

The major candidate during optimization is the determination of the best individuals and the applied comparison strategy. The comparison depends on the fitness function, which is built based on the information available from two different measures of different scale, the objective function and the total constraint violation. In order to provide a good balance, the two measures are either normalized or scaled accordingly. In stochastic optimization such as PSO method, the particles evolve with generations. During the evolutionary process, the particles exchange information during the process of updating their positions. As the particles move from one location to the other, it tries to find the right direction to reach the final target based on the historical information. This information exchange based on the iterative normalized values will lead to error when comparing the feasible particles where the normalization process based on the feasible and infeasible particle.

The previous discussed algorithm will be used in the study with a modification of selection strategy for the local and global best positions to account the error due normalization. The main problem in the selection arises when there are feasible and infeasible solutions explored where equation 4.15 will be used to formulate the fitness values of particles. The comparison between feasible particles in the current iteration with the feasible particles in previous ones to determine the best positions may lead to error. To modify the

selection strategy to account this error, the same strategy for selecting the best values based on the normalized fitness function is used in the earlier stage where the particles away from the feasible regions until the swarm catches a feasible region. After that, the comparison between the feasible particles is based on the original objective function to avoid the effect of normalization on the swarm movement. This allows the particle to discover each feasible region for the optimal solution. This means that the feasible solutions are always compared based on its original objective value while the infeasible particles are evaluated based on their objective value and their constraint violations using equation 4.15. This strategy leads to the superiority of the feasible solutions during swarm exploration of search space, which enhances the ability of the swarm to keep knowledge about the feasible regions.

The selection strategy is presented in Figure 4.2 and the application to select the local best position of each individual during the iterative process can be summarized by:

Case 1: when the current position and the previous local best position of individual are infeasible, the selection of the new best position evaluated based on the normalized fitness values according to the cases described in section 4.3.3.2.

Case 2: when current position of the individual is feasible and the best local position is infeasible, the current position is selected a new local best position

Case 3: If both the current position and the previous local best position are feasible, the selection of the new local best position is based the comparison between the original objective values.

Case 4: if the current position is infeasible and the previous local best position is feasible, the new local best position is the same as the previous local best position.

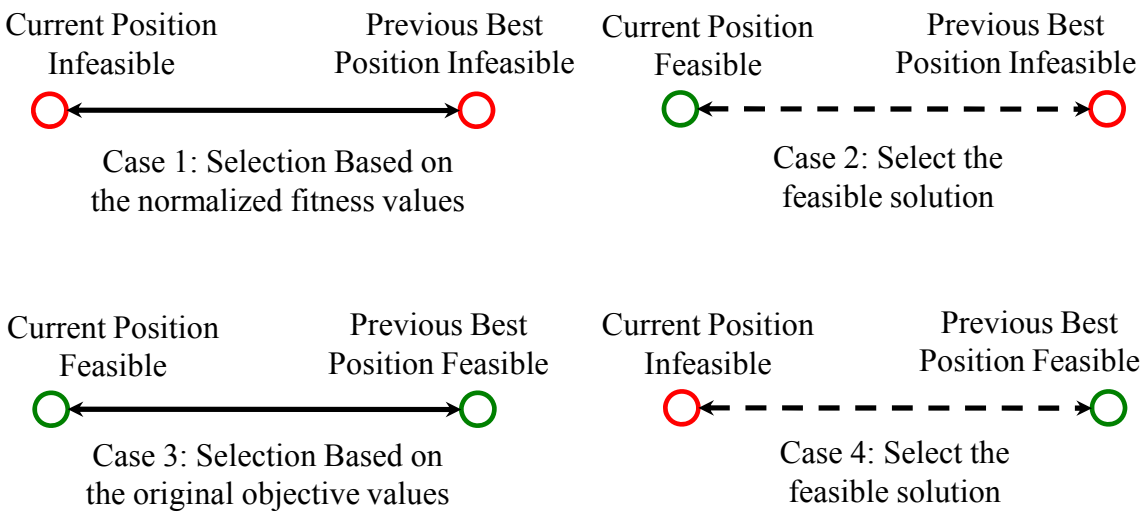

Figure 4.2 Selection strategy for the local and global best positions

The same selection strategy is applied for selecting the global best positions of the swarm. After selecting the local best position of each particle and global best position of the swarm and the corresponding fitness values, these positions are used in updating process to move the swarm towards new position.

4.4 Dynamic Stability Enhancement in Vertically Integrated Electric Utility

The classical electricity pool market is characterized by a central authorized entity, where all functions are controlled by central administration as shown in Figure 4.3. The main responsibility of the central administration is to monitor and control all power activities where the main objective of the system operator is to satisfy the system load in the most possible reliable and to

maximize the total social welfare subject to several technical constraints, such as power flow constraints, losses and system stability [66].

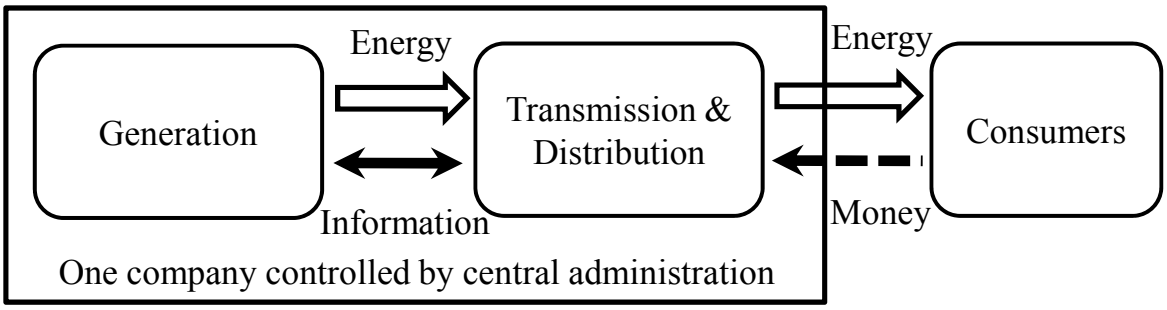

Figure 4.3 Operating strategy of vertically integrated electric utility

Power consumption has been relatively insensitive to price of the power because the price has been determined by the utilities irrespective of the consumer response. Thus, a centralized energy balance implemented and all suppliers and customers transact with the pool without physical bilateral trades. Dynamic stability enhancement in a vertically integrated environment is achieved by central administration of ISO, where participation of all participants is mandatory. The most efficient source is dispatched subject to network constraints based on price and quantity information from suppliers and consumers. Therefore, the independent generators may be forced to operate at a profit below what they could achieve under self-scheduling or market-based operation [67].

4.4.1 Closed Loop Control Actions for System Stability Assurance

The system operator should plan hours ahead or days-ahead scheduling to determine the optimal allocation of generated power from each generator based on the expected system states. Once the daily/hourly market cleared, the system stability of this solution has to be checked by the system operator in order to preserving system constraints. If the specified generation scheduling does not

fulfill the stability criteria, the generation rescheduling and control devices are required to enhance the system operation to satisfy any violated constraint. The objective is to find proper adjustments of the generated power and terminal voltage control that maintain acceptable stability levels throughout the system. The general practical procedure of closed loop preventive and emergency controls for online security assurance can be described as in the block diagram in Figure 4.4. The system operators investigate the system state and if the system is in an emergency state, the corrective counter-measures should immediately activated to relieve the emergency. If the system is in a normal insecure state, the preventive countermeasure should be evaluated to account the effects of critical contingencies on system security. When the system is secure enough, the control strategy should be enhanced to follow the current system conditions where each operating point has a new stability situation. The use of dynamic stability constrained economic dispatch meant the more efficient use of the transmission facilities, which enhances system performance.

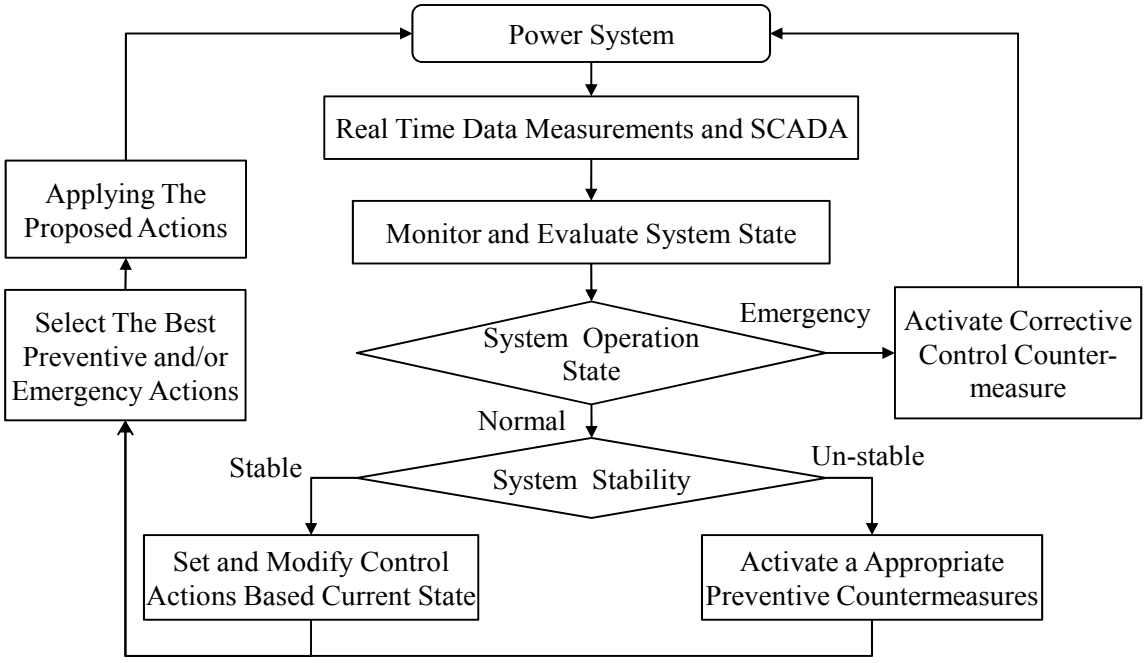

Figure 4.4 Closed loop control actions for system stability assurance

4.4.2 Generation Rescheduling Based Sensitivity Analysis

In this section, the generation rescheduling based sensitivity analysis is used to enhance system dynamic stability in vertically integrated electric utilities. The PST16-machine test system in Appendix A.1 used to implement the proposed approach. The purpose of the work is to find a generation configuration with improved stability behavior in order to stabilize harmful contingencies by rescheduling the generation while satisfying operational constraints including dynamic stability constraints. The proposed approach is be used to shift part of the power scheduled during economic dispatch with a minimum increase in the total cost of generation to enhance the system stability. To simplify the process and get a fast solution, the shifted power distributed based on the response of generating units following the most critical contingency and PSO is used to obtain the optimal solution with minimum cost.

During network disturbances, the power generators have to provide immediate support by increasing or changing the currently generated power supplied to the grid. All synchronized generating units in the system response to the power fluctuation during contingencies based on the severity of the change of power distributions in the grid. The rate of rotor angle change is proved to be as a good sensitivity index for generator response during the contingencies [68]. The rotor angle of each machine will move within certain border with respect to center of angles (COA) during stable operation.

During unstable operation, the response of generators depends on the type and location of the contingency where some generators may accelerate and others decelerate. Thus, time responses of rotor angles are used to classify all generators into two groups. Group A are those generators (critical machines, N_A) with positive sensitivity for the effect of the disturbance and so, the generation for this group should decrease to reduce their

rotors acceleration. In the other hand group B are generators (non − critical machines, N_B) with negative sensitivity following the occurrence of the contingency and their power generation should increase to compensate the generation changes in-group A to keep the total consumption constant. The change in system losses can be compensated from the slack bus. Each group can be farther split into subgroups according to the characteristics of machines and the location of the fault. Therefore, additional rules to classify the generating machines based on the dynamic response may be required for each network. The change in generation level among critical and non-critical machines provides a first approximate via a stabilization procedure, which is iterative since the relation between the change and stability is not perfectly linear. The problem can be solved as dynamic stability constraints optimal power flow to get the optimal amount of shifted power for minimum cost. Therefore, the limits of minimum CCT and MDO as indicators for system dynamic stability are relieved by adjusting output power of critical generators.

The total shifted power could be distributed with numerous patterns bases on the technical or economical consideration, which include the distribution equally on all or some of the critical machines or based on the machines ratings or response during critical contingency. In the study, PSO is used to compute the optimal amount of power needed to be shifted iteratively from most advanced generators to the least advanced generators. This amount is involved by generators in each group using sensitivity factors based on their inertia coefficients and rated capacities. The objective of optimization is to minimize the increase in the total generation cost due the transition from the economic dispatching operating point. The problem can be formulated as follows:

$$\text{Minimize:} \quad \Delta C = \sum_{i=1}^{N_g} (\beta \, \Delta P_{gi} + \gamma \left[\left(P_{gi0} + \Delta P_{gi} \right)^2 - (P_{gi0})^2 \right]) \tag{4.17}$$

Subject to:-

Power flow constraints:

$$\boldsymbol{h}(\mathbf{x}) = 0, \quad \boldsymbol{g}(\mathbf{x}) \leq 0 \tag{4.18}$$

Dynamic stability constraints:

$$\text{CCT} > 150\,ms \text{ , MDO} > 4\% \tag{4.19}$$

Where β and γ are fuel cost coefficients and ΔC is the increase in fuel cost to enhance system dynamic stability.

The distribution of the shifted power among generators from the non-critical machines, N_B, to the critical machines, N_A, can be calculated based generators capacities, S and inertia, H using the following formula:

$$\Delta P_{giA} = \alpha_{iA} \Delta P \tag{4.20}$$

$$\Delta P_{gjB} = -\alpha_{jB} \Delta P \tag{4.21}$$

$$\alpha_{iA} = \frac{H_{iA} \cdot S_i^A}{\sum_{i=1}^{N_A} H_{iA} \cdot S_i^A} \text{ , } \sum_{i=1}^{N_A} \alpha_{iA} = 1 \tag{4.22}$$

$$\alpha_{jB} = \frac{H_{jB} \cdot S_j^B}{\sum_{j=1}^{N_B} H_{jB} \cdot S_j^B} \text{ , } \sum_{j=1}^{N_B} \alpha_{jB} = 1 \tag{4.23}$$

Where ΔP is the total shifted power (MW). ΔP_{giA} is the decrease in generated power from generator i in group A. ΔP_{gjB} is the change of generated power from generator j in group B. α_{iA} and α_{jB} are the factors used to distribute the shifted power among critical and non-critical machines. H_{iA} and S_i^A are the inertia constant and capacity of generator i in group A. H_{jB} and S_j^B are the inertia constant and capacity of generator j in group B.

4.4 Dynamic Stability Enhancement in Vertically Integrated Electric Utility

High loading operating point of PST16 with total connected load of 15351.4+j 2351.45 MVA is selected as a base case loading and load distribution among generators are obtained based on economic dispatch program. The fuel cost coefficients and the initial generation distribution are presented in Appendix A.2. A three-phase fault is applied at pre-selected set of fault locations in PST16 test system to investigate the transient stability and oscillatory stability while determining the critical fault locations and corresponding critical generators. Figure 4.5 shows the time response of rotor angles with respected to COA of all generators at the worst contingency when the fault at bus A2 in area A with the corresponding CCT of 102.5 milliseconds and MDO is 1.8%. As shown in Figure 4.5, the dynamic behavior of system generators split into two groups, group A (critical machines) and group B (non-critical machines). The generation rescheduling (shifting) from critical machines to non-critical machines used to enhance the dynamic stability to be within the desired limits. The desired limits to consider the system dynamically stable are specified to be CCT of at least 150 milliseconds and MDO of 4% at the most sever fault location. PSO is used as optimization tool to determine the optimal amount of generation to be coordinated between generators to improve the system dynamic stability. In the proposed algorithm, two Offline trained ANN as described in section 3.4.3.2 and section 3.4.3.3 are used to estimate the CCT and MDO during optimization process as indicators for system dynamic stability. The block diagram of the proposed approach, which is used in DSA and enhancement, is presented in Figure 4.6.

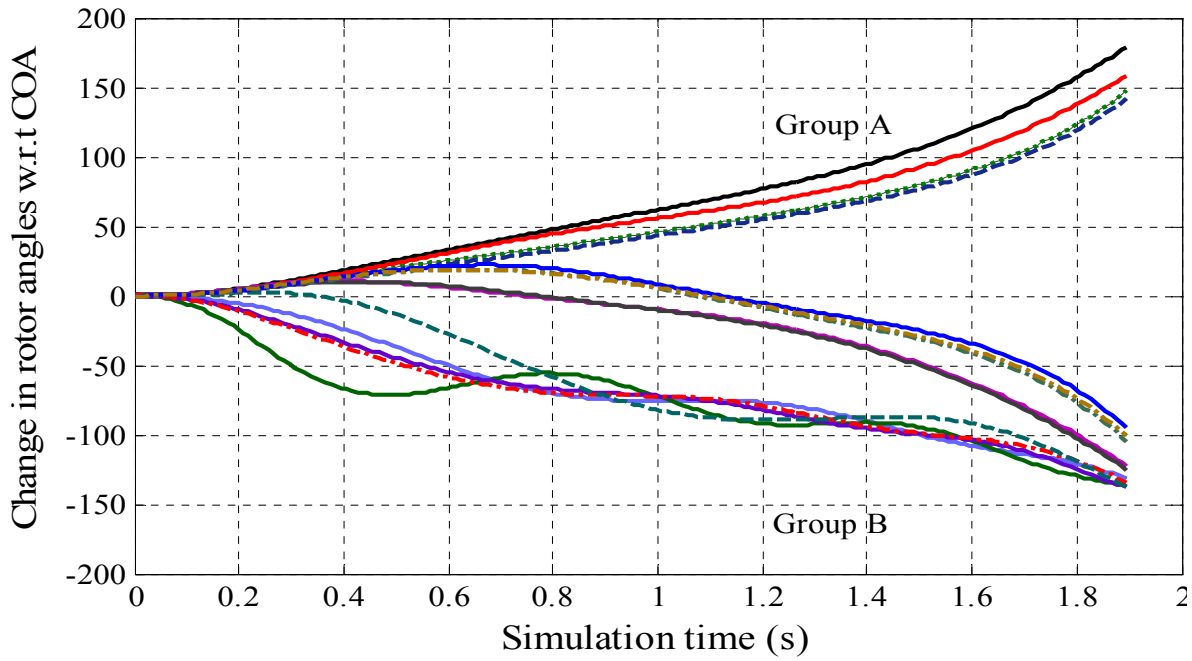

Figure 4.5 Time response of rotor angles of PST16 with three-phase fault

The results obtained show that the CCT increased to 151.25 milliseconds and the MDO improved to 8.9 %. The total increase in fuel cost for dynamic stability enhancement is 8227.461 (€/h). The variation of the increase in total fuel cost of the global best individual during the optimization process to enhance system dynamic stability is shown in Figure 4.7.

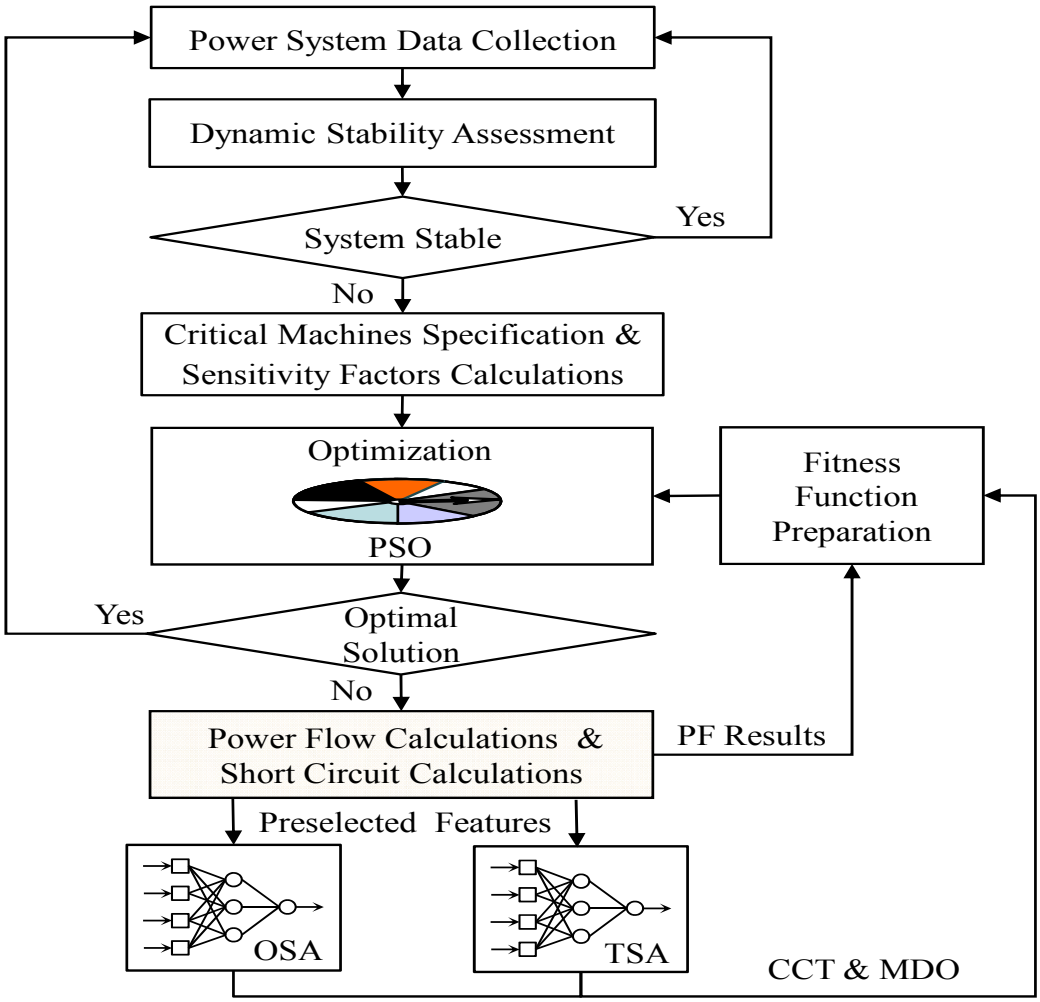

Figure 4.6 The schematic diagram of the proposed approach

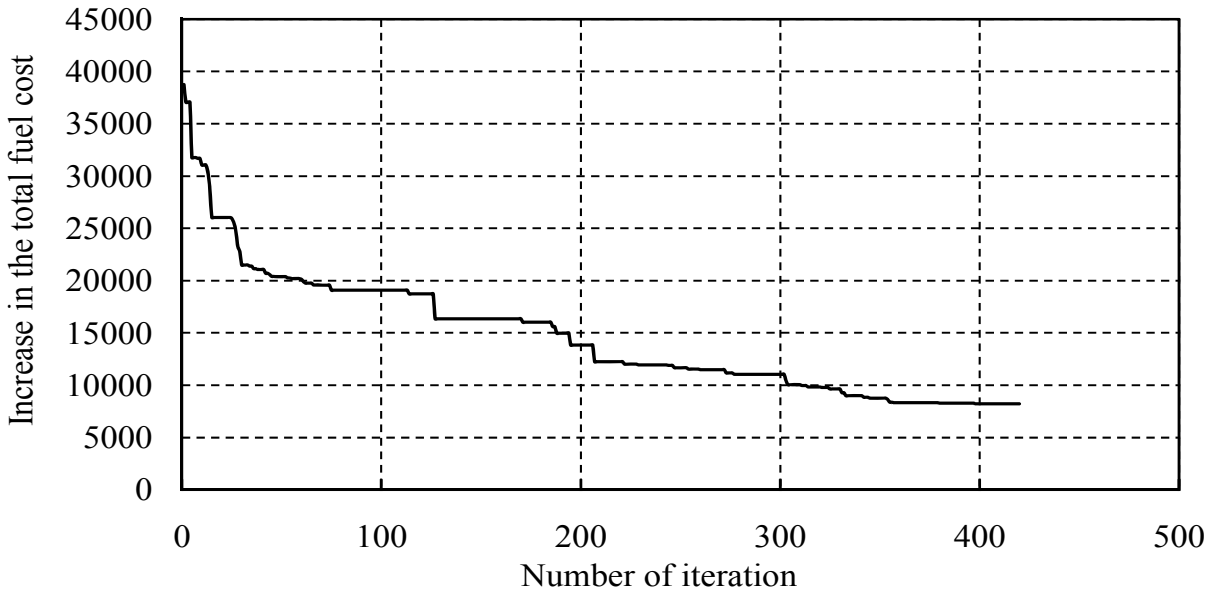

Figure 4.7 The additional fuel cost to enhance system dynamic stability

The power generation before and after rescheduling is presented in Figure 4.8. The total power to be rescheduled from the critical machines, group A, to the non-critical machines, group B, is 537 MW.

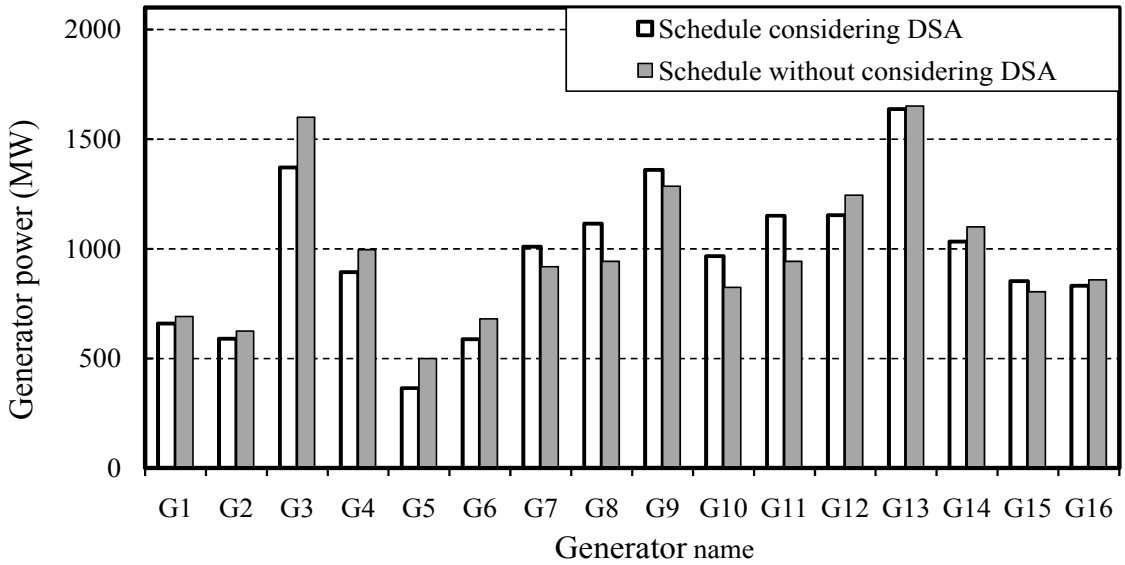

Figure 4.8 The generator active power before and after generation rescheduling

Figure 4.9 shows the per-unit change in absolute rotor angle of all generators in PST16 following a 150-millisecond three phase short circuit at bus A2 in area A (the previous critically faulted bus). Figure 4.9 clearly shows that the system is transiently stable after applying the fault.

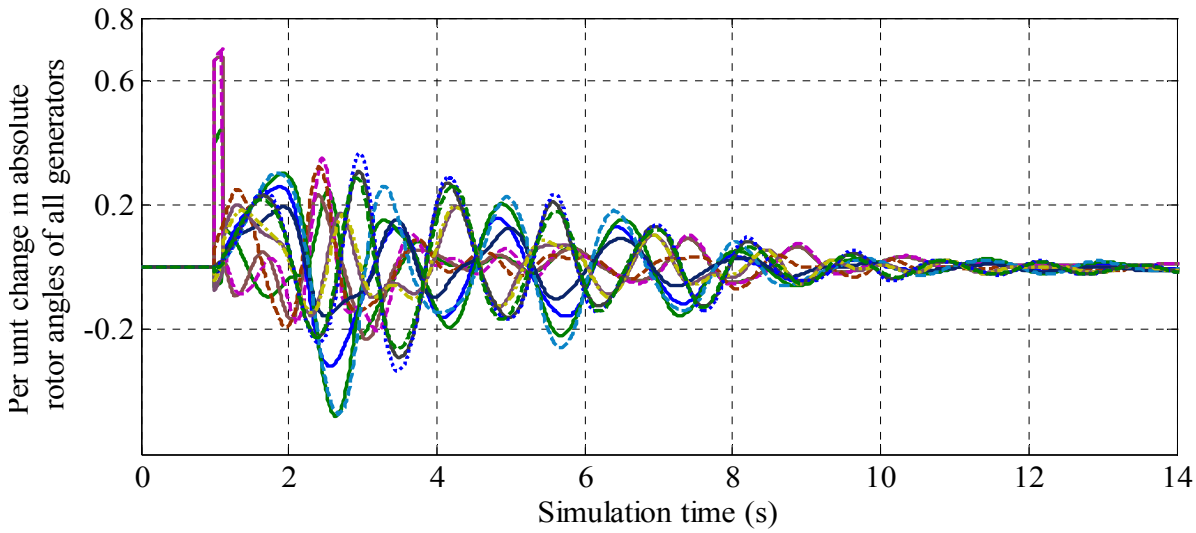

Figure 4.9 Time response of rotor angles during fault at bus A2 in Area A

4.5 Power System Operation in Competitive Environment

In deregulated markets, power generation and consumption are elastic and can be responding as a function of price. Participants in the deregulated markets decide whether and how to sell the output of their generation assets with direct bilateral contracts or participating in the spot (pool) energy market or any other official auctions to maximize their surplus based on market strategy under supervision of regulatory authorities. The system operators are the responsible to control all system transactions in a competitive environment. The general interaction among participants is shown in Figure 4.10.

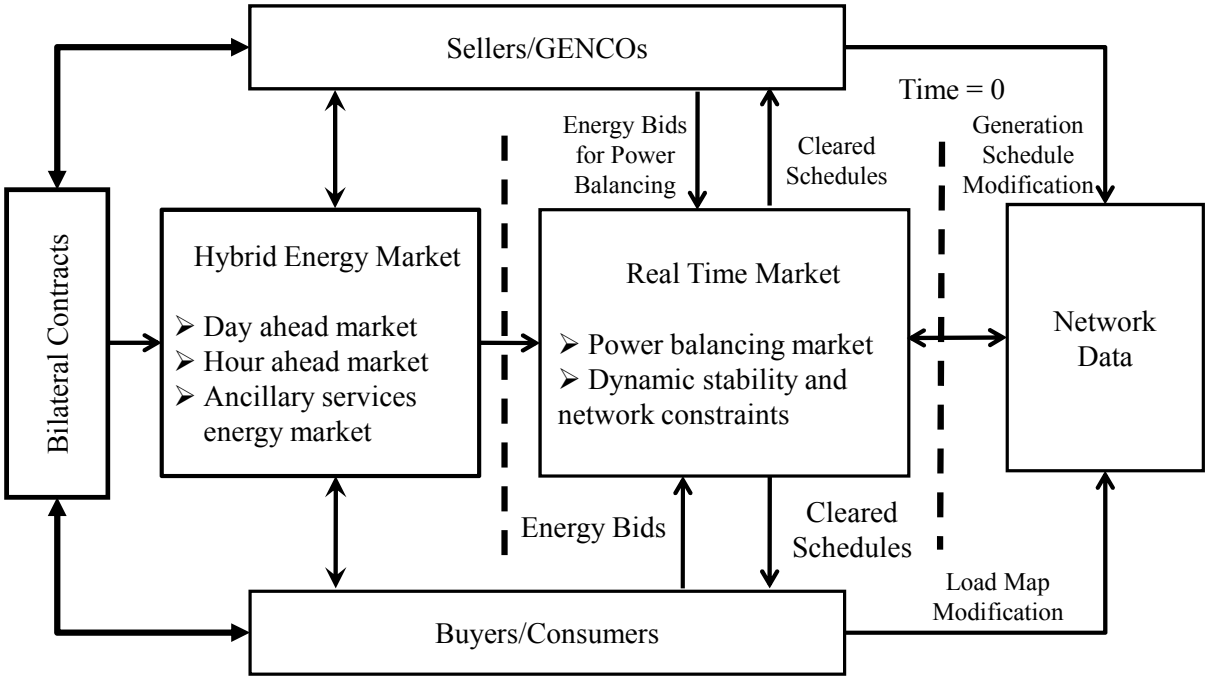

Figure 4.10 General power system operation in competitive environment

4.5.1 Participants in Deregulated Electricity Market

The inspiration behind deregulation is to use of market strategies to remain competitive and encourages investments in power system sector. The desirable

outcome of the competitive process is the achievement of a lower price and a price convergence through wholesale and retail competition [67]. The major players in a deregulated electricity industry are generation companies (GENCOs), independent power producers (IPP), transmission utilities (TRANSCOs), retail energy service companied (RESCOs), ISO and power exchange (PX) as shown in Figure 4.11. The utilities are forced to operate in a more reliable, economic and efficient manner and plan their expansion investments more accurately. In order to ensure open and fair access to all participants, the grid operated and controlled by ISO. ISO is a central entity to have emerged in all deregulated markets with the responsibility of providing available information regarding the network for all market participants and coordinating the transactions to manage system congestion and alleviate the effects of contingency events. To achieve this objective, the ISO sets the rules for transactions between suppliers and consumers, and energy markets [68]. These rules include the adjusting network situation by generation rescheduling or ordering the ancillary services so as to keep the system in normal operation.

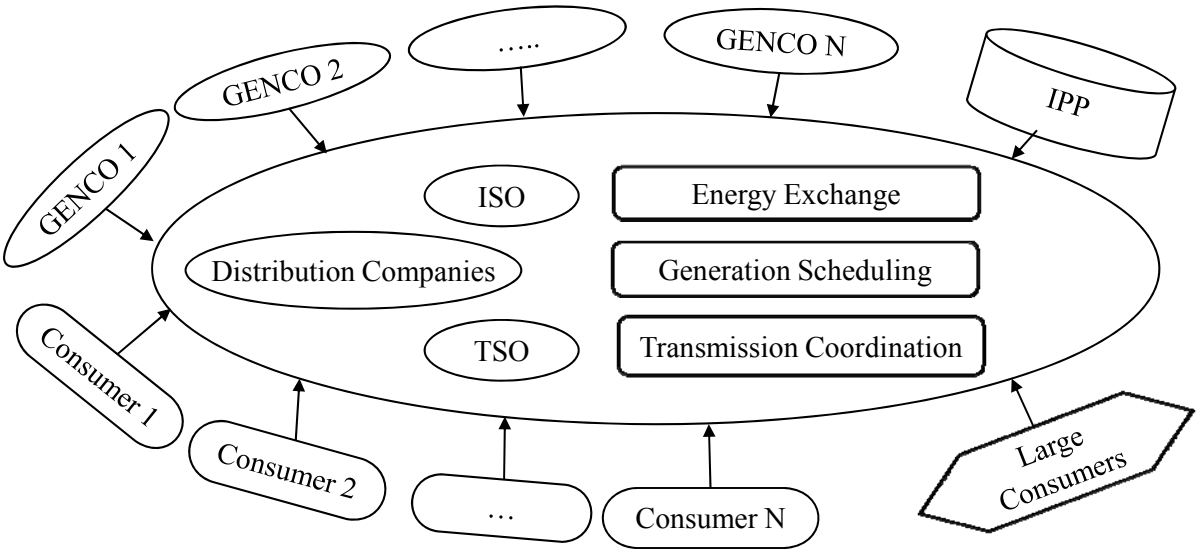

Figure 4.11 Wholesale competition model of electricity market construction

Contractual rules may include payments guarantee from grid users and all participants as well as penalty charges to TSO in case of transmission unavailability. Competitive generation provides a market within which independent firms compete based on prices to sell electricity directly to large industrial customers via bilateral contracts, and to supply electricity via common carrier transmission to final users. Additionally the spot market and ancillary service market organize which increase the generator's flexibility in scheduling production shown in Figure 4.12 [59]. In order to ensure open and fair access to all participants, the grid operated and controlled by ISO. ISO is a central entity to have emerged in all deregulated markets with the responsibility of providing available information regarding the network for all market participants and coordinating the transactions to manage system congestion and alleviate the effects of contingency events. To achieve this objective, the ISO sets the rules for transactions between suppliers and consumers, and energy markets [68]. These rules include the adjusting network situation by generation rescheduling or ordering the ancillary services so as to keep the system in normal operation. Contractual rules may include payments

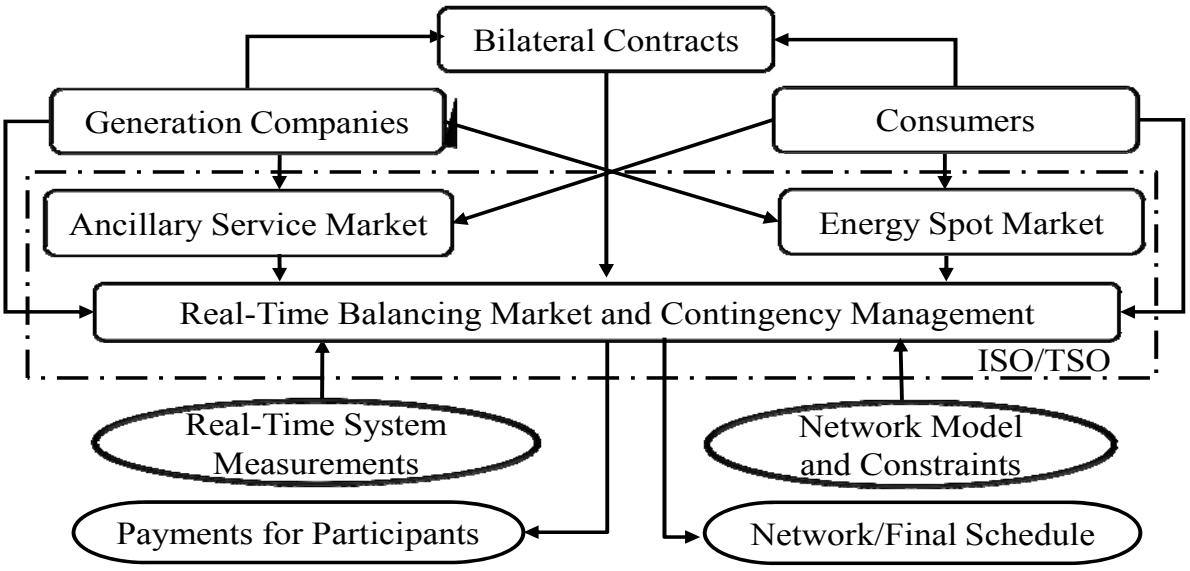

Figure 4.12 Hybrid energy and ancillary service markets

4.5.2 Participants Behavior and System Stability

System stability is not the important priority power producers and consumers in deregulated electricity markets. Power producers consider the costs of installation rather than proximity of adequate transmission facilities or the impacts associated with connecting their plants on the overall power system stability. They have the ability to compromise the trade-off between benefits and risks when they purchase energy from several sub-markets. Supplier attempt to exercise the price of electricity by either reducing the physical availability of connected generators or by increase its offer price in the critical states of power system operation without considering system stability. The expected profit maximization depends on the ability of the suppliers to solve the self-scheduling problem considering ramping and capacity limits and forecasting load profiles [69]. Such un-coordination beside the dramatic increase in the volume of bulk power transfers are causing the grid to be used in unsafe region of operation. Therefore, dispatchable load ability presented to allow ISO to future load reduction in the scheduling process and load curtailment during abnormal operation conditions [70]. Consumers have the ability to introduce voluntary offers for load interruption as a source of operating reserve, which reduce volatility of price, alleviate of transmission congestion and enhance system stability. For efficient operation, better coordination among transmission owner and other market participants is required.

4.5.3 Energy Markets and Power System Interactions

Generation and load schedules usually are not completely accurate. Real time operation should incorporate all relevant constraints to provide sufficient and efficient market results by fluctuation above or below the schedules.

Therefore, it is impossible to do enough Offline simulations to provide stability guides for all operating conditions. In the real time operation, minute-to-minute balance between production and consumption should be performed to achieve energy balance. In order to achieve the standard limits of system security, market participants who are able to regulate their generations or demands at a short notice can place bids for upward or download regulation. In the operation phase, the ISO uses the bids when a need for an adjustment of balance is necessary for fringe competitive balancing arrangements as shown in Figure 4.13. The figure presents the sequence of marketing and adjustment for secure power system operation assurance based on competitive manner.

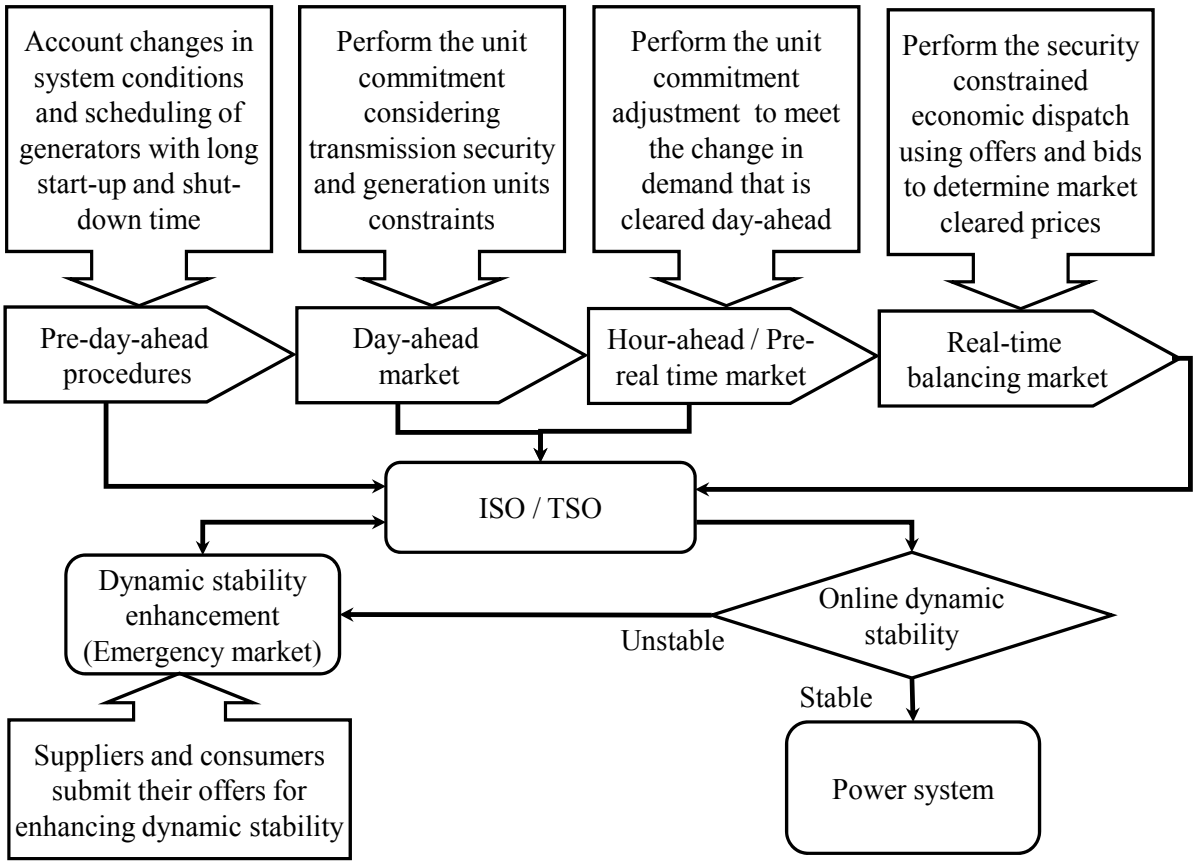

Figure 4.13 Real-time marketing and regulation for economic and reliable operation

The basic concept of real time balancing market, suppliers submit their bids to sell electricity in the form of a specified price-power curve and consumers submit their bids. Once the market is cleared and the transactions between the supply and demand curves are available, ISO carries out power flow and other simulation studies to assure system stability. Congestion and instability can occur because of limited transmission capabilities and improper power allocations. Therefore, ISO has the authority to dispatch units in line with market award to meet the loads and curtailment of certain transactions may be required. The choice of curtailment of transactions is important to the involved participants and may be financially unattractive or technically impossible to implement. Therefore, the ISO should act in an impartial and fair manner to all participants, while deciding on the curtailments and minimize the deviation from scheduled transaction. In order to seek a least-curtailment solution, the ISO might have to procure excessive reactive power support at some buses and use a compensation service from the ancillary service market to obtain power balancing. Under these circumstances, the ISO has to buy service active and reactive power support more than its requirements to minimize the curtailments in the cleared transactions [72]. This is an undesirable consequence from the prospective of the TSO, which can lead to a significant energy price impacts. These are conflicting objective, which inspire the authors to develop a new market construction to minimize the additional costs required to improve system security, particularly dynamic stability enhancement. The next sections present the real-time balancing market clearance considering DSA and enhancing system stability during critical operating conditions.

4.6 Real-Time Balancing Market Considering DSA

The energy dispatching according to energy and ancillary service markets clearance beside it may or not be adequate to meet the actual demand it may or

not be adequate to anticipate the effects of abnormal states such as sever faults or random failure of electric components during online operation. ISO based on their experience usually solves the contingency management problem by determining load shedding and generations re-dispatch in real-time operation. The main objective of contingency management of well developed and applied in real-time operation is to solve the system congestion and power balance problem [73]. The challenge still with the dynamic stability associated with unexpected states due to the significant computational burden associated with DSA where additional iterative loops are required which make dynamic stability constrained optimal power flow (DSCOPF) much more costly than steady state analysis. DSCOPF represents a trade-off between economics and security where additional payment needed to enhance the system dynamic performance.

Real-time balancing market can be established at any convenient time interval to fulfill the demand in near future. In this study, an integrated work to include DSA using ANN in real-time balancing market clearance is proposed. Real-time balancing and contingency management market is established to determine the re-dispatched generation, the reserve arrangement, and load curtailments. The main target is to minimize the cost of real-time dispatch to achieve a feasible power balancing with an acceptable level of stability. The costs incurred in providing reserves include the opportunity costs of providing reserves and the costs incurred in case the generator is actually dispatched. In this study, PSO is used as optimization tool to obtain power balance considering dynamic stability as constraint as well as all operational constraints.

4.6.1 Mathematical Formulation

The market implemented where bilateral contract owners submit a compensative price for the willing to accept curtailments in cleared transactions. Consumers and suppliers submit their offers to re-dispatch the cleared transaction from the energy market for surplus. In addition, ISO may use part of the operating reserves and which need to be replaced. Thus, participants in the market have the opportunity to participate with energy bid to sell additional reserves [74]. Therefore, the total cost should include the cost of curtailment of bilateral contracts, the cost of curtailments of the loading level of consumers, the cost of generation re-dispatching, and the cost of the replacement of the called operating reserves. The schematic form specifies the used offers from suppliers and consumers for participating in the real time balancing market is shown in Figure 4.12.

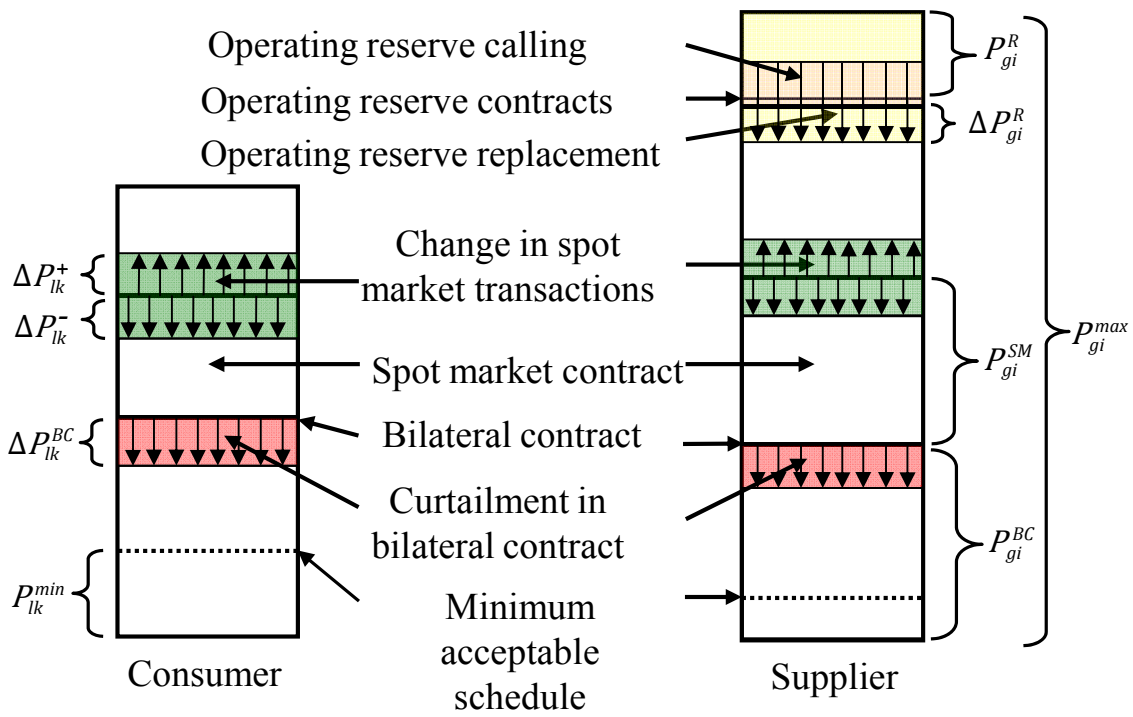

Figure 4.14 Suppliers and consumers offers to real time balancing market

In the proposed method, self-adaptive penalty function described in section 4.3.3.2 is used to modify the cost function for all constraints handling including dynamic stability constraints. In the study, the active power reallocation only considered where the cost function can extended to account any other reactive power control variables or the cost of allocation of any reactive power resources. The objective function for the total cost of power dispatch for real time balancing market can be formulated as follows:

Minimize:

$$\Delta C = \sum_{i=1}^{N_g} b_i^{\pm} \Delta P_{gi}^{\pm} \mu_{gi}^{\pm} + \sum_{i=1}^{N_g} b_i^{\mathrm{R}} \Delta P_{gi}^{\mathrm{R}} \mu_{gi}^{\mathrm{R}} + \sum_{i=1}^{N_g} b_i^{\mathrm{BC}} \Delta P_{gi}^{\mathrm{BC}} \mu_{gi}^{\mathrm{BC}} + \sum_{k=1}^{N_l} b_{lk}^{\mathrm{C}} \Delta P_{lk}^{\mathrm{C}} \mu_{lk}^{\mathrm{C}} \tag{4.24}$$

$$P_{gi} = P_{gi}^{\mathrm{BC}} + P_{gi}^{\mathrm{SM}} \pm \Delta P_{gi}^{\pm} - \Delta P_{gi}^{\mathrm{BC}} + \Delta P_{gi}^{\mathrm{R}} + \Delta P_{gi}^{\mathrm{CR}} \tag{4.25}$$

$$P_{lk} = P_{\mathrm{lk}}^{\mathrm{BC}} + P_{lk}^{\mathrm{SM}} - \Delta P_{lk}^{\mathrm{BC}} \pm \Delta P_{lk}^{\mathrm{C}} \tag{4.26}$$

Subject to the following constraints:

Power balance constraints

$$\sum_{i=1}^{N_g} P_{gi} - \sum_{k=1}^{N_l} P_{lk} = P_{loss} \tag{4.27}$$

$$P_{res} = \sum_{i=1}^{N_g} \left(P_{gi}^{\mathrm{OR}} - \Delta P_{gi}^{\mathrm{CR}} + \Delta P_{gi}^{\mathrm{R}} \right) \tag{4.28}$$

Generation constraints

$$P_{gi}^{min} \le P_{gi} \le P_{gi}^{max} \tag{4.29}$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max} \tag{4.30}$$

$$P_{lk}^{min} \le P_{lk} \le P_{lk}^{max} \tag{4.31}$$

Lines, cables and transformers flows and voltage constraints

$$|S| \le |S|^{max} \tag{4.32}$$

$$|V|^{min} \le |V| \le |V|^{max} \tag{4.33}$$

Dynamic stability constraints

$$\mathrm{CCT} > \mathrm{CCT}_{min} \tag{4.34}$$

$$\xi > \xi_{min} \tag{4.35}$$

Where ΔC is the total real-time payment (€/h). N_g and N_l are number of generators and loads respectively. $b_{gi}^{\pm}, b_{gi}^{\mathrm{R}}, b_{gi}^{\mathrm{BC}}$ and b_{gi}^{C} are bid prices for generation, reserve replacement, curtailment in bilateral contract and loads (€/MWh) respectively. $\mu_{gi}^{\pm}, \mu_{gi}^{\mathrm{R}}, \mu_{gi}^{\mathrm{BC}}$ *and* μ_{gi}^{C} are the identifiers for sharing in real-time market which could be 0 or 1. $\Delta P_{gi}^{\pm}, \Delta P_{gi}^{\mathrm{R}}, \Delta P_{gi}^{\mathrm{BC}}$ *and* $\Delta P_{gi}^{\mathrm{CR}}$ are the incremental or decremental change in generator output, reserve replacement, curtailment of bilateral contract, and called reserve power respectively. $\Delta P_{lk}^{\mathrm{BC}}$ and $\Delta P_{lk}^{\mathrm{C}}$ are the curtailments of load in bilateral contract and load interruption respectively. $P_{gi}, P_{gi}^{\mathrm{BC}}, P_{gi}^{\mathrm{SM}}, P_{gi}^{\mathrm{OP}}, P_{gi}^{min}$ and P_{gi}^{max} are the current output of generator, original bilateral contract, spot market, and limits respectively. $P_{lk}^{\mathrm{BC}}, P_{lk}^{\mathrm{SM}}, P_{loss}$, *and* P_{res} are current load in bilateral contracts, cleared load level in spot market, total power losses and total power reserve respectively. $P_{lk}^{min}, P_{lk}, P_{lk}^{max}$ are the minimum, current and maximum scheduled load level respectively. $\Delta P_{lk}^{\mathrm{BC}}$ and $\Delta P_{lk}^{\mathrm{C}}$ are the curtailment of load power in bilateral contract and change in scheduled load level cleared from spot market.

The proposed method is implemented on the PST16 test system. Initial schedule is assumed with high level loading near the network limits for dynamic stability analysis and the power imbalance assumed randomly distributed 50 MW in each area. The aim is to find the preferred schedules as close as possible

to the scheduled transactions in order to minimize the cost of real-time balancing dispatch, which should satisfy all system constraints.

4.6.2 Counter Measures for Real-Time Balancing Market

The individuals in the swarm *are* defined as a vector of control variables, **x**, including the offered energy bids of all participants and all online available control variables including transformer tap-settings (Δ**tap**). By setting the transformer taps, the TSO can adjust the voltage level at busses and control the power flow through transmission lines. The vector of control variable used in the study as follows:

$$\mathbf{x} = \left[\Delta\mathbf{P}_g \;\; \Delta\mathbf{P}_g^{OR} \;\; \Delta\mathbf{P}_g^{R} \;\; \Delta\mathbf{P}_g^{BC} \;\; \Delta\mathbf{P}_l^{C} \;\; \Delta\mathbf{Q}_g \;\; \Delta\mathbf{tap} \right] \tag{4.36}$$

Each particle represents a solution and AC power flow used to adjust the operating point and extract the required data for dynamic stability assessment, constraints calculation and objective function formulation. The constrained fitness function combines the total cost function in 2.23 and system constraints violation. PSO is applied where, each individual in the swarm contains a number of control variable presented in Table 4.1. All generators assumed to participate in the real-time market. Two consumers from each area are participating with offers in the real-time balancing market and having bilateral contracts.

Table 4.1 Control variables used during real-time balancing market

Variable name	$\Delta\mathbf{P}_g$	$\Delta\mathbf{P}_g^{\mathrm{CR}}$	$\Delta\mathbf{P}_g^{R}$	$\Delta\mathbf{P}_g^{\mathrm{BC}}$	$\Delta\mathbf{P}_l^{\mathrm{C}}$	$\Delta\mathbf{Q}_g$	$\Delta\mathbf{tap}$
Number	16	9	11	6	6	16	28

The initial generation distribution prior to real-time market presented in Appendix A.3 and the various bids from generators, consumers and bilateral contracts are given in Appendix A.4. The operating reserve can be called in the scheduling and participants provide offers for operating reserve replacement. The point-to-point bilateral contracts curtailment is applied and it assumed that the ISO would pay the spot price for participants based on hour-ahead energy auction as well as the opportunity costs for the contribution of participants to real-time market. During the optimization the generators are support the system voltage with adequate reactive power generation without additional payment. According to the results without considering the dynamic stability into consideration during the optimization, the network congestion can be relieved by calling and replacement of the operating reserve and interruption of part of bilateral contract at G2. With this schedule, the CCT is 112-millisecond and the MDO is 2%. The total additional cost for balancing the market without considering DSA is 5694.42€/h. The target value for a transient stable operation is considered as 150-millisecond as a common of all protective devices in the system and the target MDO is 4%. Talking into account dynamic stability constraints during the market clearance, the total additional cost increased to 14867.82€/h. The total cost variation of the global best individual during the optimization process with and without considering system dynamic stability into account is shown in Figure 4.15.

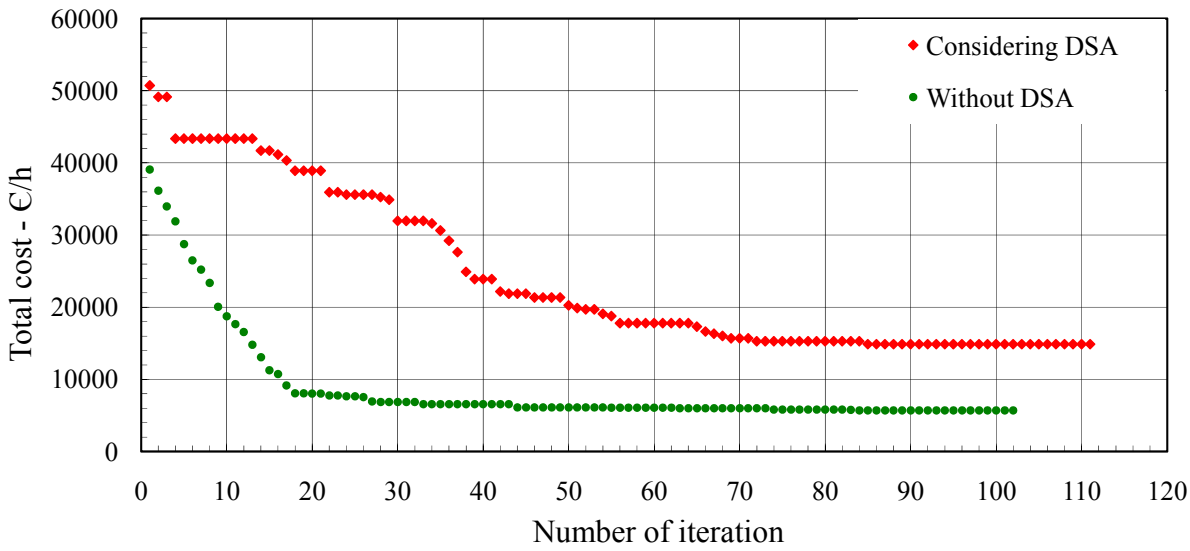

Figure 4.15 Change of the total cost for real-time balancing market

The final schedule in real-time market settlement with and without dynamic stability enhancement into consideration during market clearance and the corresponding surplus of participants are presented in Appendix A.5. Figure 4.16 presents the change in operating reserve allocation with and without considering of dynamic stability assessment.

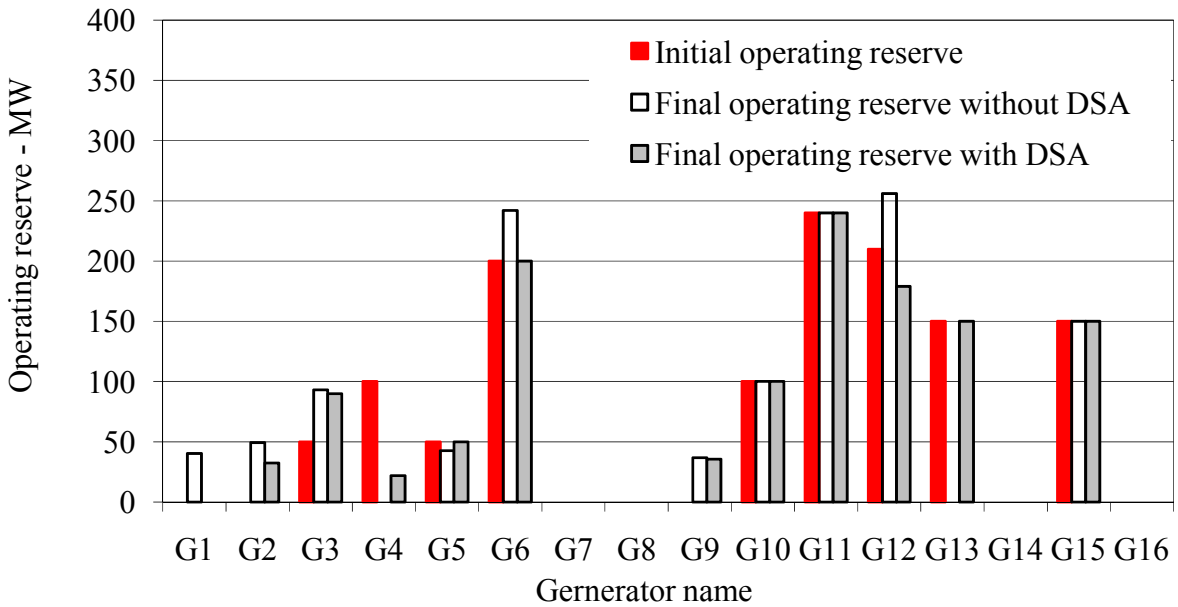

Figure 4.16 Operating reserve allocation for network constraints satisfaction

Where the initial operating point is near the feasible regions, it is found that the PSO can catch a feasible solution within few iterations and the process continues very fast towards the optimal solution until the stopping criteria satisfied. The proposed methodology is able to determine load shedding, generation re-dispatching and reserve utilization simultaneously, thereby assisting ISO to enhance system operation with minimum payments and operate the power system away from its limits to avoid blackouts at the instant of critical contingencies. As shown in Appendix A.5, the dynamic stability enhancement requires additional load interruption and increases the total cost of the real-time balancing market. Therefore additional cost should be distributed which increases the nodal prices. Thus, additional indices should be evaluated to determine the penalty payments of each supplier and consumer for dynamic stability assurance.

4.7 Dynamic Stability Enhancement during Unpredicted Abnormal Conditions

In modern power system, a large problem for system operators is to identify critical states since there are thousands of parameters, which describe and affect the state therefore the control actions are never account all possible abnormal states. However, a well-operate system will continue power delivery with very little inconvenience to its consumers. So that operating decisions should have to be on accurate online system information rather than Offline simulation of a comprehensive set of possible system operating conditions.

The dynamic stability should be investigated online as an integral part for a secure operation where system states should be monitored in a very short period of time (5-15 minutes) and when any unsecure state detected, a control action implemented to restore standard level of security. Market participants shall immediately respond to directions from the ISO to alter their operations to stay

within accepted security limits. The deviation from the energy market clearance should not diffract the equality among all participants. In case of insufficient control actions to restore standard level of security, this equality required allowing the generation companies (GENCOs) and consumers to participate in the online system operation based on market strategy [75]. To achieve this goal, the concept of compensation or opportunity costs for shifting of scheduled power in energy markets presented and applied as additional online framework to enhance dynamic stability. The opportunity cost is the revenue that a participant would expect to get by selling in a different market or change in the cleared scheduled power from any market, which represents the optimal strategy for a market participant.

The rescheduling process based on the market participants' bids is used as a remedial action to maintain system operation sufficiently away from the limits of system stability. The goal of the framework is to minimize the opportunity cost arising from the rescheduling needed to enhance system dynamic stability. The problem is formulated as a nonlinear constrained optimization problem, and modified PSO used as optimization tool to search for the optimal solution within the available hyperspace of all participants and trained ANN used to estimate the power system transient and oscillatory stability during the optimization process.

4.7.1 Proposed Market Formulation

Online power rescheduling as remedial action for dynamic stability enhancement considered as market portfolio to enhance system dynamic stability by a proper shift in power schedule by minimizing the overall cost of the action. The schematic diagram of the proposed framework presented Figure 4.17.

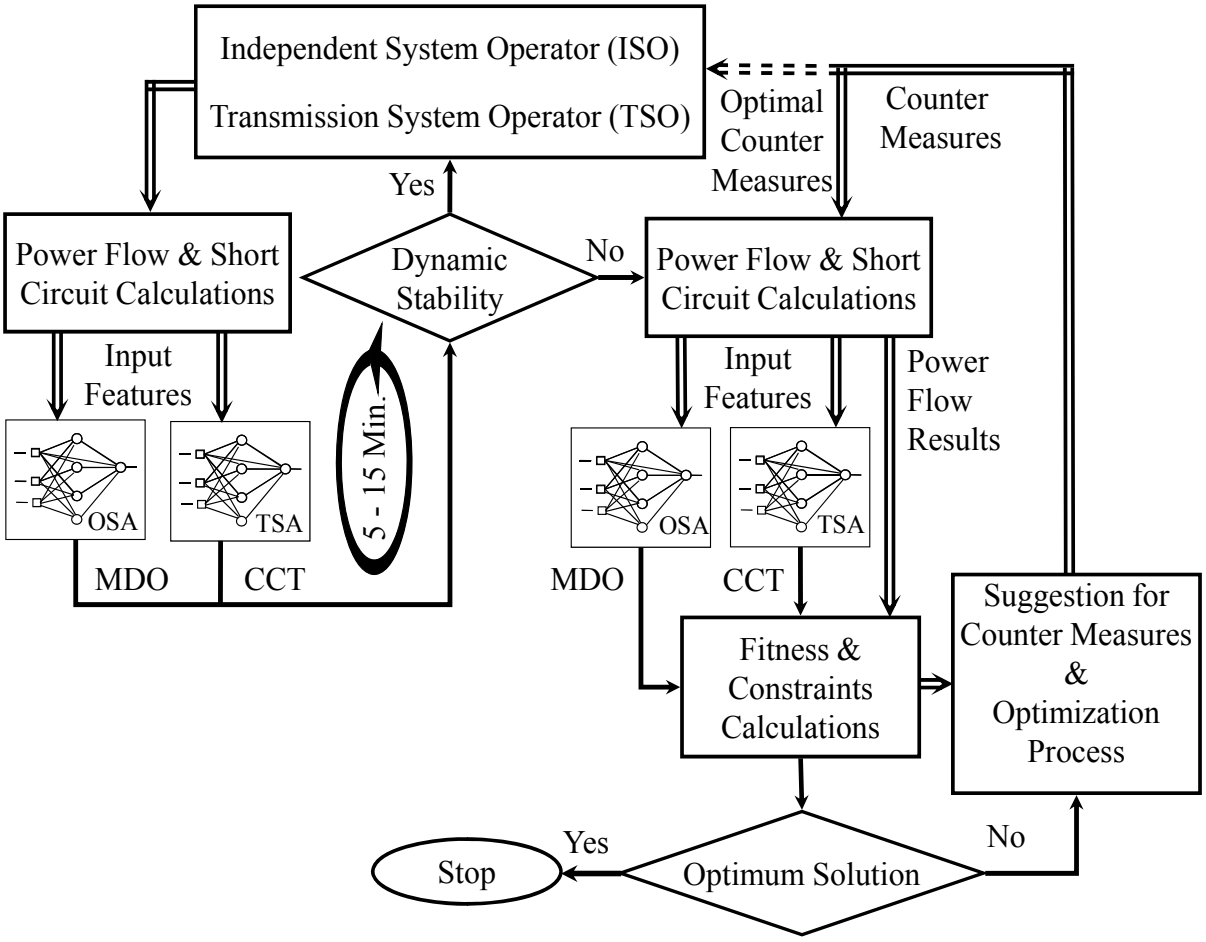

Figure 4.17 Schematic diagram of the proposed algorithm

If the stability margin is not satisfactory and the prepared control actions are insufficient, the optimization starts to search for proper counter-measures to enhance the dynamic stability for a secure operation. The application of counter-measures should be started with no cost-incurring control variables such as available reactive power sources rescheduling and transformer tap-sittings changing, and if these prove to be insufficient, additional counter-measures such as active power rescheduling are required. In this work a new market, based rescheduling strategy is proposed to reallocate the energy among suppliers and consumers participating on the online market by placing optional energy bids to enhance system stability. This market is a separate market established after the real-time market clearance during abnormal conditions.

The bids are generally in the form of quantity-price pairs on an incremental basis within the acceptable limit of rescheduling which specify how much the seller or buyer is willing to sell or buy, and at what price and also the associated operational constraints. During the optimization process, each individual in the swarm represents a solution. Power flow and short circuit computations used to collect the necessary data and selected features to be used in estimation of CCT and MDO using the trained ANN.

4.7.2 Money Flow Chart

In the proposed market, all GENCOs and consumers have equal chance to participate with voluntary energy bids. Participants required to reduce generation/load level are paid the opportunity cost to compensate reduction in the gained surplus due to partially or totally loss of electric service within a certain period. Participants increasing their outputs are remunerated based on energy market clearing price plus additional costs, which may be required to execute the required changes in the scheduled level to compensate the extra operational costs. For the GENCOs and consumers that do not participate on this market conditions on energy market clearance remain binding. The block diagram of the cash flow according to the new rescheduling process is shown in Figure 4.18. According to the practice in the energy market, the direction of cash flow in the process of market clearance is directed from consumers to GENCOs (cash flow AI and AII) based on the cleared transactions during real time balancing market. Based on the dynamic stability requirements, the new rescheduling process will shift part of scheduled generated power from GENCOs II to GENCOs I thus the power supplied from GENCOs II decreased and power supplied from GENCOs I increased. At the same time, the new market clearance may also lead to increase in energy consumption of consumers

I and decrease in energy consumption of consumers II in order to enhance dynamic stability. These additional transactions between GENCOs and consumers lead to pay additional and opportunity costs to CENCOs and consumers to apply the necessary increase in generations/consumptions (BI, BII, CI, and CII) as shown in Figure 4.18.

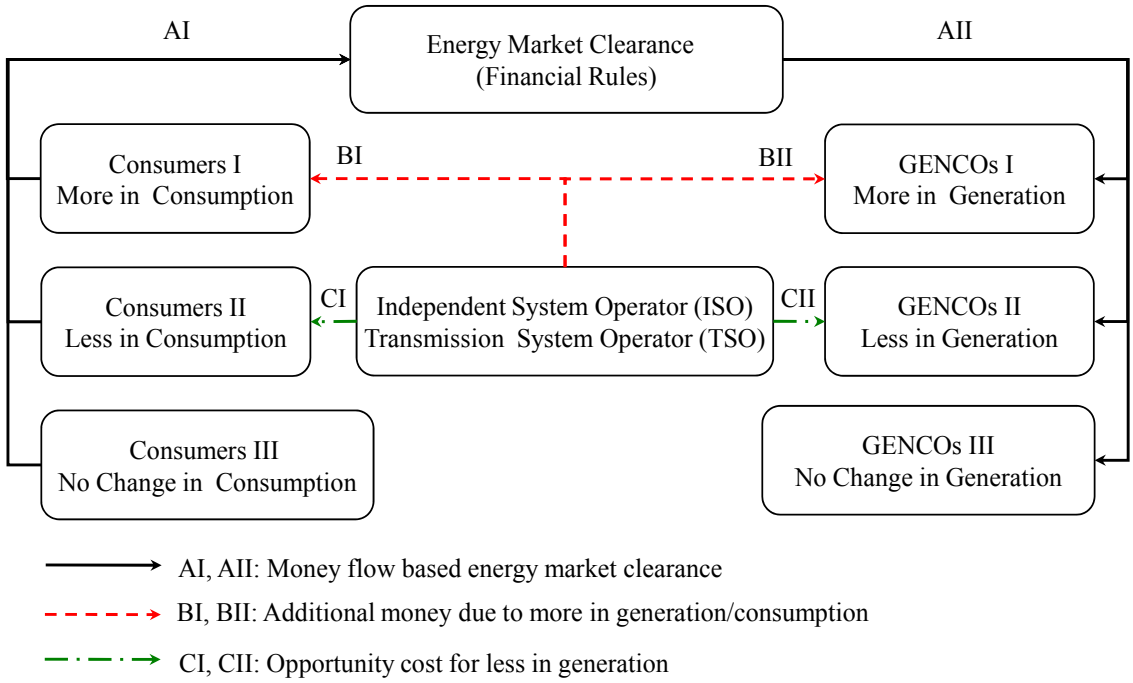

Figure 4.18 Money flow to enhance power system dynamic stability

4.7.3 Problem Formulation and Bidding Strategy

The population in PSO is defined as vector **x**, where **x** is the vector of control variables including change in active and reactive power ($\Delta\mathbf{P}, \Delta\mathbf{Q}$) of all participants together with all online available control variables such as transformer tap-settings ($\Delta\mathbf{tap}$) and FACTs devices to control the injected reactive power.

$$\mathbf{x}^{\mathrm{T}} = \left[\Delta\mathbf{P}^{\mathrm{T}} \;\; \Delta\mathbf{Q}^{\mathrm{T}} \;\; \Delta\mathbf{tap}^{\mathrm{T}}\right] \tag{4.37}$$

$$\Delta\mathbf{P} = \left[\Delta P_1 \quad \Delta P_2 \quad \cdots \quad \Delta P_{Np1}\right] \tag{4.38}$$

$$\Delta\mathbf{Q} = \begin{bmatrix} \Delta Q_1 & \Delta Q_2 & \cdots & \Delta Q_{Np2} \end{bmatrix} \tag{4.39}$$

$$\Delta\mathbf{tap} = \begin{bmatrix} \Delta tap_1 & \Delta tap_2 & \cdots & \Delta tap_{Nt} \end{bmatrix} \tag{4.40}$$

N_{p1} and N_{p2} are the number of participants in active and reactive power rescheduling, N_t is the number of transformers which have tap changers. The participants in the market submit their voluntary energy bids including limits of change of the schedule power and the corresponding cost functions. These bids can be implemented with any acceptable form based on pre-specified rules such as step-shaped functions or linear bids strategy as shown in Figure 4.19. It represents the total cost the participants are offering for a certain level of power change.

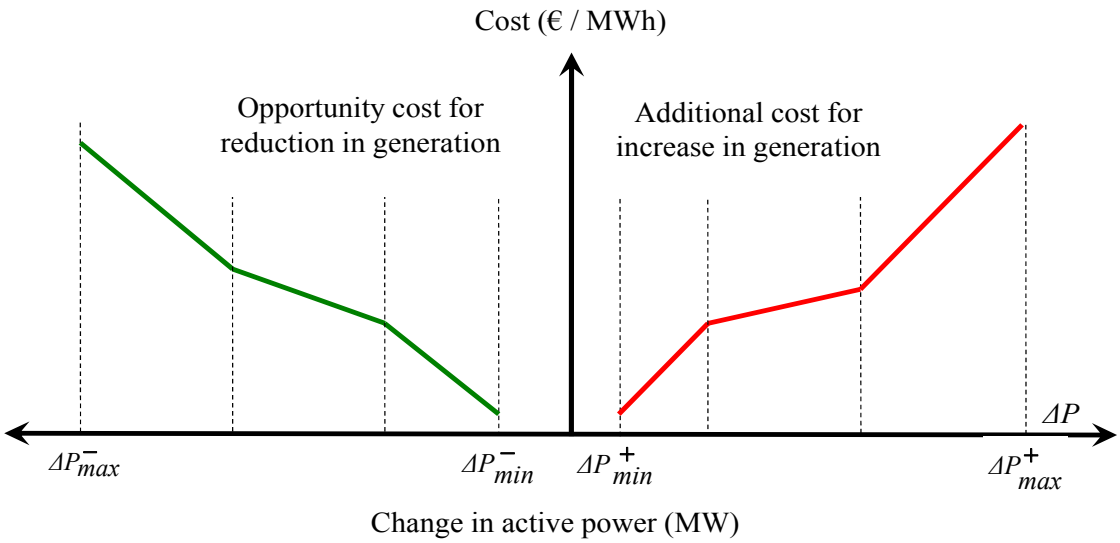

Figure 4.19 Opportunity and additional costs for generation changes

In Figure 4.19 multi-stage linear bidding for opportunity cost (for a reduction in generation with the limits $(\Delta P^{-}_{min}, \Delta P^{-}_{max})$) and additional cost above the market clearing price (for increase in generation within limits $(\Delta P^{+}_{min}, \Delta P^{+}_{max})$) is shown. In each stage, the corresponding cost clearly specified to simplify the objective function formulation. The problem is formulated as cost minimization objective function. CCT characterizing

transient stability and MDO characterizing oscillatory stability are considered as additional constraints in the optimization process and estimated using offline trained ANN. Constraints handling method is achieved using a self-adaptive penalty function based algorithm described in section 4.3.3.2. In the formulation, we assume that additional costs are required only for participant's active power rescheduling and there are no costs for other control variables such as transformer tap-settings and reactive power sources rescheduling. However, the cost function can be extended with additional cost associated with other control variables. The aggregated objective cost function for each time step based on opportunity and additional costs for active power rescheduling can be mathematically formulated as:

$$\text{Minimize}: C_d = \sum_{i=1}^{N_{d1}} f_i(\Delta P_i^+) + \sum_{j=1}^{N_{d2}} f_j(\Delta P_j^-) \tag{4.41}$$

The cost minimization problem is subject to all power flow constraints and dynamic stability constraints presented in equations 4.26 – 4.34. Where, C_d is the total additional and opportunity costs, f_i and f_j are the cost based on participant's bids to increase or decrease the scheduled level respectively. ΔP_i^+ and ΔP_j^- are the increase and decrease in scheduled power. N_{d1} and N_{d2} are the number of participants whose energy is increased or decreased respectively. The procedure can operate the stabilization of a single contingency at a time (the most critical one) or of a selected set of harmful contingencies simultaneously where the final solution should make all potentially critical contingencies stable with the necessary safety margin at the same time.

4.7.4 Application of Proposed framework

The implementation of the proposed framework is illustrated through the PST16-Machine test system presented in Appendix A.1. A highly stressed

operating point is selected to investigate the suitability of the proposed framework in dynamic stability enhancement. The real-time balancing market, in which all suppliers paid the same market-clearing price, is considered as an initial schedule. An abnormal condition is assumed with unexpected disconnection of two transmission lines simultaneously from area B (line B13-B14) and (line B4-B9) where the prepared control action are not able to stabilize the system at all expected critical contingency set. At the selected operating point, the CCT is found to be 82.6 milliseconds with three-phase fault at bus A2 in area A and the corresponding MDO is 1.02%. The target for a dynamic stable operation is assumed 150-millisecond uniformly for all circuit breakers in the system and the acceptable MDO is 4%. To enhance the dynamic stability, the online scheduling market is implemented and the pre-submitted energy bids from GENCOs and consumers are used.

All GENCOs connected to the power system are assumed to provide the necessary reactive power service to support the grid voltage without additional costs and all GENCOs participate in the market. In addition, two consumers from each Area are participating in the competition for surplus. The optimization searches within the no-cost counter-measures that include reactive power and transformer tap-sittings to reduce the total cost required during active power rescheduling. However, sometimes only reactive power rescheduling is required to enhance system dynamic stability. The opportunity and additional cost coefficients ($\alpha_d, \beta_d, \alpha_u, \beta_u$) and acceptable limits of change in scheduled power are presented in Appendix A.6.

The considered system control variables are 66 control variables during optimization process; these variables contain 22 changes of participant's active power, 16 generators reactive power and 28 transformers tap-settings. The step size for adjusting all transformer tap settings are 0.005 per unit for their

adjustable voltage range between 0.90 and 1.10 per unit. Table 4.2 presents the value of transformers tap settings before and after rescheduling process for dynamic stability enhancement respectively. Figure 4.20 shows the progress of the total cost of the global best particle minimization during optimization process. Figure 4.20 presents the ability of PSO to minimize the total cost within few numbers of iterations, which helps to follow the online application of the proposed framework. Figure 4.21 and Figure 4.22 present the change of CCT and MDO of the global best particle to achieve the required dynamic stability limits. Figure 4.23 shows the change in the scheduled active power of all participants to enhance the dynamic stability with minimum payments.

Table 4.2 Per unit tap settings of transformers before and after rescheduling

Transformer name	Taps before rescheduling	Taps after rescheduling	Transformer name	Taps before rescheduling	Taps after rescheduling
T1	1.025	0.960	T15	1.005	1.002
T2	1.000	0.950	T16	0.995	1.025
T3	1.025	1.025	T17	0.975	1.005
T4	1.050	1.025	T18	1.025	1.025
T5	1.030	1.000	T19	0.985	1.025
T6	0.950	1.025	T20	1.025	1.000
T7	0.995	1.000	T21	1.005	1.005
T8	0.985	1.020	T22	1.030	1.030
T9	0.955	1.005	T23	1.020	1.020
T10	1.015	1.030	T24	1.050	1.025
T11	1.020	1.020	T25	1.025	0.975
T12	1.020	1.020	T26	1.025	1.000
T13	1.025	1.005	T27	1.050	0.970
T14	1.015	1.020	T28	1.025	1.050

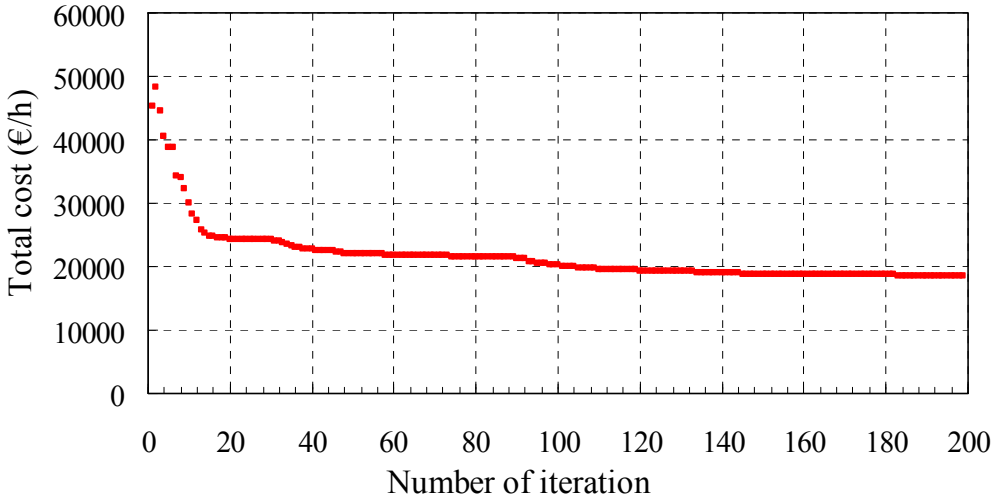

Figure 4.20 The total cost function during optimization process

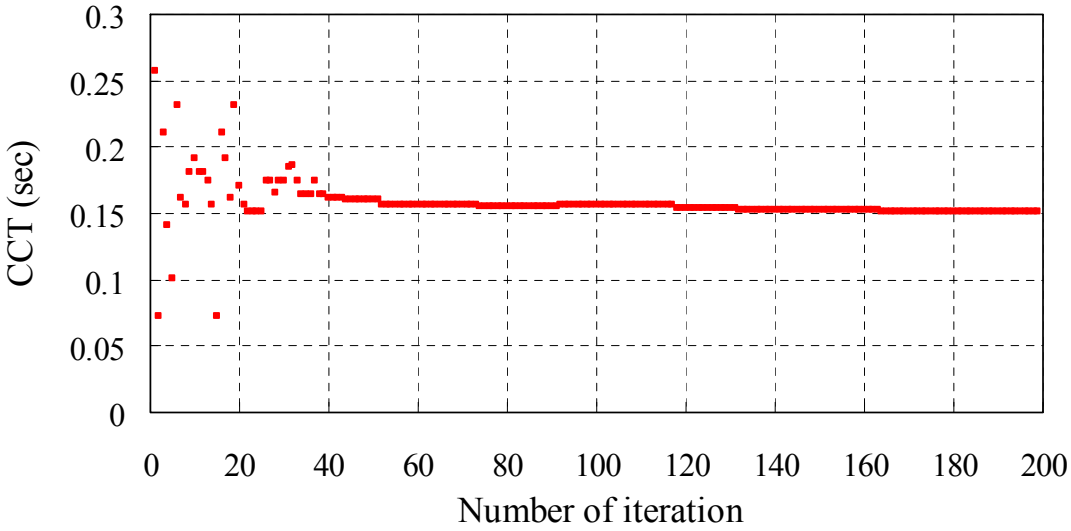

Figure 4.21 Change of CCT at most critical contingency

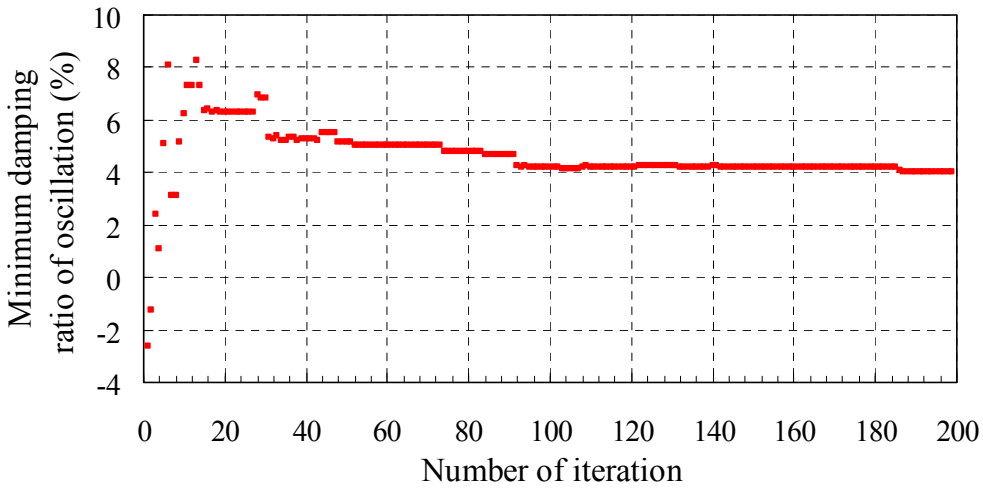

Figure 4.22 Change of MDO at most critical contingency

The positive sign refers to the increasing of the power level and the negative sign refers to the decreasing of power level. According to the results, there are no changes in the scheduled power of three GENCOs to satisfy the minimum limit of change in schedule power.

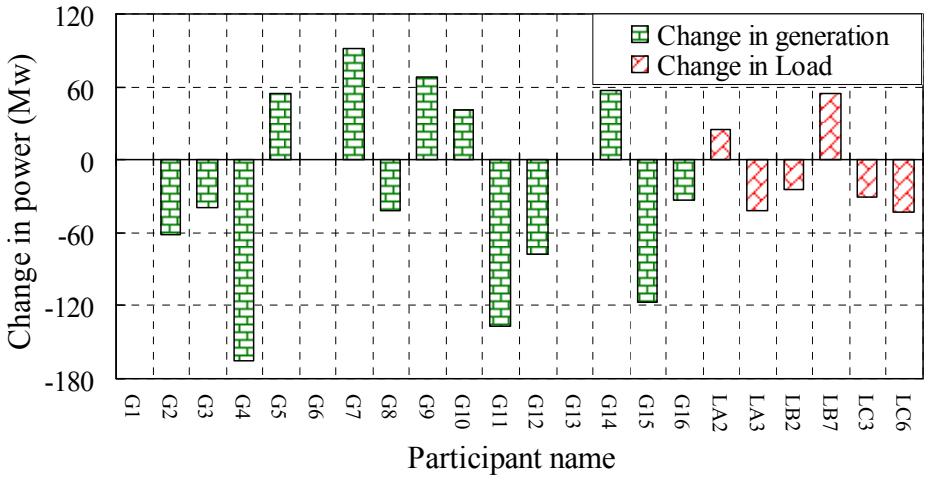

Figure 4.23 Change in scheduled power to enhance the dynamic stability

After rescheduling, the dynamic stability enhanced and the required limits are satisfied. The total costs required to be paid to participants in the market is 18579.89 €/h. The proposed framework is successfully applied to enhance the dynamic stability. Figure 4.24 presents the payments for participants after clearing the market to enhance the system dynamic stability.

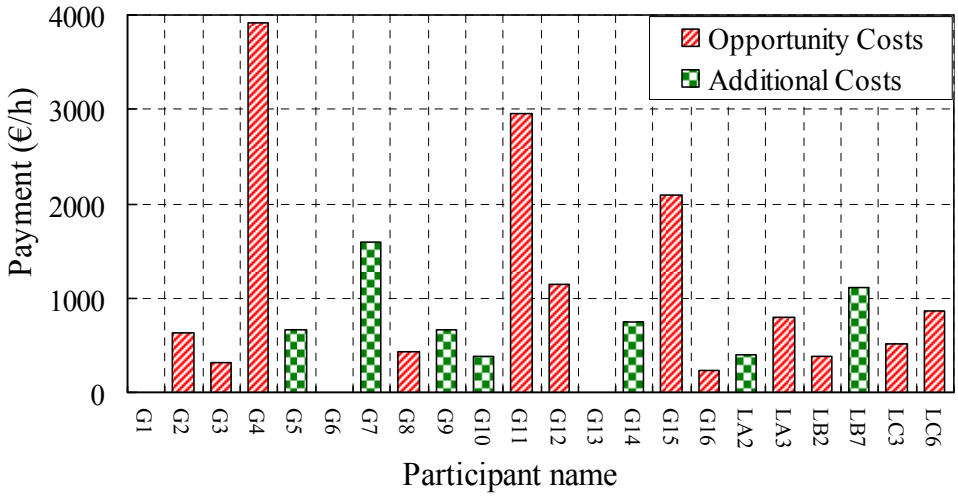

Figure 4.24 The payments for participants based on their energy bids

Chapter 5
Conclusion

5.1 Summary and Conclusion

This thesis focuses on the most extremely important aspects related to power system stability, particularly dynamic stability assessment and enhancement. Power system dynamic stability is absolutely crucial for operation of liberalized and vertically integrated modern power system where power system operation faces greater uncertainties and fluctuations than in the past. Fast and effective tool for assessment of power system stability is well developed in this dissertation for online applications. Enhancing of power system stability in deregulated power system and vertically integrated power system is achieved based on online rescheduling strategy process.

The main contributions of this dissertation can be summarized as follows:

5.1.1 Dynamic Stability Investigation

In the study, the power system dynamic stability investigated based on the system transient stability and oscillatory stability. The level of transient stability deduced from the values of the critical fault clearing time (CCT) of the system for per-selected set of credible disturbances. The minimum damping of oscillation (MDO) corresponding to a pre-selected set of small disturbances considered as indicator for small signal stability assessment (oscillatory stability). The CCT and the MDO are presenting valuable information for ISO/TSO about the distance of the current operating scenario of operation from the system stability limits. During the preparation of the collected data, where

the complete power system model and the required computation time are available, detailed time domain simulation is used to describe the dynamic behavior of power system and to calculate CCT at each contingency. Bisection technique is implemented to shortage the time of calculation during applying time domain simulation to calculate CCT.

Similarly, the oscillatory stability assessment can be performed analytically by eigenvalue computation from the linearized system model using modal analysis. In order to account the possible error in oscillatory stability assessment due to the linearization process and change of nature of the small disturbances, Prony analysis is applied on the time response of generators active power to estimate the MDO during a small disturbance at the pre-selected set of fault locations. The generated active power is selected because of the system oscillations are mainly due to the power imbalance between swinging generators. Prony analysis is used to obtain the parameters of the exponentially modulated sinusoidal signals of the time response of electrical signals following a small disturbance. This method also is important for large-scale power system where the detailed information may be not available and the computations are time-consuming. Expert knowledge and computation time which are required for applying time domain simulation for transient stability assessment and Prony analysis for oscillatory stability assessment limit their application in online applications.

In this dissertation, the computational intelligent techniques successfully applied to map the nonlinearity of the system for online applications. Therefore, the first focus of this dissertation was the development of new tools based CI applications for fast online TSA and OSA, which can be used as online tools by TSO/ISO to evaluate system states.

5.1.2 Dynamic Stability Assessment by using Computational Intelligence

Computational intelligence selected to develop tool for dynamic stability assessment because of its ability to generalize and map the complex relationships using a very small portion of all possible inputs in the problem space. It does not require a complete system model where the outputs are directly related to the stability problem. ANN as an efficient computational intelligence tool is selected to map the system dynamics for transient stability assessment and oscillatory stability assessment. Dynamic stability assessment using ANN provides a fast indicator for system state. This helps to account the effect of harmful situation by preparing a pre-contingency solution such as changing load levels and generators output power to maintain a stable system operation. ANN applied as a fast and robust tool for the TSA and OSA to monitor the dynamic stability of a power system with a reasonable degree of accuracy. Before designing ANN, the training data must be generated to cover all the expected operating scenarios in order to enhance the accuracy of interpolations during actual application of the trained ANN. The training data are generated to cover all the expected situations from the viewpoint of load level, system topology and fault location. Optimal power flow has been used to ensure the generation of feasible training data within typical operating limits of power system considering all system constraints. Feature selection is very important for accurate ANN design. There are huge number of available input features, which can be obtained from the large scale power systems. To ensure the selection of the most important features, input features selected in two stages. In the first stage, initial feature sets selected based on engineering judgments and network experiences. In the second stage, features selected from the initial sets in three steps:

Step 1: The generators terminal voltages immediately after a single step integration fault are proposed as important input features. These features selected to characterize the fault locations and the severity of the fault on the dynamic behavior of generators.

Step 2: New indication factors, specifying the power distributions among each area within the entire system have been proposed based on the capacity and inertia of generators in each area. These features are important to characterize the disconnection of generators during faults.

Step 3: A systematic feature selection algorithm based on clustering analysis is used to select the most important features from the rest of initial selected feature sets. K-means based Euclidean distance clustering algorithm selected for its simplicity and efficiency in a variety of applications. Different number of features selected based clustering algorithm. Iterative process used to select the best ones, which enhance the accuracy of the ANN for dynamic stability assessment.

Once the input-output patterns combined and arranged, two feed-forward ANNs trained for TSA and OSA using back-propagation algorithm. Back-propagation training algorithm of Levenberg-Marquardt optimization based for weights and biases updating is selected because it provides a fast convergence and a better performance. Matlab software is used in ANN modeling. The modeling of ANN depends on the interrelationship between the selected input features and targets and should be specified iteratively. The computed CCT by using TDS and MDO, which is calculated by using DSI toolbox are used as targets during ANN training and performance evaluation based estimation errors are used to verify the quality of the estimation of CCT and MDO by ANN. The results clarify that ANN can be successfully used in estimation of CCT and MDO to assess the dynamic stability effectively in online application.

The second focus of this dissertation was the enhancement of power system dynamic stability. In the case of a critical situation, The ISO also would like to know how to prevent the system from collapse and which action will be suitable in case of the prepared actions are not able to stabilize the system. Rescheduling process and load curtailments are the common way to stabilize the system during abnormal operating conditions.

Particle swarm optimization has been used as optimization tool to guarantee the minimum cost for dynamic stability enhancement throughout the dissertation. A modified self-adaptive penalty function is used to account all system constraints including dynamic stability. Two Offline trained ANNs are used to estimate the CCT and MDO as indices for DSA. During optimization, the feasible solution will be ever preferable during selection of local and global best particles. Therefore, a comparison strategy proposed for selecting the best individuals during the iterative optimization process.

5.1.3 Dynamic Stability Enhancement in Vertically Integrated Electric Utility

In case of classical electricity pool market, the market is cleared economically where the most efficient energy sources are dispatched subject to the network constraints for minimum cost of generation. With existing of harmful contingency, control action should be used to stabilize the system with minimum increase of the total generation cost. In this dissertation, a generation rescheduling based sensitivity analysis has been used to shift part of the power generated from the most critical machines to the non-critical machines. Therefore, time response of rotor angles used to classify all generators into certain number of coherent groups. The generation from critical generators is decreased to reduce their rotor acceleration while generation from the non-

critical machines should increase to keep the total consumption constant. The amount of shifted power distributed among generators in each selected group by using a sensitivity factors, which based on their inertia coefficients and the rated capacities. These sensitivity factors created in order to get the optimal solution very fast. The solution can be obtained also with considering the generated power from the selected generators as variables. The objective is to minimize the increase in the total cost of generation due to the deviation from the economic dispatch solution. Particle swarm optimization used as optimization tool where all system constraints including dynamic stability constraints are considered by using self-adaptive penalty function. The proposed method is applied on the PST16 and the results shows that the swarm converges very fast to a feasible solution with enhanced dynamic stability.

The main contribution of this dissertation is the development of a framework for dynamic stability enhancement based online market strategy. The online market proposed for fair and non-discriminated energy reallocation among participants in competitive electricity markets.

5.1.4 Dynamic Stability Enhancement in Deregulated Power Systems

5.1.4.1 Real-Time Balancing Market Considering Dynamic Stability Enhancement

In this study, considering dynamic stability assessment as an integral work during real time balancing market has been proposed. Real-time balancing market considering dynamic stability enhancement has been established to determine the re-dispatched generated power, the power reserve arrangement and load curtailments simultaneously in a competitive manner. The market is implemented where bilateral contract owners submit a compensative price for

accepting curtailments in their cleared transactions in energy markets. Consumers and suppliers submit their offers to re-dispatch the cleared transactions from energy market for surplus. In addition, ISO manages the power reserve during the real time balancing market to obtain acceptable level of power reserve. PSO has been used to obtain the optimal solution, which accounts the power unbalancing and dynamic stability enhancement. The vector of control variables is including the offered energy bids of all participants and all online available control variables such as transformers tap-settings and reactive power resources.

5.1.4.2 Dynamic Stability Enhancement during Unpredicted Abnormal Conditions

In modern power systems, the control actions are never accounting all possible abnormal operating states. Therefore, a new online market proposed for accurate operating decisions to enhance system stability in case those available control actions are insufficient. New online market implemented in case of previously prepared control actions are insufficient to stabilize the system during abnormal situations. This market implemented to specify new counter-measures to stabilize the system with minimum payments. In the proposed market, all suppliers and consumers have equally chance to participate in the market with offers describe the willing to change the scheduled transaction from real time balancing market for surplus. The offered bids should describe clearly the amount of the power to be rescheduled and the corresponding requested cost. The participants in the market whose schedule decreased may be paid an opportunity cost for applying the required reduction in generation or demand. At the same time participants whose schedule are increased will be paid based on the real time balancing market clearance prices beside additional cost may be

paid for applying the required change. The optimization process starts with the free costs counter-measures, which include reactive control facilities before energy re-allocations among participants. The market cleared with specifying the amount of shifted power between participants and the corresponding amount of money to be paid for each participant for dynamic stability enhancement.

The application of DSA using ANN applied successfully on the pool markets and deregulated markets to enhance the system stability. The results verified where the power system operates at the new operating point with enhanced the system damping and transient stability. Therefore, a power system could be made more stable and robust against larger disturbances with applying the proposed strategy of online market based generation rescheduling. This strategy helps to determine the timing and the amount of remedial control actions to anticipate the unpredicted abnormal operating conditions at the time of detection.

5.2 Future Directions

The rapidly increase of the electric power industry develops many reasons for system instability. Therefore, the assessment and the enhancement of power system stability still an active research area. The ultimate goal of this research is to develop robust and fast assessment tool for all categories of system stability together with the necessary framework, which can be used to enhance the power system stability during all operating scenarios. The following are suggestions for future research direction in this area:

1. This dissertation proposed algorithm to solve the power system transient and oscillatory stability. This research work may be extended to include several aspects of power system stability

assessments and security monitoring in the context of computational intelligence applications.

2. The proposed framework should be applied on large-scale power system, where the system can be divided into multiple regions to enhance the accuracy of ANN to estimate the enclosed stability aspects in each region. This should be accomplished with developing a methodology to account the effect of stability of each region on the other regions during implementing ANN.
3. ANN is selected as a computational intelligence algorithm for dynamic stability assessment. The work can be extended to compare various computational intelligence methods to enhance the accuracy of dynamic stability enhancement.
4. The search can be extended to include the security-related components in the price of transmission services.
5. In this work, only active power rescheduling is considered. Therefore, studying the issue of affecting of reactive power providers pricing on system stability by exercising market power and indulging in gaming can be investigated.

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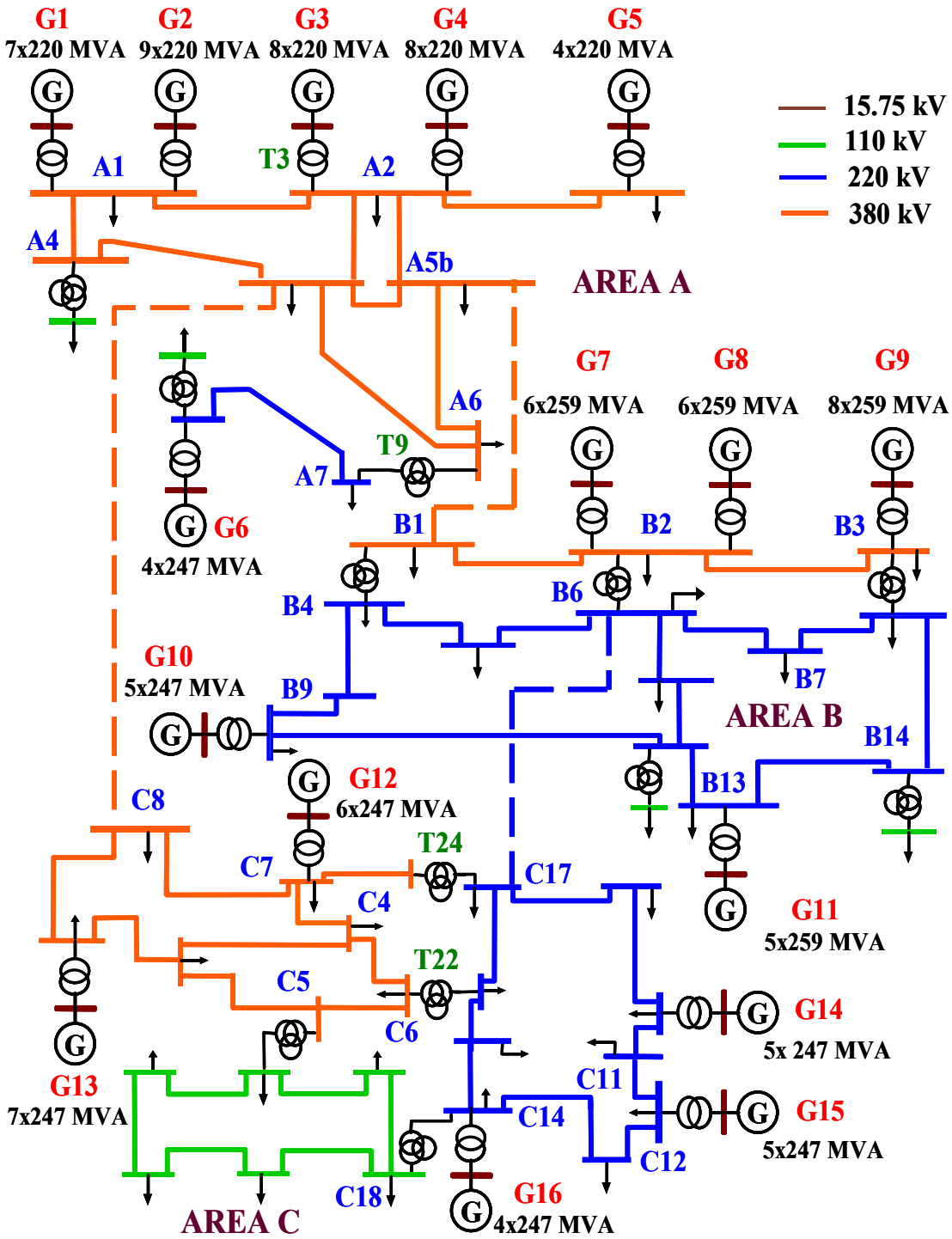
Appendix

A.1 The 16-Machine Dynamic Test System

A.1.1 General Description

The PST 16-Machine Test System used in this study is developed to study the power system dynamics. The main focus of this system is on the power system dynamic stability in the time range of a few seconds to minutes. The PST 16-machine Test System is modelled by using real data from new generators and controllers for different units. The power system is assumed to operate with two different types of generators, which are hydro power generators and thermal driven generators. For hydro generators, the rated generator power is 220 MVA per unit. For thermal driven generators, the block size is 247 MVA or 259 MVA. However, a power plant in the network is modeled by connecting a particular number of generating units at the station to the transmission system. The generator models are 5th order and the exciter models are obtained from IEEE standard type. Herby, the hydro generators are controlled by a slightly modified version of AC1A exciter model. The thermal driven generators use the DC1A exciter model. The system consists of three areas, which are connected through long tie- lines to study the effect of stress on the power system operation. Each area has 5 or 6 generators. However, the system is designed for power exchange between these areas. The Area A is considered to export power to the other two Areas at the normal load level. The total voltage levels cover the 380 kV, 220 kV, and the 110 kV level.

A.1.2 One-Line Diagram of PST16 Test System



A.1.3 Distribution of System Electrical Equipment

	Buses	Lines	Transformers	Generators
Area A	17	13	9	6
Area B	21	16	10	5
Area C	28	25	9	5
Total	66	54	28	16

A.1.4 Distribution of Generators and Level of Load and Generation

	Number of Generators		Generation MW	Load MW
	Thermal	Hydro		
Area A	5	1	8028	2000
Area B	3	2	7710	6100
Area C	2	3	6669	7465
Total	10	6	22407	15931

A.2 Cost Coefficients and Economic Generation for Electricity Pool Market Operation

	Initial Operating Point		α €/h	β € / MWh	γ € / MWh^2
	P_g (MW)	Q_g (MW)			
G1	0690.8	76.892	25	12	0.009
G2	0624.4	75.395	40	13	0.0092
G3	1600.0	218.40	25	10	0.00076
G4	0996.3	170.28	30	10	0.007
G5	0500.0	59.273	22	13	0.008
G6	0680.0	243.61	24	12	0.0085
G7	0918.3	330.23	20	11.4	0.0095
G8	0942.4	325.47	21	11.7	0.009
G9	1285.7	356.35	40	11	0.007
G10	0823.3	236.29	22	13.5	0.0094
G11	0942.3	147.58	17	11.9	0.009
G12	1244.7	295.16	14.5	10	0.007
G11	1650.0	139.40	35	9	0.00085
G14	1100.0	301.81	23	11	0.0008
G15	0804.0	101.46	17	11.5	0.009
G16	0858.2	324.69	22	13	0.008

A.3 Initial Schedules for Open Access Energy Market Generation

	Generation Capacity		Spot Market (MW)	Bilateral Contract (MW)	Operating Reserve (MW)
	P_{max} (MW)	P_{min} (MW)			
G1	1450	500	925.62	075.0	0.000
G2	1450	600	920.51	080.0	0.000
G3	1650	650	1000.7	0.000	50.00
G4	1650	650	1000.2	0.000	100.0
G5	1050	200	500.18	0.000	50.00
G6	1150	300	500.8	0.000	200.0
G7	1450	600	920.4	400.0	0.000
G8	1450	600	1020.7	300.0	0.000
G9	2000	400	661.42	0.000	0.000
G10	1150	500	990.78	0.000	100.0
G11	1200	500	1145.5	0.000	240.0
G12	1600	500	1220.3	0.000	210.0
G11	1400	500	1220.5	0.000	150.0
G14	0950	300	0600.2	300.0	0.000
G15	1150	500	1079.9	0.000	150.0
G16	0900	300	0397.7	400.0	0.000
L1	400.0	100	125.60	75.0	-
L2	400.0	70	140.00	080.0	-
L3	1000.0	300	260.00	400.0	-
L4	700.0	200	140.00	300.0	-
L5	800.0	200	360.00	300.0	-
L6	800.0	200	150.00	400.0	-

A.4 Offers of Participants in Real-time Balancing Market

	Supplemental Bids						Reserve Replacement			Bilateral Contract Curtailment		
	Increase		Decrease		ΔP_{max} (MW)	ΔP_{min} (MW)	Bids		ΔP_{res} (MW)	Bids		ΔP_{bc} (MW)
	€ / MWh	€ / MWh^2	€ / MWh	€ / MWh^2			€ / MWh	€ / MWh^2		€ / MWh	€ / MWh^2	
G1	4	0.154	5	0.202	-150	200	6	0.164	150	10	0.204	-050
G2	3.0	0.156	4	0.213	-150	200	5.0	0.158	150	6	0.201	-050
G3	2.5	0.146	4.5	0.250	-100	250	3.6	0.186	150	8	-	0.0
G4	3.0	0.132	4	0.224	-200	250	4.1	0.162	150	7	-	0.0
G5	3.9	0.158	4.9	0.214	-150	150	-	-	100	6	-	0.0
G6	4.0	0.17	5	0.284	-100	150	4.8	0.198	150	8	-	0.0
G7	3.5	0.123	4	0.292	-150	050	4.6	0.153	0.0	10	0.216	-150
G8	4.3	0.134	5	0.296	-150	100	6.3	0.164	0.0	14	0.194	-100
G9	3.0	0.102	4	0.212	-200	300	-	-	200	13	-	0.0
G10	4.3	0.156	4	0.280	-100	100	-	-	050	15	-	0.0
G11	2.8	0.138	3.8	0.285	-150	0.0	5.8	0.178	0.0	12	-	0.0
G12	3.6	0.162	3.6	0.218	-150	150	4.6	0.182	160	13	-	0.0
G11	3.4	0.124	4.4	0.209	-150	150	-	-	0.0	14	-	0.0
G14	4.3	0.128	3.3	0.290	-150	050	5.8	0.158	0.0	15	0.228	-150
G15	4.6	0.136	2.6	0.231	-150	050	5.6	0.116	0.0	12	-	0.0
G16	3.0	0.13	2.5	0.218	-150	050	-	-	0.0	13	0.25	-100
L1	17.0	0.401	19.5	0.792	100	0.0						
L2	15.30	0.514	21.9	0.800	080	0.0						
L3	18.5	0.665	23.5	0.520	050	0.0						
L4	16.00	0.725	23.0	0.79	070	0.0						
L5	18.9	0.532	25.9	0.685	100	0.0						
L6	17.0	0.449	20.0	0.558	100	0.0						

A.5 Real-Time Market Clearances With and Without DSA

	Initial Schedule (MW)	Schedule without DSA		Schedule with DSA	
		(MW)	Surplus (€/h)	(MW)	Surplus (€/h)
G1	1000.2	1001.53	593.45	960	527.44
G2	1000.8	944.75	1791.85	997.09	1957.22
G3	1000.7	1012.28	705.84	985.7	577.39
G4	1000.2	1103.29	10.53	910.7	73.98
G5	500.18	548	908.55	489.36	78.07
G6	500.8	493.21	54.311	516.48	104.52
G7	1320.4	1329.44	41.69	1355.5	274.39
G8	1320.74	1297.8	270.45	1333.65	77.846
G9	661.42	668.4	448.67	631.74	738.73
G10	990.78	987.94	13.62	1040.92	607.79
G11	1145.5	1145.5	0	1145.5	0
G12	1220.3	1218.81	696.56	1179.47	56.77
G13	1220.5	1372.5	7.30	1218.36	10.37
G14	900.2	900.2	0.0	888.25	80.61
G15	1079.9	1090.2	61.40	1059.24	151.49
G16	797.74	782.34	90.20	735.63	996.2
L1	200	200	0	150.6	2955
L2	220	170	0	170	0
L3	660	660	0	610	2475
L4	440	440	0	390	3125
L5	660	660	0	660	0
L6	550	550	0	550	0
Total Cost (€/h)			5694.424		14867.82

A.6 The energy bids of participants and cost coefficients

Participants names	ΔP^{max} MW	ΔP^{min} MW	α_u € / MWh	β_u € / MWh^2	α_d € / MWh	β_d € / MWh^2
G1	150	10	5	0.154	5	0.3
G2	150	10	3	0.156	2.7	0.12
G3	150	10	2.5	0.146	2.5	0.14
G4	150	10	3	0.132	2.1	0.13
G5	150	10	3.9	0.158	2.9	0.21
G6	200	15	4	0.17	3.8	0.22
G7	200	15	2.5	0.163	4	0.29
G8	200	15	4.3	0.144	3.5	0.23
G9	200	15	3	0.102	2.7	0.21
G10	100	20	4.3	0.276	2.7	0.17
G11	100	20	2.8	0.258	2.2	0.14
G12	100	20	3.6	0.162	2.3	0.16
G13	100	20	4.2	0.364	4.4	0.28
G14	100	20	4.28	0.158	3.28	0.29
G15	100	20	4.56	0.156	2.56	0.13
G16	100	20	3	0.15	2.5	0.15
LA2	75	5	11.2	0.21	9.5	0.32
LA3	75	5	10.3	0.284	7.6	0.27
LB2	75	5	12.5	0.265	9.1	0.28
LB7	75	5	9	0.215	8	0.39
LC3	75	5	12.9	0.212	7.7	0.29
LC6	75	5	13	0.289	8.5	0.26

List of Abbreviations

CCT	Critical Fault Clearing Time
TSA	Transient Stability Assessment
MDO	Minimum Damping of Oscillations
OSA	Oscillatory Stability Assessment
ANN	Artificial Neural Network
TDS	Time Domain Simulation
CI	Computational Intelligence
TSO	Transmission System Operator
ISO	Independent System Operator
FACTS	Flexible AC Transmission System
HVDC	High-Voltage Direct Current
DSCOPF	Dynamic Stability Constrained Optimal Power Flow
DSA	Dynamic Stability Assessment
TEF	Transient Energy Function
PSD	Power System Dynamic Simulation Software
DSI	Dynamic Stability Identification software
PSO	Particle Swarm Optimization
GENCO	Generation Company
PST16	16-Machine Dynamic Test System

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List of Publications

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