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Optimal allocation of static and dynamic reactive power support for enhancing power system security

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Optimal allocation of static and dynamic reactive power support for enhancing power system security

by

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NOMENCLATURE

SETS

B, *G*, *D*, *C*	Buses, generators, Loads, controls
CON, *SCON*	Contingency, Severe contingency
I	Discretization step

PARAMETERS

NB, *ND*	Number of buses, load buses
NG, *NC*	Number of generator buses, candidate control buses
Nt	Total number of finite elements
t_0, t_{cl}, t_s, t_f	Initial time, Fault clearing time, time to reach steady state, final time
C_{fc}, C_{vc}	Fixed and variable VAR cost at control bus *c*
Q_{cc}, Q_{ic}	Capacitive Q_c and inductive Q_i at control bus *c*
M_g	Inertia coefficient of generator *g*
ρ^L, ρ^U	Rotor angle lower and upper stability limit
$\underline{V}_b$, $\overline{V_b}$	Lower and upper limit of voltage at bus *b*
$\underline{Q}_{ic}$, $\overline{Q_{cc}}$	Lower and upper inductive and capacitive limit at control bus *c*
$\underline{P}_G$, $\overline{P_G}$, $\underline{Q}_G$, $\overline{Q_G}$	Lower and upper limit of real and reactive power generation by a generator

VARIABLES

x, y, u, w	State, algebraic, control, and binary
τ_i	Duration of unacceptable low voltage
δ_g	Rotor angle of generator *g*
δ_{COI}	Position of inertial center
V_b	Voltage at bus *b*
P_G, Q_G	Real and reactive power generation by a generator
Q_{ic}, Q_{cc}	Inductive and capacitive installation at control bus *c*

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ABSTRACT

Power systems over the recent past few years, has undergone dramatic revolution in terms of government and private investment in various areas such as renewable generation, incorporation of smart grid to better control and operate the power grid, large scale energy storage, and fast responding reactive power sources. The ongoing growth of the electric power industry is mainly because of the deregulation of the industry and regulatory compliance which each participant of the electric power system has to comply with during planning and operational phase.

Post worldwide blackouts, especially the year 2003 blackout in north-east USA, which impacted roughly 50 million people, more attention has been given to reactive power planning. At present, there is steady load growth but not enough transmission capacity to carry power to load centers. There is less transmission expansion due to high investment cost, difficulty in getting environmental clearance, and less lucrative cost recovery structure. Moreover, conventional generators close to load centers are aging or closing operation as they cannot comply with the new environmental protection agency (EPA) policies such as Cross-State Air Pollution Rule (CSAPR) and MACT. The conventional generators are getting replaced with far away renewable sources of energy. Thus, the traditional source of dynamic reactive power support close to load centers is getting retired. This has resulted in more frequently overloading of transmission network than before. These issues lead to poor power quality and power system instability. The problem gets even worse during contingencies and especially at high load levels.

There is a clear need of power system static and dynamic monitoring. This can help planners and operators to clearly identify severe contingencies causing voltage acceptability problem and system instability. Also, it becomes imperative to find which buses and how much are they impacted by a severe contingency. Thus, sufficient static and dynamic reactive power resource is needed to ensure reliable operation of power system, during stressed conditions and contingencies. In this dissertation, a generic framework has been developed for filtering and ranking of severe contingency. Additionally, vulnerable buses are identified and ranked.

The next task after filtering out severe contingencies is to ensure static and dynamic security of the system against them. To ensure system robustness against severe contingencies optimal location and amount of VAR support required needs to be found. Thus, optimal VAR allocation needs to be found which can ensure acceptable voltage performance against all severe contingency. The consideration of contingency in the optimization process leads to security constrained VAR allocation problem. The problem of static VAR allocation requirement is formulated as minlp. To determine optimal dynamic VAR installation requirement the problem is solved in dynamic framework and is formulated as a Mixed Integer Dynamic Optimization (MIDO).

Solving the VAR allocation problem for a set of severe contingencies is a very complex problem. Thus an approach is developed in this work which reduces the overall complexity of the problem while ensuring an acceptable optimal solution. The VAR allocation optimization problem has two subparts i.e. interger part and nonlinear part. The integer part of the problem is solved by branch and bound (B&B) method. To enhance the efficiency of B&B, system based knowledge is used to customize the B&B search process.

Further to reduce the complexity of B&B method, only selected candidate locations are used instead of all plausible locations in the network. The candidate locations are selected based upon the effectiveness of the location in improving the system voltage.

The selected candidate locations are used during the optimization process. The optimization process is divided into two parts: static optimization and dynamic optimization. Separating the overall optimization process into two sub-parts is much more realistic and corresponds to industry practice. Immediately after the occurrence of the contingency, the system goes into transient (or dynamic) phase, which can extend from few milliseconds to a minute. During the transient phase fast acting controllers are used to restore the system. Once the transients die out, the system attains steady state which can extend for hours with the help of slow static controllers.

Static optimization is used to ensure acceptable system voltage and system security during steady state. The optimal reactive power allocation as determined via static optimization is a valuable information. It's valuable as during the steady state phase of the system which is a much longer phase (extending in hours), the amount of constant reactive power support needed to maintain steady system voltage is determined. The optimal locations determined during the static optimization are given preference in the dynamic optimization phase.

In dynamic optimization optimal location and amount of dynamic reactive power support is determined which can ensure acceptable transient performance and security of the system. To capture the true dynamic behavior of the system, dynamic model of system components such as generator, exciter, load and reactive power source is used. The approach developed in this work can optimally allocate dynamic VAR sources.

The results of this work show the effectiveness of the developed reactive power planning tool. The proposed methodology optimally allocates static and dynamic VAR sources that ensure post-contingency acceptable power quality and security of the system. The problem becomes manageable as the developed approach reduces the overall complexity of the optimization problem. We envision that the developed method will provide system planners a useful tool for optimal planning of static and dynamic reactive power support that can ensure system acceptable voltage performance and security.

CHAPTER 1. INTRODUCTION

1.1 Motivation

Power systems over the recent past few years, has undergone dramatic revolution in terms of government and private investment in various areas such as renewable generation, incorporation of smart grid to better control and operate the power grid, large scale energy storage, and fast responding reactive power sources. The ongoing growth of the electric power industry is mainly because of the deregulation of the industry and regulatory compliance which each participant of the electric power system has to comply with during planning and operational phase.

In the recent past the power industry got its maximum uphill momentum to improve its age old infrastructure. Some of the main reasons were the year 2003 blackout in Northeast part of USA, and the economic crisis of USA in the year 2008. The post-mortem of year 2003 blackout identified several reasons for the blackout which also included the lack of dynamic reactive power sources in the system, and lack of transmission capacity. In the year 2008, out of several reasons for economic crisis, one of the reason was high oil price. Post economic recession of 2008, the government of USA wanted to reduce its dependency on imported oil. The government proposed a new regulation whereby each state of USA has to have certain percentage of electric generation by renewable energy sources. To encourage private investment in the area of renewable generation the government provided incentives to the private investors. This led to a big reform in the power industry and suddenly there was lot of development in the area of wind and solar generation. The government also provided incentive to the utilities in the area of smart grid. The investment in the area of smart grid was to make use of modern control and communication resources to better manage and operate the age old electric power network. Most of the investment in the area of smart grid is at distribution level and very little at transmission level.

The government incentive for developing renewable generation lured lot of private investors. This resulted in a significant investment and development of renewable generation. The growth of renewable generation was a good development but it also brought lot of operational issues. One of the operational issue was low/high voltage problem. In USA there is a big gap between installed generation and transmission capacity, the later being much less than the former. In the deregulated electric power industry, power system operators want to make maximum use of the available transmission capacity. Thereby, the transmission lines are being operated very close to their thermal limits. The high flow of current on long transmission line leads to more reactive power loss. That means that only a small fraction of reactive power generated at a far away location from the load center can reach the load center. This results in a low voltage at the load center, which may eventually lead to system voltage instability. This problem is a growing concern due to very less incentive towards transmission line expansion because of political and financial reasons. In addition to all these problems there are contingencies in the system such as line outage, transformer outage or generator outage which lead the system to stressed level to the extent of collapse. These all problems lead to instability of power system and are a threat to reliable and secure power delivery.

During a contingency, the system may experience severe voltage dip problem, delayed voltage recovery problem, voltage instability or complete voltage collapse. During past few decades, power industries all over the world have witnessed voltage instability related system failures. In 1965 Northeast blackout in North America, eastern coast interconnection separated into several areas and 30 million people were affected [1]. In the August 14, 2003 Northeast blackout in USA, power supply to 50 million people was interrupted and the financial losses were estimated between $4 billion and $6 billion U.S. dollars [2], [3]. In order to ensure the reliability and stability of power system proper control action is needed.

To ensure acceptable system voltage performance, the nature of voltage problem (static or dynamic) in the system is identified. Once the problem type is identified, system planners have the option of using static and dynamic VAR sources to resolve them. To address static voltage problem static VAR sources are preferred. The preferred approach to address the issue of dynamic voltage instability is installation of dynamic reactive power support close to load centers or in between long transmission lines. Installations of dynamic reactive power device, under Flexible AC Transmission Systems (FACTS), to better operate and control the transmission network is now considered under smart grid program.

Once the nature of voltage problem is identified and the type of VAR device needed to provide reactive power support is selected, the next task is to identify the location to install the VAR device and its amount. Transmission owners want to ensure voltage security of the system but with the minimum investment cost. In order to reduce the overall investment cost of installing VAR sources its important to install them in such a location, where least VAR amount is needed to ensure system voltage security against all severe contingencies. At present there is no industry grade tool for reactive power planning which can solve the optimal VAR allocation problem for a set of severe contingencies. Even to date optimal VAR allocation problem remains an open challenging problem and researchers both in academia and industry are trying to address this complex problem. The problem is a complex one due to its nonlinear nature, coupled with integer problem, and due to its large size which is proportional to the size of power system and the number of severe contingencies.

The main motivation for the research work presented in this dissertation is derived from the real world problems observed by the power system planners and operators. The following are four major problems identified during the study that require close attention:

1. Steady state voltage issues due to contingency that may lead to voltage collapse and shedding of load.
2. Voltage dip and slow voltage recovery after the fault is cleared that may lead to poor power quality, trip wind generators and stall induction motors.
3. Enhancement of existing transmission capacity especially near major load pockets to compensate the lack of transmission expansion.
4. Inefficient and expensive VAR allocation due to lack of industry grade tool.

1.2 Voltage Stability and Reactive Power Allocation

Like any other dynamical system it is advantageous to classify power system stability based upon physical phenomena. In the IEEE/CIGRE report [4], classification of power system stability is done based upon different criteria. Power system stability can be classified based upon:

- Physical nature of instability: rotor angle stability, frequency stability and voltage stability.

- Size of disturbance: small-disturbance stability (load increase) and large-disturbance stability (contingency).
- Time of stability: short-term stability and long-term stability

All the three above mentioned stability problems can lead to system instability [5]. As mentioned above voltage instability has been a cause of several blackouts worldwide [4, 5]. In this work, the focus is on voltage stability related problem. The proposed definition of voltage stability in [5] is:

Voltage stability refers to the capability of a power system for maintenance of steady voltages at all buses in the system subjected to a disturbance under given initial operating conditions.

Contingencies are a major threat to power system stability. In order to ensure system reliability NERC (North American Electric Reliability Corporation)/WECC (Western Electricity Coordinating Council) [6] has a minimum post-disturbance performance specifications with respect to voltage. During a contingency or disturbance, system may experience voltage dip/swell [7]. Excessive voltage deviation from normal permissible limit may cause voltage collapse [8]. Reference [9] summarizes NERC/WECC voltage dip criteria following a fault.

The WECC voltage dip criteria is specified as: (A) no contingency, (B) an event resulting in the loss of a single element, (C) event(s) resulting in the loss of two or more (multiple) elements, and (D) an extreme event resulting in two or more (multiple) elements removed or cascading out of service conditions, as follows:

- NERC Category A: Not applicable.
- NERC Category B: Not to exceed 25% at load buses or 30% at non-load buses.

Not exceed 20% for more than 20 cycles at load buses.

- NERC Category C: Not to exceed 30% at any bus. Not to exceed 20% for more than 40 cycles at load buses.
- NERC Category D: No specific voltage dip criteria.

Figure 1.1 shows the WECC voltage performance parameters with the transient voltage dip criteria clearly illustrated [6]. Again, appropriate power system controls can be utilized to mitigate the post-contingency transient voltage dip problem.

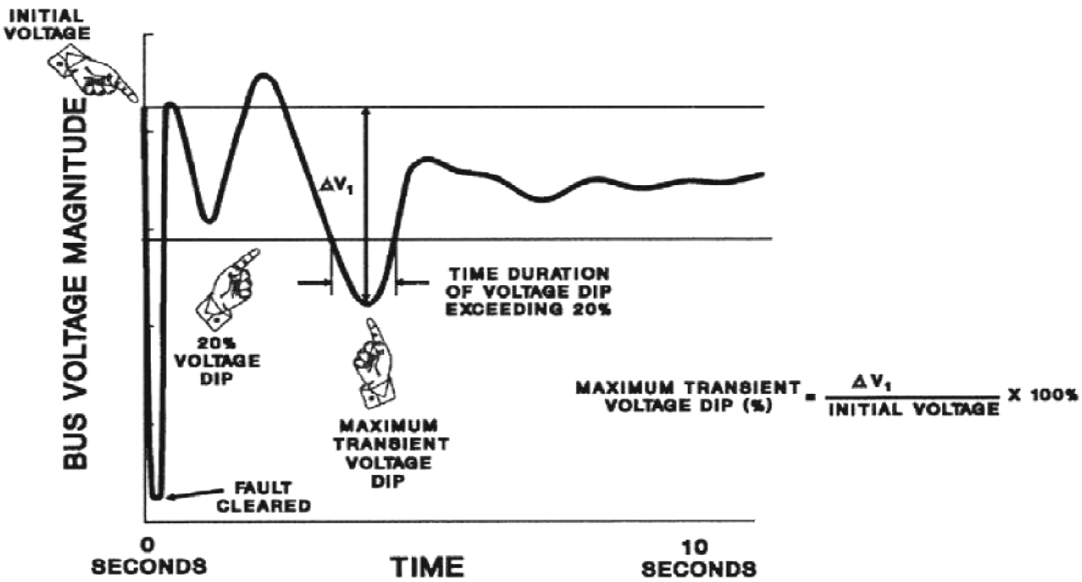

Figure 1.1 Voltage performance parameters for NREC/WECC planning standards.

The major challenge during a contingency is that system reliability and security is maintained without power interruption to consumers. The challenge is to ensure that the system will remain robust even under such large disturbance. The post-contingency system transition to new operating state should not violate dynamic limits and the new operating point should be stable. Incase if this is not the case then we need proper control action to ensure that system limits are respected. There are two commonly used control devices, static such as Mechanically Switched Capacitor (MSC) and dynamic such as SVC and other FACTS devices. The static devices have a slow and discrete response whereas dynamic devices have fast and continuous response. In order to take care of transient voltage dip and short term voltage instability, use of dynamic devices is inevitable.

Mechanically switched capacitors cannot address the problem of transient voltage dip as they can not be switched on or off rapidly and frequently. Once the MSC is switched off it can be switched on again only after a delay of few seconds. On the other hand FACTS devices such as SVC can address this issue very efficiently. The different reactive power support achievable from static and dynamic VAR sources is given in Table 1.1. The cost comparison of static and dynamic VAR sources is shown in Table 1.2. As can be seen from Table 1.1 and 1.2 that cost of providing fast dynamic VAR support is higher than that of static VAR support. In order to ensure the stability and reliability of the system for least cost proper location and amount of VAR support should be determined. The problem of optimal allocation of static VAR support is formulated as mixed integer non-linear problem and that of dynamic VAR support as mixed integer dynamic optimization problem.

Table 1.1 Capabilities of static and dynamic VAR sources.

	Static VAR	Dynamic VAR
Affect on steady state voltage	Yes	Yes
Affect on transient voltage	No	Yes

Table 1.2 Cost comparison of static and dynamic VAR sources.

	Static VAR (MSC at 230kV)	Dynamic VAR (SVC)
Variable cost ($ million/100 MVAR)	0.41	5.0
Fixed cost ($ million)	0.28	1.5

1.3 Objectives

The specific objectives of this research are outlined below:

- To develop an approach to identify severe contingencies and vulnerable buses so that voltage prone areas can be outlined in the network that need reactive power support. Also, the degree and nature of voltage problem is identified to better understand the reactive power support requirements.
- To develop a methodology to better identify optimal locations with reduced integer (location) optimization complexity.
- To develop a methodology for optimally allocating static and dynamic VAR source for a single contingency.
- To develop a methodology with reduced complexity for optimally allocating static and dynamic VAR source for multiple severe contingencies considered simultaneously.

1.4 Contribution of this Dissertation

The research work presented in the dissertation is motivated by the issues and problems faced by system planners in managing acceptable system voltage and security. The following are the major original contributions of this dissertation:

1. This dissertation introduces a systematic methodology by integrating the information obtained from static and dynamic analysis for optimally allocating static and dynamic VAR sources. This results in optimal allocation of static and dynamic VAR sources and enables coordinated use of static and dynamic VAR sources. This minimizes the overall amount of installed VAR sources and maximizes their overall utilization.
2. A methodology is developed to reduce the optimization problem size by considering only a smaller but relevant set of severe contingencies and focusing on areas prone to voltage problem. To do this, *severity indices* based upon static and dynamic voltage response has been proposed and used.
3. A methodology to reduce the complexity of location (integer) problem has been developed. First, out of all plausible locations in the network only few but most effective candidate locations are selected and used in the integer optimization. Second, to solve the integer problem well known B&B method is used. To increase the efficiency of B&B while solving the integer problem, customization of the solver is done.
4. To ensure acceptable system voltage performance and system security optimal VAR allocation needs to be done by considering all severe contingencies simultaneously. By considering all severe contingencies simultaneously the

problem size and thereby the complexity of optimization problem increases. To address this issue, an optimization framework is proposed which solves the problem in two phases.

5. Developed an approach for dynamic VAR allocation completely in dynamic framework where the problem is formulated as mixed integer dynamic optimization. To solve the DO problem efficient numerical techniques are implemented.

1.5 Thesis Organization

This dissertation is organized as follows:

Chapter 2, presents a methodology for assessing contingencies which cause steady state voltage problems, power quality and short term voltage problem. Thus at first from a list of credible contingencies, the contingencies which are not severe are filtered out. Then the severe ones are ranked in terms of their severity. Additionally buses that are impacted by contingencies are identified and ranked in terms of their vulnerability. Thus, a general framework for filtering, ranking and assessing contingencies is given in this chapter. This chapter also presents a methodology to select candidate control locations that are used as an input to integer (control location) optimization. The candidate control location is selected by the information obtained from dynamic and static analysis.

In Chapter 3, a detailed account of the steady state reactive power planning tool developed in this work to find the optimal allocation of static VAR source has been presented. The overall static optimization (SO) problem is solved in two phases. In first phase i.e. PHASE1, the optimization problem is solved by considering only one contingency at a time. In PHASE1 dominant contingencies are identified and solved out of all the severe contingencies. The PHASE1 problem is formulated as MINLP problem. To solve the integer part of MINLP problem B&B method is used. The B&B method is customized based upon the nature of the problem to increase its efficiency. The output of PHASE1 gives optimal locations and rough estimate of VAR amount requirement. In second phase i.e. PHASE2, all the severe contingencies are considered simultaneously and the VAR amount found in PHASE1 is refined to achieve optimal amount.

In Chapter 4, the dynamic reactive power planning tool proposed in this work to find the optimal allocation of dynamic VAR source has been presented. During this analysis, the optimal location information obtained from static VAR allocation results is incorporated. The optimal locations determined in static VAR allocation are given preference during the dynamic VAR allocation process. The overall mixed integer dynamic optimization (MIDO) problem is solved in two phases. In first phase i.e. PHASE1, the optimization problem is solved by considering only one contingency at a time. In PHASE1 dominant contingencies are identified and solved out of all the severe contingencies. The output of PHASE1 gives optimal location and a rough estimate of VAR amount requirement. In second phase i.e. PHASE2, all the severe contingencies are considered simultaneously and the VAR amount found in PHASE1 is refined to achieve optimal amount.

Finally, the conclusions from the analysis of this dissertation are presented in Chapter 5.

CHAPTER 2. CONTINGENCY ANALYSIS AND CANDIDATE VAR LOCATION SELECTION

2.1 Introduction

Due to competitive electricity market and less incentives of transmission expansion in the recent years, power system operation has become highly stressed, unpredictable and vulnerable [10]. For a stressed system more contingencies may become severe and system becomes more vulnerable to frequent voltage instability problem to the extent of complete voltage collapse [11, 12]. Reference [4] gives IEEE definitions on voltage instability and collapse. Voltage instability is divided into long term and short term voltage instability respectively. In long term, the aim is to ensure acceptable steady state voltage after the occurrence of contingency or due to varying load. In short term the operators encounter dynamic limitations prior to steady state limits. Short term voltage instability problem is growing with increase in induction motor loads and at places where HVDC links weak areas [13, 14, 15]. This has necessitated a deeper analysis of short term voltage instability in addition to long term voltage instability analysis. The problem of power quality gets aggravated after large disturbance; such as line contingency; which may cause large voltage dip resulting in stalling of induction motors, mal-operation of protection devices especially zone 3 relay [16, 17]. In recent years; blackouts occurring throughout the globe [18] and increased power quality problem [19], has attracted more attention from power system planners.

This work addresses the issue of contingency assessment scheme for steady state voltage problem, and especially for voltage dip and short term system security problem. It is crucial to understand dynamic impact of contingency on system voltage profile. The vital point in voltage instability study is to determine the risk level or severity of each voltage contingency. Ranking severe contingencies out of credible ones based upon their impact on system voltage profile will help planners in deciding the most effective preventive action before system moves towards instability. Dynamic security assessment deals with the determination of contingencies causing power system limit violations such as transient voltage dip, unacceptable low voltage duration and/or short term system instability.

In steady state analysis, mostly contingency selection algorithms are based on real power flow limits. The commonly used DC power flow is used to screen and rank voltage contingencies based upon line overloading due to contingency [20, 21]. As DC power flow could not address the issue of voltage w.r.t. reactive power so AC power flow was used to address that issue.

After the occurrence of a contingency, the system state is transferred to transient state, where bus voltage has a dynamic behavior. So time-domain methods are used for dynamic analysis to accurately observe and analyze the behavior of system and voltage in particular w.r.t. time. Eigenvalue sensitivity analysis has been proposed in literature for voltage contingency ranking [22, 23], but they are subjected to error due to approximation by the first two terms of Taylor series. This sensitivity analysis is based on dominant eigenvalue, but in [24] it showed that severe voltage contingencies can change dominant eigenvalue and singular value position. Thus, monitoring dominant eigenvalue/singular value of base case in sensitivity analysis can result in ranking errors for severe voltage contingencies. Thus the problem of efficiently filtering and ranking contingencies for voltage problem in DSA framework still remains an area of improvement and research.

Incase of power quality, to compare the severity of voltage violation due to different contingencies, dynamic performance criteria established by NERC/WECC [9] is used for ranking. In this work, we focus on the problem of dynamic voltage contingency ranking w.r.t. both Contingency Severity Index (CSI) and Bus Vulnerability Index (BVI). Defining appropriate classification methodology for filtering and severity measures (performance indices) for ranking are difficult in dynamic framework and still an area which is yet to be explored deeply. Time-domain methods can be used to classify contingencies into "severe" and "non- severe" with respect to a given performance criteria. They can certainly compute stability limits; but at the expense of prohibitive computing times.

As power system is huge so there are a large number of credible contingencies which need to be analyzed. Thus, for dynamic contingency filtering and ranking there are two important aspects. First, to reduce computational time for contingency filtering. Different researchers have addressed this problem and have tried to reduce computational time by taking advantage of computer hardware such as parallel computing [25] and distributed computing [26]. Others have tried to reduce detailed system model to a simplified one; to save computational time, but at the sake of accuracy. Two, the methodology which is used for filtering and ranking of contingencies should be accurate and efficient i.e. zero misclassification and false alarm rate.

The filtering and ranking process is divided into two blocks: first block for filtering and second for ranking of severe contingencies. As will be discussed in section II, this structure yields a unified approach for contingency filtering and ranking:

i) same time domain method is used to filter, and rank contingencies.

ii) information obtained from filtering block is used to rank severe contingencies based upon their order of severity.

iii) buses are ranked in order of their vulnerability to contingencies.

Once contingency assessment is done for static and dynamic security, the next task is to decide appropriate control location from where preventive/corrective control action needs to be taken. The basic framework of the proposed contingency analysis scheme for static and dynamic security assessment is shown in Figure 2.1 and is described in detail in the following section.

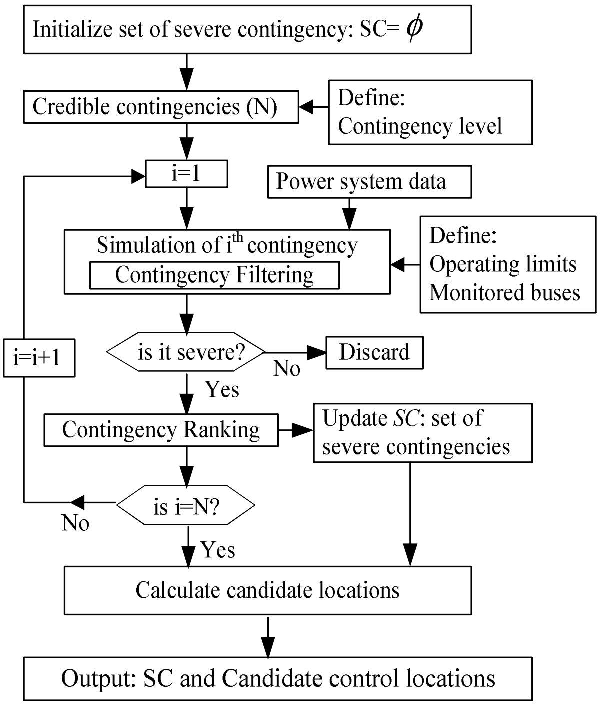

Figure 2.1 Flow chart of the proposed contingency analysis technique.

2.2 Contingency Analysis

The number of credible contingencies may vary depending upon the level of analysis, number of elements (*N*) exposed to failure, and level of contingency. That is; zero level of contingency corresponds to *N-0* (no element is subject to failure), first level of contingency corresponds to *N-1*, i.e. loss of one element; second level of contingency corresponds to *N-2*, i.e. loss of two element and so forth. Thus, the number of k^{th} level contingencies can be given by NC_k for k = 0, 1, 2,…, N. Then total number of all possible contingencies, *TNC*, can be given as:

$$TNC = \sum_{k=0}^{N} NC_k \tag{2.1}$$

where, NC_k can be given as:

$$NC_k = \frac{N!}{K!*(N-K)!} \tag{2.2}$$

For an interconnected large scale power systems total number of credible contingencies may be large. So, normally *N-1* and sometimes *N-2* contingencies are also considered. In this work zero and first level of contingency are considered. So the total number of contingencies to be considered can be given as:

$$TNC = \sum_{k=0}^{1} NC_k = 1 + N \tag{2.3}$$

Its important to note here that in a practical power system not all credible contingencies are severe. This will be discussed in the following section.

2.2.1 Static Contingency Analysis

In static analysis, system steady state voltage is observed following the contingency. Normally the occurrence of a contingency may affect the bus voltage. However, system planners/operators want to confine the post-contingency bus voltage deviation. It would be preferred if post-contingency bus voltage is close to its pre-contingency value. System planners want to identify any contingency that leads to abnormal bus voltage post-contingency. This identification is critical as adequate control needs to be placed in the system to avoid abnormal system voltage in case of severe contingency.

Contingency severity analysis is used in this work to detect contingencies that may lead to any voltage problem in steady state. It also, helps in filtering out severe contingency and ranking them in order of their severity. Power system abnormal state during contingency is clearly reflected by low/high voltage at buses. Thus, a severity index, SI_v, is used to quantify voltage limit violation. In this case both low and high voltage deviation (especially in case of generator buses) are considered and given as:

$$SI_{vb}^{k} = \left|V_b^0 - V_b^k\right| / V_b^0 \qquad \forall b \in B, \forall k \in CON \tag{2.4}$$

Thus, the severe contingencies can be filtered out from all the credible contingencies and Static Contingency Severity Index (SCSI) can be obtained by summing the severity of all individual violated buses. SCSI can then be used for ranking contingencies in the order of their severity.

$$SI_{vb}^{k} = \begin{cases} \left|V_b^0 - V_b^k\right| / V_b^0, & if \quad \left|V_b^0 - V_b^k\right| / V_b^0 \geq 0.05 \\ 0 & otherwise \end{cases} \qquad \forall b \in B, \forall k \in SCON \tag{2.5}$$

$$SCSI_k = \sum_{b=1}^{Nb} SI_{vb}^k / Nb \qquad \forall b \in B, \forall k \in SCON \tag{2.6}$$

In static contingency analysis the impact of a contingency on the system is observed, which is important from planning point of view. From planner's perspective, another crucial information is, what are weak voltage buses in the system. In other words "how different severe contingencies will impact a particular bus voltage". Thus, here abnormal voltage behavior of a particular bus is observed due to different contingencies. From this study, the total number of contingencies making a particular bus vulnerable can be known. Also, severity due to different contingencies can be quantified by defining a performance index. This can help in identification of weak buses in power system. This information can be used in monitoring vulnerable buses for voltage and VAR margin requirements. Once, a performance index for all voltage violating buses is obtained, they can be ranked in order of their vulnerability. Thus "Bus Vulnerability Index" (BVI) is defined, which can provide useful information related to voltage prone areas in the network. The planner can use this information in deciding VAR placement to strengthen weak areas.

The extent of vulnerability of a particular bus due to severe contingencies can be given by Static Bus Vulnerability Index (SBVI).

$$SBVI_b = \sum_{k=1}^{Nsk} SI_{vb}^k / Nsk \qquad \forall b \in B, \forall k \in SCON \tag{2.7}$$

2.2.2 Dynamic Contingency Analysis

In dynamic analysis the transient period immediately after the occurrence of fault is of interest. After the fault is cleared and during the transient period, there maybe a sudden dip in voltage or slow recovery of voltage. The severe dip or slow recovery of bus voltage after the fault is cleared is mainly due to the presence of induction motors and lack of dynamic VAR support in the nearby area.

A severe contingency may lead to bus voltage dip or delayed voltage recovery. This may violate NERC/WECC criteria, and is also unacceptable from system security and power quality point of view. The NERC/WECC transient voltage dip criterion [9] for N-1 contingency is, “Not to exceed 25% at load buses or 30% at non-load buses. Not to exceed 20% for more than 20 cycles at load buses”.

To effectively measure these factors two different performance indices based upon NERC/WECC N-1 contingency criteria are developed and discussed as follows. During a contingency power system may shift from normal to abnormal state. This abnormality is clearly reflected by voltage dip and predominantly low voltage at buses. Thus a severity index, SI_v, is used to measure and quantify voltage limit violation for contingency ranking. SI_v gives measure of voltage deviation by finding sum of maximum voltage deviation at all buses where unacceptable voltage deviation occurs. In this both low voltage as well as high voltage deviation (especially in case of generator buses) are considered and given as:

Let $D = \{V(t) | t \in \lfloor t_{cl}, t_f \rfloor\} \quad for \quad V_0 \ \exists V_d \in D \ni$

$$|V_0 - V_d| \geq |V_0 - V(t)| \quad \forall \quad V(t) \in D$$

(2.8)

For load buses

$$SI_{vd}^{k} = \begin{cases} \left|V_d^0 - V_d^k\right| / V_d^0, & if \ \left|V_d^0 - V_d^k\right| / V_d^0 \geq 0.25 \\ 0 & otherwise \end{cases} \qquad \forall d \in D, \forall k \in SCON \qquad (2.9)$$

For non-load buses

$$SI_{vb}^{k} = \begin{cases} \left|V_b^0 - V_b^k\right| / V_b^0, & if \ \left|V_b^0 - V_b^k\right| / V_b^0 \geq 0.30 \\ 0 & otherwise \end{cases} \qquad \forall b \in B \setminus D, \forall k \in SCON \qquad (2.10)$$

The time for which system voltage remained below the specified time limit is also crucial and can be used for better ranking of contingencies. More severe a contingency is, the longer it will take for the voltage to recover or the system will become unstable faster. Thus a performance index, SI_t, to measure this factor is also included in present contingency ranking. SI_t gives the measure of time for which voltage deviation was unacceptable by finding the sum of time (beyond 20 cycles for N-1 contingency) for which the voltage deviation is beyond the specified limit (20% for N-1 contingency) at all the unacceptable voltage deviation buses. Figure 2.2 shows different cases when low voltage duration can be unacceptable.

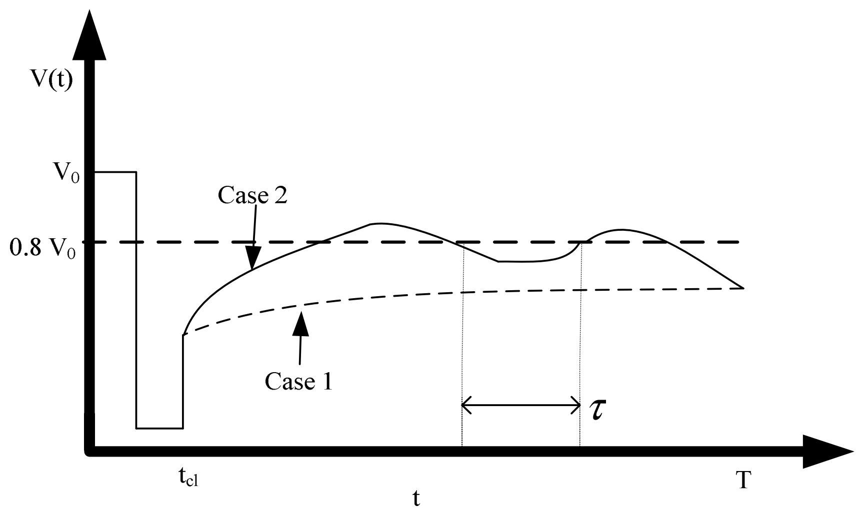

Figure 2.2 Different cases of unacceptable duration of low voltage.

Let $L = \{t \mid V(t) = 0.8V_0, V(t) \in D\}$ (2.11)

Case 1

If $L = \phi$ and $\exists\, t \in \lfloor t_{cl}, t_f \rfloor \ni V(t) < 0.8V_0$

then

$$SI_{td}^{k} = 1 \quad \forall d \in D, \forall k \in SCON$$

else

$$SI_{td}^{k} = 0 \quad \forall d \in D, \forall k \in SCON \qquad (2.12)$$

Case 2

Let $Q = \{t_1, \dots, t_n\} = LV$

$t_0 = t_{cl}$, $t_{n+1} = t_f$, $t_i < t_{i+1}$ $\forall i = 0, \dots, n$

$if\ \exists\ t_l \in (t_i, t_{i+1})\ \forall\ i = 0, \dots, n\ \ni V(t_l) < 0.8V_0$

Then $\tau_i = t_{i+1} - t_i$ else $\tau_i = 0$

Let $Li = \{i \mid \tau_i * 60 \geq 20\ cycles\}$

$$SI_{td}^{k} = \sum_{i \in Li} \tau_i \Big/ \left(t_f - t_{cl}\right) \qquad \forall d \in D, \forall k \in SCON \qquad (2.13)$$

Thus, Dynamic Contingency Severity Index (DCSI) can be obtained by summing all the individual severity indices and can be given as:

$$DCSI_k = \sum_{b=1}^{Nb} SI_{vb}^{k} \Big/ Nb + \sum_{d=1}^{Nd} SI_{td}^{k} \Big/ Nd \qquad \forall b \in B, \forall d \in D, \forall k \in SCON \qquad (2.14)$$

During dynamic contingency analysis the impact of a contingency on a system is observed, which is important from planning point of view. From planner's perspective, another crucial information is, "how different severe contingencies will impact a particular bus voltage". This helps in the planner in identifying which are voltage weak buses in the network. Thus, here abnormal voltage behavior of a particular bus is observed due to different contingencies. From this study, the total number of contingencies making a particular bus vulnerable can be known. Also, severity due to different contingencies can be quantified by defining a performance index. This can help in identification of weak buses in power system. This information can be used in monitoring vulnerable buses for voltage and VAR margin requirements. Once, a performance index for all voltage violating buses is obtained, they can be ranked in order of their vulnerability. Thus "Bus Vulnerability Index" (BVI) is defined, which can provide useful information related to voltage prone areas in the network. The planner can use this information in deciding VAR placement to strengthen weak areas.

The extent of vulnerability of a particular bus due to severe contingencies can be given by Dynamic Bus Vulnerability Index (DBVI).

For load buses

$$DBVI_d = \sum_{k=1}^{Nsk} \left(SI_{vd}^{k} + SI_{td}^{k} \right) / Nsk \qquad \forall d \in D, \forall k \in SCON \tag{2.15}$$

For non-load buses

$$DBVI_b = \sum_{k=1}^{Nsk} SI_{vb}^{k} / Nsk \qquad \forall b \in B \setminus D, \forall k \in SCON \tag{2.16}$$

2.3 Candidate VAR Location Selection

One highly important issue in VAR planning is selection of candidate VAR location. A good selection of candidate location can reduce problem size and obtain a better optimal solution. A system with at least one voltage unstable bus may make the system voltage unstable. Thus a weak bus seems to be a reasonable candidate bus for installing new VAR device [47]. Also, a bus with high load demand is usually very voltage sensitive. Thus VAR compensation at these buses is imperative. So they are also chosen as candidate VAR locations [48].

In [49] sensitivity analysis is used to identify candidate control locations which can improve voltage of weak bus. Buses which have more reactive power deficiency [50], or with more voltage dip are chosen for installing dynamic VAR support [51]. Also there are several other factors which are taken into account for selecting candidate locations such as; physical size of the device, location, and short circuit strength of the station [52].

Mostly steady state based approach is available in literature to solve optimal VAR allocation problem [53]-[56]. For finding the size of dynamic VAR device an approximate amount of reactive power compensation is found, which will bring the generating units below their maximum reactive power capability. Then dynamic devices with different capacity range are chosen for the analysis. Thus, iterative studies are done to find the location and size of the dynamic device [57].

Normally steady state based optimal power flow (OPF) is used to determine the size and optimal location of VAR compensation [58]. Once this information is obtained then time domain simulation is performed to confirm the OPF results and adjust VAR amount to take care of short term voltage problems.

In most of the analysis only the most severe contingency is considered. If more than one severe contingency is considered then the location and amount of VAR support is found for each contingency separately not simultaneously [59]. This may lead to over or under compensation of VAR support. Some researchers have also utilized the concept of reactive power spot price as an index to optimally locate SVC [60].

In [61], [72] linear sensitivity information such as sensitivity of steady state voltage stability margin [73], [74] or transient voltage dip with respect to size of VAR source [75] is used to solve the problem. Thus, the problem of static and dynamic VAR allocation is formulated as mixed integer linear optimization problem. Linear sensitivities are used in the constraints. The problem is solved iteratively to get the final result.

In this work, an approach is being proposed whereby useful information obtained from static and dynamic analysis is used simultaneously to better refine candidate VAR location. As it is well know that dynamic devices are expensive, so it would be great idea to make maximum use of static VAR amount, if possible, to reduce the amount of dynamic support. Also, an informed decision for selecting good candidate locations can immensely help in reducing the integer optimization computational time and help in identifying the best location. For example, if a particular location is a weak bus (that means that it needs VAR support) and has a high positive $\Delta V/\Delta Q$ sensitivity is much preferred than a location which is only a weak bus, or only has a high positive $\Delta V/\Delta Q$ sensitivity, or is neither a weak bus nor has a high positive $\Delta V/\Delta Q$ sensitivity. Another possible case is when a location has a high positive $\Delta V/\Delta Q$ static sensitivity and also has a high positive $\Delta V/\Delta Q$ dynamic sensitivity is much preferred than a location which only has one of this or none of this. Selecting a location with a high positive $\Delta V/\Delta Q$ static sensitivity and also high positive $\Delta V/\Delta Q$ dynamic sensitivity enables to make a co-ordinated use of static and dynamic VAR source, thereby reducing the dynamic VAR requirement. A major drawback in the existing literature is that candidate locations are found for a contingency. Thereby the optimal location found is optimal for that contingency and not for all the contingencies. This critical factor is being addressed in this approach by considering all severe contingencies in selecting the candidate location. This is really useful as the candidate locations selected by this approach seem to provide a better optimal location for all severe contingencies. The relevant inputs that can be considered are: sub-station space, bus vulnerability index of a location considering all severe contingencies, and bus sensitivity index of a location considering all severe contingencies.

To summarize, the candidate control location selection proposed in this work takes many relevant and important inputs to make a better decision. In this work a procedure combining industry practice and information gathered by system performance is developed.

2.3.1 Static Sensitivity Analysis

Selection of candidate VAR locations is an important issue in VAR allocation. A good selection can reduce problem size and obtain a better optimal solution. Here, sensitivity of bus voltage to size of switched shunt is used to determine candidate location.

Sensitivity with respect to addition of VAR at a specific location is computed following a contingency. The procedure is implemented by running the power flow, for a specific contingency with a capacitive limit of Q and then with $Q+\Delta Q$; here ΔQ is small. Sensitivity of voltage to capacitive limit S_v is change in voltage for a given change in VAR capacitive limit and can be given as:

$$\Delta SI_v = S_v \Delta Q \tag{2.17}$$

$$S_v = \frac{\partial SI_v}{\partial Q} \approx \frac{\Delta SI_v}{\Delta Q} = \frac{SI_v(Q+\Delta Q) - SI_v(Q)}{\Delta Q} \tag{2.18}$$

The sensitivity of voltage at bus b with respect to the size of switched shunt at location c under contingency k can be given as

$$S_{v,b,c}^{k} = -\frac{\Delta V_{b,c}^{k}}{V_b^0 \Delta Q_c} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON \tag{2.19}$$

The sensitivity of voltage at all buses with respect to the size of switched shunt at location c under contingency k can be given as

$$S_{v,c}^{k} = \sum_{b=1}^{Nb} S_{v,b,c}^{k} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON \tag{2.20}$$

The overall Static Sensitivity (SS) of a candidate location i.e. the sensitivity of voltage at all buses, under all severe contingencies with respect to the size of switched shunt at location c can be given as:

$$S_{v,c} = \sum_{k=1}^{Nsk} S_{v,c}^{k} \qquad \forall c \in C, \forall k \in SCON \tag{2.21}$$

which can also be written as

$$S_{v,c} = \sum_{k=1}^{Nsk} \sum_{b=1}^{Nb} S_{v,b,c}^{k} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON \tag{2.22}$$

Therefore, the overall Static Sensitivity Index (SSI) of a candidate location can be given as:

$$SSI_c = S_{v,c} \qquad \forall c \in C \tag{2.23}$$

2.3.2 Dynamic Sensitivity Analysis

Dynamic Sensitivity (DS) analysis is used to determine candidate location of VAR source, based upon sensitivity of SVC capacitive limit to voltage dip and duration of low voltage. The sensitivity with respect to the addition of a specific VAR source at a specific system location is computed along the trajectory of dynamical system following a disturbance. The selection of monitored buses can be also critical. For example if vulnerable buses are not included in the set of monitored buses then the information obtained from sensitivity analysis may be misleading. So inclusion of vulnerable buses is important in the set of monitored buses. The dynamic simulation is being performed numerically using numerical integration technique. Calculating trajectory sensitivities of voltage to capacitive amount by this method requires solution of DAEs. This procedure of calculating sensitivity can be computationally expensive as it requires integration of a set of differential algebraic equations. The size of DAE defining the trajectory sensitivity is dependent upon the power system size. Thus, as the size of the DAE describing the problem increases, the corresponding computational cost increases significantly. To avoid this, a methodology based upon numerical approximation is proposed here. Also, this procedure is easy to model and implement.

The severity of voltage dip and severity of duration of low voltage due to a contingency was calculated in Section 2.2. Thus, the sensitivity of maximum voltage dip to capacitive limit S_v is change in voltage dip for a unit change in capacitive limit. Similarly, sensitivity of duration of low voltage to capacitive limit S_τ is change in duration of low voltage for a unit change in capacitive limit. In this procedure the simulation is run with a capacitive limit of Q and then with $Q + \Delta Q$.

For voltage dip sensitivity to capacitive limit:

$$\Delta SI_v = S_v \Delta Q \tag{2.24}$$

$$S_v = \frac{\partial SI_v}{\partial Q} \approx \frac{\Delta SI_v}{\Delta Q} = \frac{SI_v(Q + \Delta Q) - SI_v(Q)}{\Delta Q} \tag{2.25}$$

The sensitivity of voltage dip at bus *b* with respect to the size of SVC at location *c* under contingency *k* can be given as:

$$S_{v,b,c}^{k} = -\frac{\Delta V_{b,c}^{k}}{V_b^0 \Delta Q_c} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON \tag{2.26}$$

The overall dynamic sensitivity to voltage dip of a location i.e. the sensitivity of voltage dip at all buses, under all severe contingencies with respect to the size of SVC at location *c* can be given as:

$$S_{v,c} = \sum_{k=1}^{Nsk} \sum_{b=1}^{Nb} S_{v,b,c}^{k} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON \tag{2.27}$$

Similarly, sensitivity of duration of low voltage to capacitive limit S_τ is change in duration of low voltage for a given change in dynamic VAR capacitive limit and can be given as:

$$\Delta SI_t = S_\tau \Delta Q \tag{2.28}$$

$$S_\tau = \frac{\partial SI_t}{\partial Q} \approx \frac{\Delta SI_t}{\Delta Q} = \frac{SI_t(Q+\Delta Q) - SI_t(Q)}{\Delta Q} \tag{2.29}$$

The sensitivity of low voltage duration at bus *b* with respect to the size of SVC at location *c* under contingency *k* can be given as:

$$S_{\tau,b,c}^{k} = -\frac{\sum_{i=0}^{n} \Delta\tau_{i,b,c}^{k}}{\Delta Q_c} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON \tag{2.30}$$

The overall dynamic sensitivity to low voltage duration of a location i.e. the sensitivity of low voltage duration at all buses, under all severe contingencies with respect to the size of SVC at location *c* can be given as:

$$S_{\tau,c} = \sum_{k=1}^{Nsk} \sum_{b=1}^{Nb} S_{\tau,b,c}^{k} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON \tag{2.31}$$

Therefore, the overall Dynamic Sensitivity Index (DSI) of a location can be given as:

$$DSI_c = S_{v,c} + S_{\tau,c} \qquad \forall c \in C \tag{2.32}$$

2.3.3 Refinement of Candidate Location

In the previous sections we have calculated all the relevant and important information to get an overall effectiveness of each location. The next step is to use the information to calculate the overall Candidate Location Index (CLI). After the CLI is obtained for each location, the candidate locations are then ranked in descending order. Then based upon a criteria only a percentage of candidate locations are selected out of all the credible locations.

It maybe highly possible that two credible locations are electrically close to each other. Thus it maybe a good idea to select only one or few locations out of all the locations in its proximity. This will avoid small installations at neighboring buses. It will also result in reduction of number of candidate locations, thereby reduction in integer optimization computation time. This approach helps in reducing the number of candidate locations while maintaining a diverse set of locations.

In order to decide how many locations to choose as candidate control locations, the concept of electrical proximity between any two nodes is used. The elements of matrix $\partial V/\partial Q$ reflect the propagation of voltage deviation throughout the system due to reactive power injection at a node. So the amount of voltage coupling between two nodes can be quantified by maximum attenuation of voltage deviation between these two nodes [76]. Thus attenuation between two buses i and j can be given as

$$\Delta V_i = \alpha_{ij} \Delta V_j$$

where $\alpha_{ij} = \dfrac{(\partial V_i / \partial Q_j)}{(\partial V_j / \partial Q_j)}$ is normalized voltage attenuation on bus i due to deviation at bus j. Generally $\alpha_{ij} \neq \alpha_{ji}$, so symmetric electrical distance between bus i and bus j can be given as

$$D_{ij} = D_{ji} = -\log(\alpha_{ij}\ \alpha_{ji}) \tag{2.33}$$

The function D_{ij} holds all properties of real mathematical distance; it is symmetric, positive, and satisfies triangular inequality if the system is not overcompensated.

The sensitive bus area selection criterion depends on electrical distance to all sensitive buses. Thus, bus k is chosen in area if $D_{sk} < D_c$, where D_c represents the bound of area. D_c is decided by electrical distance from most sensitive bus s to other sensitive buses.

$$D_c = D_{s\max} + \rho(D_{s\min} - D_{s\max}) \tag{2.34}$$

where

ρ is constant between 0 and 1

$D_{s\min}$ is minimum distance from bus s to other sensitive buses

$D_{s\max}$ is maximum distance from bus s to other sensitive buses

In the next section we are going to look at a test system and will see the impact of different contingencies on the system.

2.4 Results and Discussion

2.4.1 Test System

The effectiveness of the proposed methodology is demonstrated on the modified 1996 IEEE Reliability Test System [77], [78]. The system used in this work has 75 buses, 32 generating units, 90 branches and 17 loads. In order to create a peak load scenario, the real and reactive power load is multiplied by 1.1 times with associated increase in real power of generating units proportional to their original value. This is done to more specifically analyze the problem of low voltage. All the generators are connected to the low side of generator step-up transformer (GSU) and remotely control the high side on their GSU. The loads are connected to low side by a step down transformer. The test system represents a practical power system very closely.

In the steady state analysis, the load is represented as constant power load. The reactive power output limits are modeled to capture its impact on system voltage. The transformer tap position is locked in the analysis as this is a planning problem and the idea is to capture the most conservative scenario.

In dynamic analysis, dyn32amic models of generator, exciter and load are used. The simulation time step is chosen to accurately capture the behavior of the system.

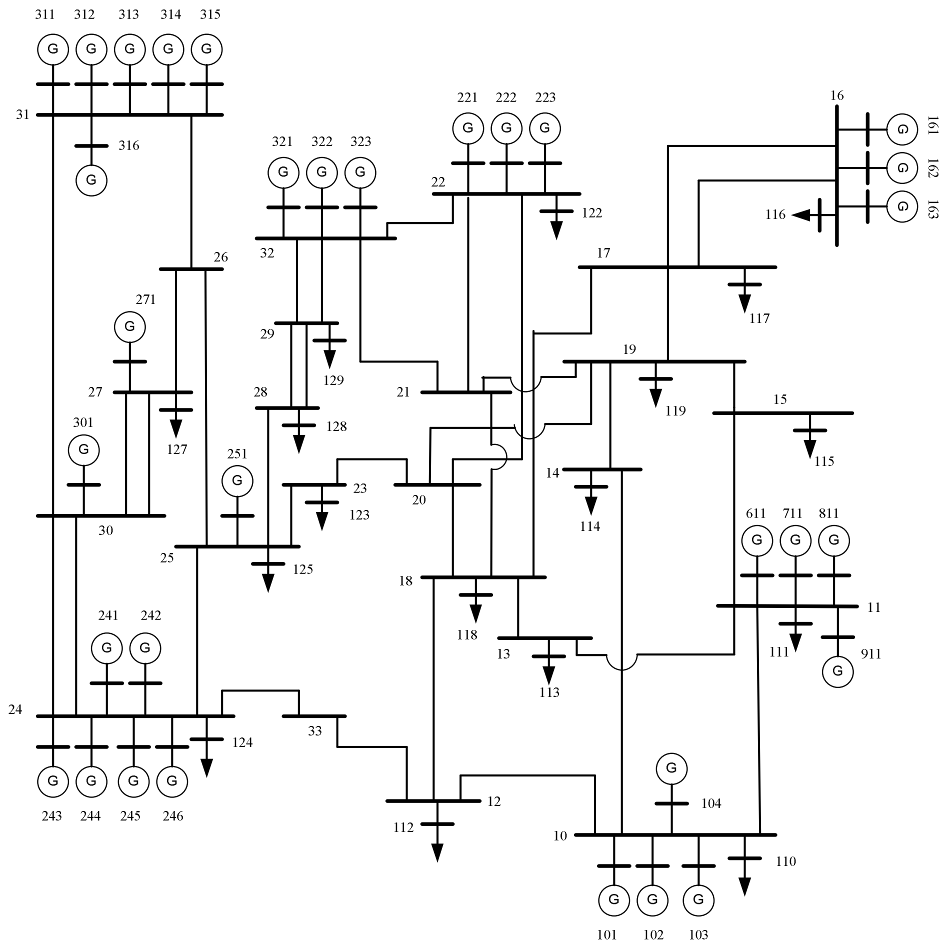

Figure 2.3 Test system one line diagram.

2.4.2 Contingency Analysis

Out of all the N-1 contingencies considered, 13 contingencies resulted in steady state voltage problem. Table 2.1 shows the list of severe contingencies, and their associated normalized Static Contingency Severity Index (SCSI). The SCSI is also used to rank the contingencies in their order of severity. Thus, for example contingency 18-21 is most severe followed by contingency 14-10 and so on.

Table 2.1 Steady state contingency severity index.

S.N.	Line Contingency		Normalized Steady State CSI (rank)
	From Bus	To Bus	
1	12	10	0.0843 (12)
2	12	18	0.11800 (9)
3	14	10	0.85850 (2)
4	18	20	0.16950 (6)
5	18	21	1.00000 (1)
6	19	20	0.0900 (11)
7	19	21	0.25940 (4)
8	20	22	0.12690 (8)
9	21	22	0.0963 (10)
10	21	32	0.36890 (3)
11	25	26	0.20500 (5)
12	28	25	0.15700 (7)
13	28	29	0.0173 (13)

The impact of all severe contingencies on system buses is calculated to identify which buses are impacted the most. The vulnerability of a bus is given as Static Bus Vulnerability Index (SBVI) which is shown in Table 2.2. Thus, it can be seen that a total of 9 buses are impacted by all the severe contingencies. The set of vulnerable buses give an information about weak spots in the system.

After the steady state contingency analysis is done, the next step is to analyze dynamic response of contingencies. Dynamic analysis of a contingency helps in analyzing the time based response of system voltage, reactive power demand at a bus and so forth.

Table 2.2 Steady state bus vulnerability index due to all severe contingencies.

Bus No. (rank)	Normalized Steady State BVI
12 (6)	0.1259
13 (5)	0.2144
14 (4)	0.2709
18 (3)	0.3801
19 (2)	0.5647
20 (8)	0.0040
21 (7)	0.0671
28 (9)	0.0020
33 (1)	1.0000

Dynamic analysis of a contingency also helps in identifying the nature of voltage problem such as delayed voltage recovery or severe voltage dip at a bus. Contingencies that were found severe in steady state formed the set of contingencies that were further analyzed in dynamic analysis. In dynamic analysis any contingency that resulted either in voltage dip violation, slow voltage recovery or both was termed as severe else non-severe. It was found that all 13 contingencies either resulted in voltage dip violation, or slow voltage recovery. The severity indices defined earlier are used to calculate the dynamic severity of each severe contingency. The normalized Dynamic Contingency Severity Index (DCSI) for each severe contingency is shown in Table 2.3. From the Table it can be observed that contingency 19-21 is most severe, followed by contingency 20-22 and so on. The voltage dip violation and delayed voltage recovery problem caused by the contingency 19-21 is shown in Table 2.4 and Table 2.5 respectively.

Table 2.3 Dynamic state contingency severity index.

No.	Line Contingency		Normalized Dynamic CSI (rank)
	From Bus	To Bus	
1	12	10	0.0603 (13)
2	12	18	0.0638 (12)
3	14	10	0.1718 (11)
4	18	20	0.7211 (8)
5	18	21	0.7903 (5)
6	19	20	0.8063 (3)
7	19	21	1.00000 (1)
8	20	22	0.8344 (2)
9	21	22	0.7262 (7)
10	21	32	0.7277 (6)
11	25	26	0.8003 (4)
12	28	25	0.6019 (10)
13	28	29	0.6032 (9)

In Table 2.4 buses which resulted in transient voltage dip violation due to contingency 19-21 are shown. The maximum voltage dip violation at a bus due to contingency 19-21 is 42.16%, which is very severe. Such a significant drop of voltage at a bus may lead to severe power quality issues and maloperation of electric devices.

In Table 2.5 buses which resulted in unacceptable duration of voltage recovery due to contingency 19-21 are shown. The maximum duration of voltage to recover to 0.8pu at a bus due to contingency 19-21 is 41.29 cycles, which is very severe. Such a significant duration of low voltage at a bus may lead to severe power quality issues and maloperation of electric devices.

Table 2.4 Buses resulting in transient voltage dip violation due to contingency 19-21.

Bus No.	Voltage Dip (%)
14	32.98
15	37.57
19	34.77
110	30.29
111	29.92
112	26.65
113	31.46
114	38.25
115	41.09
116	28.70
117	31.09
118	28.14
119	42.16

Table 2.5 Buses resulting in low voltage duration violation due to contingency 19-21.

Bus No.	Time of low voltage (cycles)
110	21.17
111	21.17
113	24.19
114	33.25
115	40.33
116	24.19
117	27.21
119	41.29

The impact of all severe contingencies on system buses is calculated to identify which buses are impacted the most. The vulnerability of the buses is given as Dynamic Bus Vulnerability Index (DBVI) which is shown in Table 2.6. Thus, it can be seen that a total of

14 buses are impacted by all the severe contingencies. From the set of vulnerable buses, the information about voltage weak buses is obtained. This helps in identifying weak spots in the system. Out of 14 vulnerable buses, bus number 19 is impacted the most. It's worth observing here that more buses are impacted in dynamic analysis than in steady state analysis. The reason for this is that in dynamic analysis a more complete detailed load model is used which comprises of motors in addition to static load. The presence of motor load results in high reactive power demand which causes significant voltage dip or slow voltage recovery problems. Therefore, more buses are impacted in dynamic analysis that in steady state analysis. Also in dynamic analysis, static controllers which have slow response time, are not able to participate in improving the system voltage just after the occurrence of the contingency.

Table 2.6 Dynamic state bus vulnerability index due to all severe contingencies.

Bus No. (Rank)	Normalized Dynamic BVI
12 (3)	0.9037
13 (4)	0.8835
14 (6)	0.8306
15 (2)	0.9418
17 (7)	0.5722
18 (5)	0.8585
19 (1)	1.0000
20 (14)	0.0601
21 (13)	0.0704
23 (8)	0.4183
25 (10)	0.2486
28 (9)	0.3155
29 (12)	0.1272
33 (11)	0.1764

The load is connected to the main high KV network through a step down transformer. Due to the consideration of motor load both high KV and low KV buses are impacted. Thus the dynamic vulnerability of buses is calculated by summing up the impact at the high KV bus and the low KV bus where the load is connected.

Figure 2.4 shows voltage response of bus 19 and bus 119 due to line contingency 19-21 without SVC. From the voltage response it can be observed that after the fault is cleared there is a significant delay in voltage recovery.

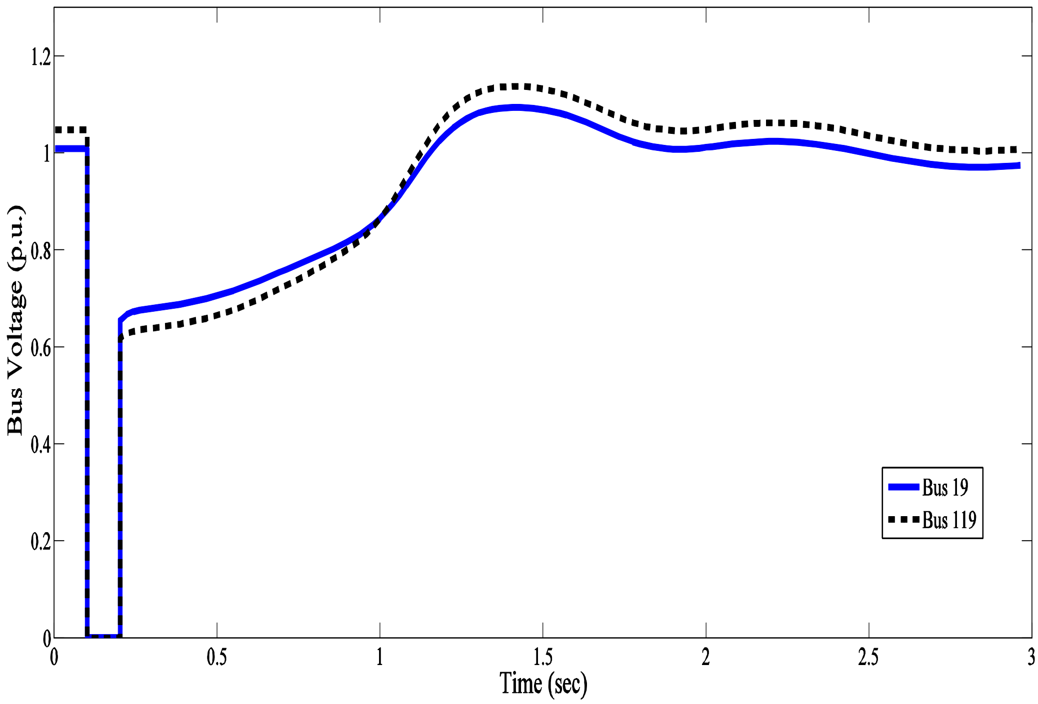

Figure 2.4 Bus voltage response due to contingency 19-21 w/o SVC.

The delay in voltage recovery leads to sustained low voltage. Due to sustained low voltage there is significantly high absorption of reactive power by the load as shown in

Figure 2.5. It can be clearly observed that for the duration when the voltage is low, the reactive power demand of load is significantly high. Roughly after 2 secs when the voltage recovers to its pre-contingency value, that's also roughly the time when the reactive power demand of load reduces to its pre-contingency value.

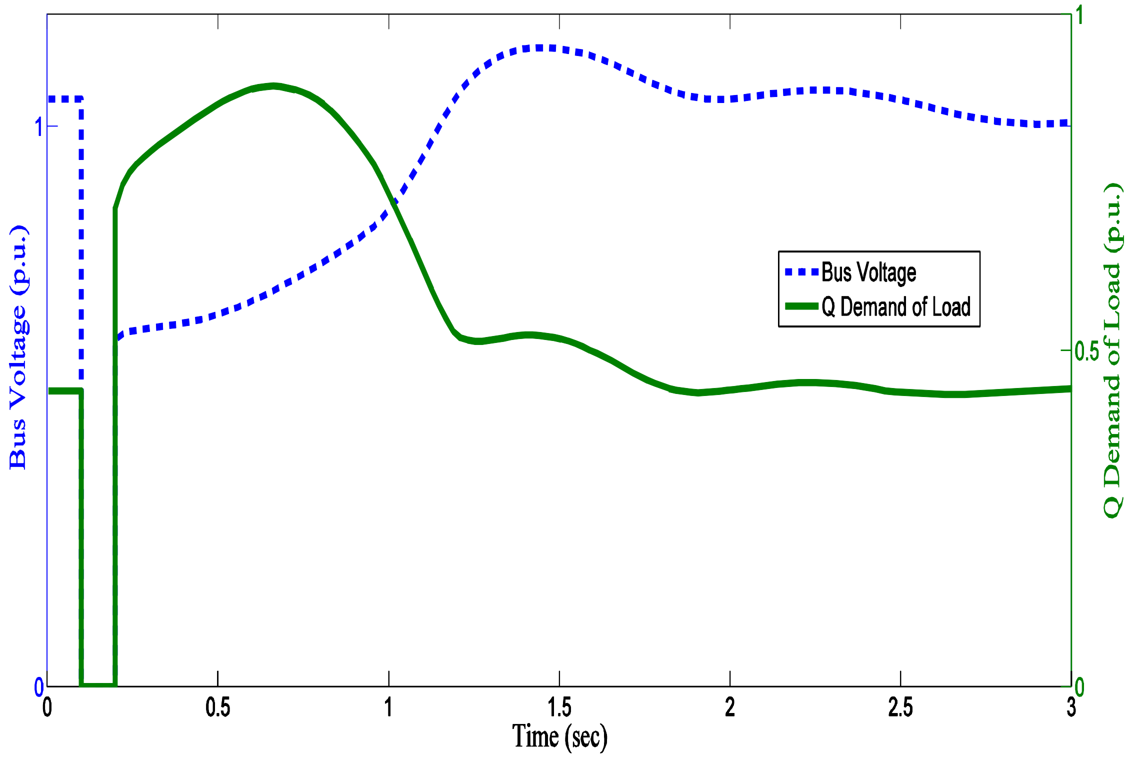

Figure 2.5 Bus voltage and Q demand @bus 119 due to contingency 19-21 w/o SVC.

When there is low voltage and high reactive power demand by the induction motor, the motor speed starts decreasing as shown in Figure 2.6. It can be clearly observed that for the duration when the reactive power demand of load is significantly high, the motor speed deviation is also high. Roughly after 2 secs when the reactive power demand of load reduces to its pre-contingency value, that's also roughly the time when the motor speed deviation recovers to its pre-contingency value.

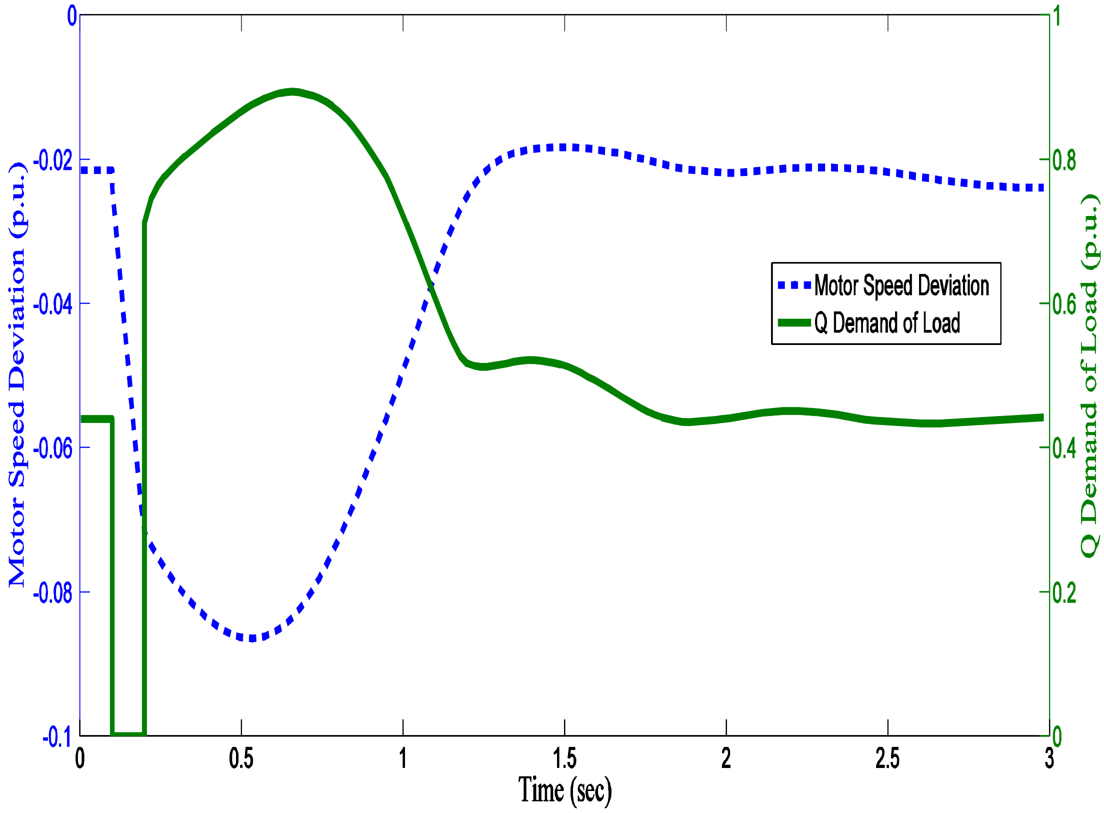

Figure 2.6 Motor speed deviation and Q demand @bus 119 due to contingency 19-21.

From Figure 2.7 it can be clearly observed that as the voltage decreases the reactive power demand of the load increases, which leads to the decrease in motor speed. If the motor rapidly slows down and stalls then it leads to high consumption of reactive power, which may eventually lead to a voltage instability situation. This indicates the necessity of having sufficient dynamic VAR support available in the system to avoid delayed voltage recovery.

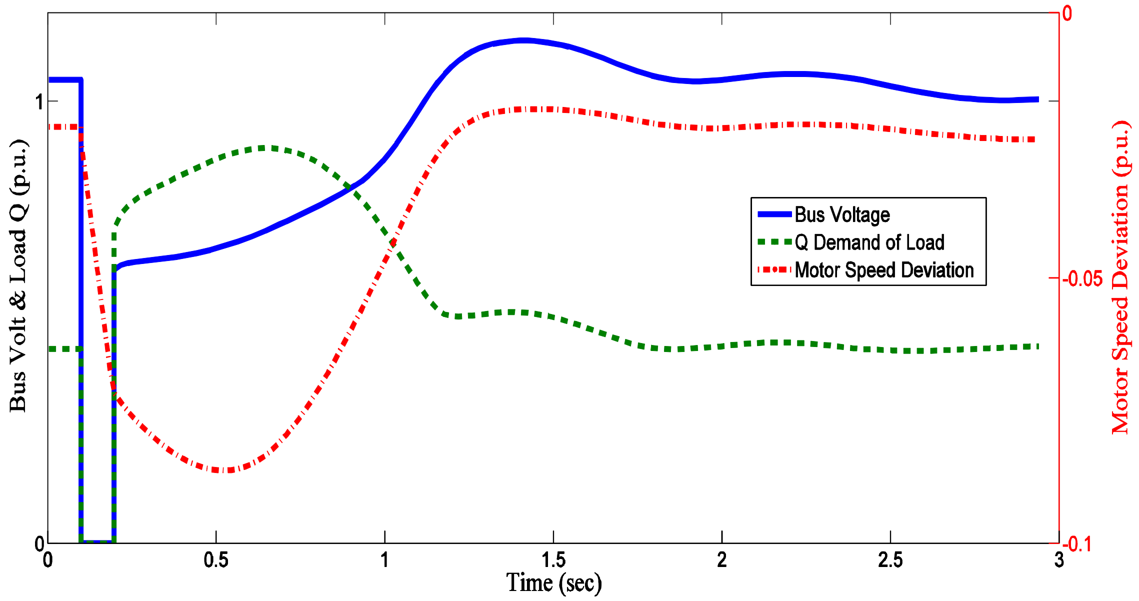

Figure 2.7 Bus voltage, Q and motor speed @bus 119 due to contingency 19-21.

2.4.3 Candidate VAR Location Selection

In a practical power system there are many buses, but its not feasible to install VAR source at all the locations. Also, its not economical to install VAR source at all the locations. Thus it's highly desirable to select the most effective locations out of all the plausible locations in the system. Selection of candidate control locations is based upon the approach as discussed in Section 2.3. Thus, all the relevant information of a location is used to calculate the effectiveness of a particular location.

In steady state, the sensitivity of voltage at buses to switched amount is calculated for all severe contingencies. Calculating the sensitivity of a location under all severe contingencies can help the planners in analyzing the effectiveness of that location under different severe contingencies. The normalized static sensitivity index of bus voltage to switched shunt amount for all severe contingencies is given in Table 2.7.

Table 2.7 Bus static sensitivity index for all severe contingencies.

Bus No. (rank)	Normalized Static Sensitivity Index
12 (1)	1.0000
13 (9)	0.2268
14 (8)	0.2879
17 (10)	0.1811
18 (2)	0.7639
19 (3)	0.7392
20 (5)	0.6146
21 (6)	0.6022
26 (12)	0.0248
28 (7)	0.3692
29 (11)	0.1053
33 (4)	0.6478

In dynamic state, the sensitivity of voltage dip or voltage recovery time at buses to SVC amount is calculated for all severe contingencies. Calculating the sensitivity of a location under all severe contingencies can help the planners in analyzing the effectiveness of that location under different severe contingencies. The normalized dynamic sensitivity index of bus voltage to SVC amount for all severe contingencies is given in Table 2.8.

Table 2.9 gives the Candidate Location Index (CLI) for each location. This information can be utilized in understanding which locations are most effective and which locations are least effective. Also the CLI for a given location is calculated for all severe contingencies. Thus a location with high CLI means that the given location is most effective for that set of severe contingencies. From the Table it can observed that bus 19 is most effective followed by bus 18 and so on. This result can be supported from the fact that buses in the neighborhood of bus 18, and 19 had relatively more voltage problem.

Table 2.8 Bus dynamic sensitivity index for all severe contingencies.

Bus No. (rank)	Normalized Dynamic Sensitivity Index
12 (3)	0.7564
13 (7)	0.4503
14 (6)	0.4675
17 (4)	0.6266
18 (2)	0.9701
19 (1)	1.0000
20 (10)	0.2307
21 (9)	0.2716
26 (12)	0.0951
28 (5)	0.5223
29 (11)	0.1767
33 (8)	0.3567

Table 2.9 Candidate location index of buses for all severe contingencies.

Bus No. (rank)	Normalized Candidate location Index
12 (3)	0.9121
13 (9)	0.5198
14 (7)	0.5530
17 (6)	0.5714
18 (2)	0.9542
19 (1)	1.0000
20 (10)	0.4935
21 (8)	0.5368
26 (12)	0.1932
28 (5)	0.5821
29 (11)	0.2809
33 (4)	0.5979

After the candidate location index of each bus is obtained, the concept of electrical distance is used to further reduce and form a diverse set of candidate control locations. This is an important step as it avoids small installations at neighboring buses. Indirectly by considering less candidate locations in the integer optimization the complexity of integer optimization reduces as well. The best 6 candidate buses to install VAR source are buses 18, 19, 20, 21, 26, and 28.

2.4.4 Discussion

This chapter aims at development of a systematic methodology by integrating the information obtained from static and dynamic analysis. It is physically known that static and dynamic behavior of power system have something in common. For example if a contingency is severe in static analysis, the chances are high that it will be severe in dynamic analysis too. So, this chapter integrates the information obtained from static and dynamic analysis to help the planners in making an informed decision. Instead of looking at each piece one at time, the proposed approach here combines all the relevant information and brings it together as one. This approach enables a better understanding of system behavior under steady state and dynamic state. It also provides useful information which enables coordinated use of static and dynamic VAR sources.

To reduce the number of contingencies to be considered during optimization process the concept of Contingency Severity Index (CSI) is used to filter and rank severe contingencies. Also, to get an idea of weak areas in system or voltage prone areas the concept of Bus Vulnerability is utilized. The BVI gives an idea of buses which are impacted and their vulnerability due to all the severe contingencies.

To reduce the complexity of integer optimization the concept of candidate control location is used. The candidate locations are determined by considering both physical limitations, such as availability of space at a sub-station; and system performance, such as sensitivity of a bus. This approach leads to a better set of candidate locations which can be used in both static and dynamic VAR allocation. This enables coordinated use of static and dynamic VAR sources and maximizes their utilization.

CHAPTER 3. OPTIMAL ALLOCATION OF STATIC VAR SUPPORT

3.1 Introduction

Steady-state security assessment is one of the most essential function in power system operation. One of the key aspects in the steady state security of power system, following a contingency, is steady-state performance of bus voltage. To ensure acceptable steady state bus voltage performance, allocation of static VAR source is done.

One of the major challenges in a (de)regulated power system during long term reactive power planning is optimal allocation of reactive power sources. The motivation to address this problem arises due to future load growth, inadequate transmission expansion due to high investment cost and difficulty in obtaining right-of-way [79]. As it is getting harder to build new transmission lines, it has become more desirable to maximize the use of existing transmission lines by using reactive power sources. As more renewable generation is build, more power is transferred from remote locations [80]. In load pockets where reactive power support is most needed, sometimes there is an inability to install reactive power support at major load centers due to lack of space. In addition to these issues, power system is always prone to contingencies, which may lead to unacceptable system voltage and threaten the security of the system. Thus, the importance of optimally allocating reactive power sources has been increasing over time. To address this challenging issue, its important to develop a methodology for long-term reactive power allocation to ensure steady state system security.

It is important that reactive power allocation is done as economically as possible, while ensuring system security.

The goal of reactive power allocation is to determine the most economical installation of new reactive power sources, in terms of location and size of the source. The installation of new reactive power sources can ensure satisfactory system operation against contingencies. In an interconnected system, it is becoming important for system planners to consider a very large number of contingencies in a planning study. This necessitates the need for security-constrained optimization model, which can handle large number of contingencies and produce accurate results. Thus, it is significantly important that the problem of reactive power allocation is solved for all contingencies. This problem can be formulated in an optimization framework, where multiple contingencies can be considered, commonly known as a Security Constrained Optimal Power Flow (SCOPF) or security constrained reactive power planning. A good reference for static VAR source planning is [81], which covers different forms of problem formulation and numerical methods employed to solve the problem.

In static VAR planning problem, the VAR support needs to be allocated such that it ensures acceptable steady-state voltage performance for all severe contingencies. The size of SCOPF problem increases proportionally as the number of contingencies increase. In past researchers have used Linear Programming (LP) [82] or Mixed Integer Linear Programming (MILP) [83] based techniques to linearize and solve the nonlinear reactive power allocation problem. The LP based approach was mainly used because of it's reliable convergence properties, and ability to solve large problem size (mainly resulting from consideration of multiple contingencies). Although LP based approach has some advantages, but its application in the area of reactive power allocation has remained somewhat restricted. This is mainly because of the inability to find exact optimal solution as opposed to an accurate nonlinear power system model.

In the recent past, meta-heuristic methods such as genetic algorithm (GA), simulated annealing (SA), and tabu search (TS) [84], have also been used to solve reactive power allocation problem. These methods are still evolving and guarantee global optimal solution without being trapped in local optima. The major drawback of these approaches is proper selection of solution parameters and significantly large computational time.

The proposed method in this work determines optimal allocation of new reactive power source which is required to avoid voltage violation and ensure system security against contingencies. The static VAR allocation problem is formulated as an optimization problem. The methodology developed, in this work, considers all severe contingencies in the optimization framework. The overall optimization problem considering all the severe contingencies is formulated as Mixed Integer Non-Linear Programming (MINLP). The resultant multi-contingency constrained VAR allocation problem is too big to be implemented efficiently. The formulated problem, in the form of MINLP, has two complex issues:

i. Integer optimization – due to location selection
ii. Large size of Non-Linear problem – due to consideration of multiple contingencies

The above two issues are very critical as they affect the overall efficiency of the problem that is being solved. The above two issues need to be tackled efficiently; such that the overall complexity of the problem is reduced while ensuring the accuracy of the results.

A methodology is proposed in this work which decomposes the overall optimization problem into two Phases. In first phase i.e. PHASE1, the MINLP optimization is performed by considering only one severe contingency at a time, instead of optimizing for all severe contingencies simultaneously. Thus, the complexity of PHASE1 is independent of number of severe contingencies as it solves only one contingency at a time. The concept of dominant contingencies is introduced in this work which limits the number of contingencies to be processed in PHASE1. This helps in indentifying dominant contingencies out of all severe ones. Thus, only dominant contingencies are solved in PHASE1 instead of all severe contingencies, thereby reducing the overall computational time of PHASE1. At the end of PHASE1 near optimal VAR allocation information is obtained. The information obtained at the end of PHASE1 is close to optimal, thereby it serves as a very good starting point for further refinement and in obtaining optimal solution. The VAR allocation obtained in PHASE1 is refined in second phase i.e. PHASE2 by considering all the contingencies simultaneously. This phase refines the solution obtained in PHASE1 and ensures optimal solution but with less computation burden. In PHASE2, the sensitivity of voltage to VAR amount information is used to model the optimization problem. The optimization problem in PHASE2 is modeled as Linear Programming (LP) problem. The advantage of the overall proposed methodology, i.e. PHASE1 and PHASE2 coupled, is that large number of contingencies can be considered with an acceptable run time and memory requirement while ensuring the accuracy of the results.

3.2 Problem Formulation

The objective of static VAR allocation problem is to find minimum static VAR capacity at optimal locations that ensure static security of system and acceptable voltage performance against severe contingencies.

The mathematical formulation of static VAR allocation problem while considering multiple severe contingencies is similar to that of single contingency. The major difference here is that due to consideration of *k* contingencies simultaneously the problem size becomes *k* times larger. Thus the overall optimization problem can be given mathematically as:

$$\min \quad J = IC(u, w, p)$$

subject to

Equality constraint

$$g^k(y^k, u^k, w_c, p^k) = 0 \qquad \forall c \in C, \forall k \in SCON$$

Control and operational limit constraints

$$l^k(y^k, u^k, w_c, p^k) \leq 0 \qquad \forall c \in C, \forall k \in SCON$$

Binary constraint

$$w_c \in \{0,1\}^{n_w} \qquad \forall c \in C$$

where, $y \in \Re^{n_y}$ are vectors of algebraic variables; $u \in \Re^{n_u}$ is vector of control variables; $p \in \Re^{n_p}$ is parameter vector such as C_f and C_v which are fixed and variable cost of static VAR source respectively. g represents system power balance equation in nonlinear form.

3.2.1 Objective Function

Static VAR allocation has fixed cost associated with installation location and variable cost proportional to its rating (maximum capacity). So, the objective is to find optimal locations which have minimum VAR capacity:

$$\min \quad J = \sum_{c \in C} w_c \left(C_{fc} + C_{vc}\left(Q_{cc} - Q_{ic}\right)\right)$$

In this work the fixed cost and variable cost are used as shown in Table 3.1.

3.2.2 Power Flow Equations

The power flow equations are defined by the active and reactive power balances at all the buses:

$$P_{Gb} - P_{Db} - P_{Tb} = 0 \qquad \forall b \in B$$

$$Q_{Gb} - Q_{Db} - Q_{Tb} + Q_{cb} + Q_{ib} = 0 \qquad \forall b \in B$$

Here, load can vary for different contingencies depending upon the model.

3.2.3 Operating Limits

The real and reactive power produced by the generator is limited by its capacity.

$$\underline{P}_{Gg} \leq P_{Gg} \leq \overline{P}_{Gg} \qquad \forall g \in G$$

$$\underline{Q}_{Gg} \leq Q_{Gg} \leq \overline{Q}_{Gg} \qquad \forall g \in G$$

In the above model, generators active power dispatch is assumed to be specified. So, the generator's active power operation limit constraint can be ignored.

During contingency bus voltage may deviate from its normal operating point. To avoid low/high bus voltage and voltage instability, lower and upper limit on bus voltage is enforced. This ensures acceptable bus voltage during contingencies.

$$\underline{V}_b \leq V_b \leq \overline{V_b} \qquad \forall b \in B$$

3.2.3 Investment Constraints

To ensure acceptable system voltage and security during contingency additional reactive power support may be installed. However, the capacity of reactive power support that needs to be added at a sub-station should be less than maximum allowable capacity. In this work, maximum allowable capacity that can be installed at different transmission voltage levels is given in Table 3.1.

$$0 \leq Q_{cc}^k \leq Q_{cc} \qquad \forall c \in C, \forall k \in SCON$$

$$0 \leq Q_{cc} \leq w_c \, \overline{Q}_{cc} \qquad \forall c \in C$$

$$Q_{ic} \leq Q_{ic}^k \leq 0 \qquad \forall c \in C, \forall k \in SCON$$

$$w_c \, \underline{Q}_{ic} \leq Q_{ic} \leq 0 \qquad \forall c \in C$$

$$w_c \in \{0,1\} \qquad \forall c \in C$$

It should be noted here that static VAR placement variable w_c is independent of different contingency cases.

3.3 Dominant Contingency

In a practical power system there are many contingencies which may lead to voltage violations. One approach to do reactive power planning is to consider all the contingencies in SCOPF. SCOPF with all the contingencies suffers from a major affliction of high dimensionality of the problem. This issue becomes even more pronounced in case of large power systems and/or when number of contingencies to be considered are many. The first problem although manageable, is huge memory space requirement. Secondly including all contingencies in SCOPF, leads to shrinking of the feasible region which increases the complexity of the problem to be solved. Thirdly, as the problem size of SCOPF increases, the computational time also increases proportionally.

In real life and mathematically not all postulated contingencies, constraint the optimum. So in this work, an approach is devised to mitigate these drawbacks. At first from all the postulated contingencies a subset of potentially severe contingencies can be obtained by contingency filtering. A further reduction in number of contingencies can be obtained by forming dominant contingency set. Dominant contingencies are subset of severe contingencies, but truly represent the characteristics of severe contingencies. Here the concept of dominant contingencies is exploited to reduce the overall optimization run time. Dominant contingencies are able to achieve the same or nearly similar level of security and performance as when all credible contingencies are considered.

A contingency K_0 is said to be a dominant contingency of contingencies $K_1,\ldots,K_n$ if the condition that the system is secure with respect to K_0 implies that the system is also secure with respect to $K_1,\ldots,K_n$. Thus, dominant contingencies can be used to limit the number of severe contingencies to be analyzed. In this work, the identification of dominant contingencies is done by a heuristic approach based upon system empirical evidence. Additionally, planners experience can also be added to refine the list of dominant contingencies. There are two approaches to identify dominant contingency out of severe ones. One method 'METHOD1' uses information obtained from contingency analysis to determine dominant contingency. The second method 'METHOD2' uses optimization approach to determine dominant contingency. The two methods are described next.

METHOD1:

Let $SCON_J$ and $SCON_K$ be severe contingencies.

Let V_A be the buses affected by $SCON_J$.

Let V_B be the buses affected by $SCON_K$.

Let ΔV_A be voltage deviation at bus V_A due to $SCON_J$.

Let ΔV_B be voltage deviation at bus V_B due to $SCON_K$.

Hypothesis: Severe contingency $SCON_J$ is dominant over severe contingency $SCON_K$, If $V_B \subseteq V_A$, AND $\Delta V_B \leq \Delta V_A$.

METHOD2:

After the completion of METHOD1 some dominant contingencies maybe identified based upon their degree of impact and location of impact. To further identify dominant contingencies out of remaining severe contingencies the optimization approach is used. In this method, if optimal VAR allocated to a contingency is adequate to address voltage problem for other contingency, then it's a dominant contingency.

Let $SCON_J$ and $SCON_K$ be severe contingencies.

Let VAR_ALLOC_A be the VAR allocation for $SCON_J$.

Hypothesis: Severe contingency $SCON_J$ is dominant over severe contingency $SCON_K$, If VAR_ALLOC_A is sufficient enough to ensure acceptable voltage performance for $SCON_K$.

3.4 Solution Methodology for Static VAR Allocation

The aim of reactive power allocation is to determine the optimal location and amount of new reactive power sources on transmission system. The optimization is performed to ensure the security of the system and that the system bus voltage is within an acceptable range for different contingencies. The problem considering all the severe contingencies is formulated as Mixed Integer Non-Linear Programming (MINLP). This simultaneous consideration of contingencies may lead to huge problem size and large number of integer variables. This may increase the complexity of the problem exponentially. Thus, solving the problem simultaneously for a set of contingencies can be very complex. Some of the critical issues related to handling all contingencies simultaneously are:

1. The overall problem size increases by the number of contingencies considered. Say for *Nc* contingencies, the new problem size is *Nc* times bigger than that of single contingency.
2. In a nonlinear problem, the complexity to solve $m \times m$ Jacobian matrix is say m^2 due to its sparse structure. So when *Nc* contingencies are considered simultaneously then the complexity increases by a factor of Nc^2 and becomes Nc^2m^2.
3. With respect to the integer part, the worst case complexity to solve *w* integer variables is 2^w. Thus the integer part has exponential complexity. For *Nc* contingencies simultaneously the overall complexity is roughly $(2^w)*Nc^2m^2$.
4. Another critical issue of the resulting large size nonlinear problem could be that the model may fail to provide a solution due to non-convergence.

The problem considering all the severe contingencies is formulated as Mixed Integer Non-Linear Programming (MINLP). The resultant multi-contingency constrained VAR allocation problem is too big to be implemented efficiently. So, a methodology is proposed which decomposes the overall optimization problem into two Phases. In first phase i.e. PHASE1, the MINLP optimization is performed on one severe contingency at a time, instead of optimizing all of them simultaneously. Thus, the complexity of the PHASE1 is much less than the original problem complexity. Also, it is independent of the number of severe contingencies. The concept of dominant contingencies is introduced in this work which limits the number of contingencies to be processed in PHASE1. At the end of PHASE1 near optimal VAR allocation is obtained. The VAR allocation obtained in PHASE1 is refined in second phase i.e. PHASE2, by considering all the severe contingencies simultaneously. The PHASE2 problem is modeled as Linear Programming (LP). The advantage of the overall proposed methodology is that large number of contingencies can be considered with an acceptable run time and memory requirement while ensuring the accuracy of the results.

3.4.1 PHASE1: Single Contingency Optimization

In PHASE1, reactive power allocation is done for a single contingency. In this Phase, there are two categories of static VAR sources:

1. Existing VAR source: These VAR source location and amount are needed for any solved single contingency optimization. The VAR location and the amount already found for solved contingency is retained for subsequent optimizations in PHASE1. During subsequent optimization of PHASE1, the existing VAR amount at a previously found optimal location can only increase not decrease. This ensures that the current VAR amount still satisfies the previously solved contingencies.
2. Candidate VAR source: These are additional VAR sources which may be needed during PHASE1 of optimization if there is insufficient existing VAR support to satisfy system security and voltage violation.

In PHASE1, optimal VAR allocation is done for one contingency at a time. The same problem and equations as defined in Section 3.2 are used by considering only one contingency. The information obtained from contingency ranking is used in this Phase to determine the sequence in which single contingency optimization will be performed.

Contingencies to be processed in PHASE1 are selected in the order of their descending severity, i.e. most severe contingency is processed first followed by less severe and so on. It is very likely that VAR allocated for a severe contingency is adequate in resolving voltage problem for a less severe contingency. Thus, solving contingencies in descending order in PHASE1 leads to better solution and speeds up the overall process.

In PHASE1 if for any contingency candidate VAR sources are used, then these VAR sources are added to the network as existing VAR sources and retained for subsequent single contingency optimization. This means that if a location is selected for any contingency then it's retained while solving for subsequent contingencies. By fixing the already found optimal locations the number of binary variables that need to be considered while solving the subsequent contingency are reduced. This proposed approach may lead to significant reduction in the number of binary variables that need to be considered during the optimization of next dominant contingency. Thus the complexity of integer optimization in PHASE1 may reduce significantly after each contingency is processed. While solving for any subsequent contingency, the existing VAR support is available in the optimization at zero cost, i.e. zero location cost and zero existing VAR amount cost. This helps in utilizing the existing VAR resource in the system while solving for the subsequent contingency. While solving for the subsequent contingency there are three possible outcomes: (a) an extra VAR amount is needed at an existing location, (b) a new location is selected with a VAR amount, (c) a combination of both (a) and (b). The lower and upper bound of existing VAR sources (for the contingency solved before) are increased if needed, they cannot be decreased however. The increase of lower and upper bound of existing VAR sources do not cause any constraint violation for contingency solved earlier because (non-fixed) VAR sources are not obliged to output at limits for all the contingencies. In minimizing the cost of VAR allocation, existing VAR sources are used preferentially. If it is not possible to satisfy system constraints with existing VAR support then potential VAR support is used.

After the result of first severe contingency is obtained, the allocated VAR support is used to check if the remaining severe contingencies have become non-severe. This is validated by simulating the outage while utilizing the previously allocated VAR support. For the remaining contingencies the outage is simulated, with the automatic adjustment of switched shunt being enabled. If for the available VAR support the bus voltages are acceptable then the particular severe contingency is tagged as non-severe.

The contingencies that become non-severe are discarded from the list of severe contingency. Contingencies that are still severe, are retained in their original descending order of their severity. Then the single contingency optimization is done on the most severe contingency present in the stack. The contingency severity index is not updated in this case as PHASE1 VAR allocation is a rough estimate not an optimal. So the original descending order of contingency severity is used to select the next contingency to be processed in PHASE1. After solving a contingency in PHASE1, the set of optimal location and maximum capacity of existing VAR source is updated. This process is repeated in PHASE1 until all contingencies have been solved.

At the end of PHASE1, two important information's are obtained: (a) the set of dominant contingencies out of severe ones. (b) installed VAR location and amount for all the contingencies.

The solution approaches for solving location problem can be divided into three categories:

1. Classical optimization methods: integer programming, cutting plane techniques, and branch and bound.

2. Heuristic methods: priority list.

3. Meta-Heuristic methods: expert systems, genetic algorithms, tabu search and simulated annealing.

Heuristic methods are easy to implement but only suboptimal solution can be obtained due to incomplete search of solution space. Meta-Heuristic methods are promising and still evolving. They can also handle non-convex cases, but they do not guarantee optimal solution. Also, the computational time is normally huge due to its random search process and this problem becomes more evident in case of large scale system. Classical optimization method, branch and bound is well suited for solving large scale NP-hard combinatorial problem. Branch and bound method guarantees optimal solution.

To solve the PHASE1 MINLP problem, the Branch and Bound (B&B) approach is used. At every node of B&B the problem is solved by relaxing or fixing the integer variables and solving a continuous NLP. The relaxed NLP problem is solved here by Sequential Quadratic Programming (SQP) method. The MINLP optimization problem is solved in GAMS modeling language [85]. For solving MINLP, customized B&B method [86] is used. SNOPT [87] a NLP solver, based upon sequential quadratic programming (SQP) method is used. The overall framework of solving the problem is described in subsequent sections.

3.4.1.1 Branch and Bound

A general MINLP problem can be written as

$$\min \quad f(x,w) \tag{3.1}$$

subject to

$$0 = g(x,w) \tag{3.2}$$

$$0 \geq c(x,w)$$

$$x \in R^n$$

$$w \in Z^m$$

Here x is continuous variable and w is binary variable.

Branch and Bound (B&B) algorithm was first proposed by Land and Doig in 1960. Branch and Bound algorithm has been successfully applied to solve NP complex problems. For example it has been utilized in solving the famous travelling salesman problem.

Branch and Bound algorithm searches the complete space by dividing the solution space into two subspaces iteratively as shown in Figure 3.1. Branch and Bound is an iterative algorithm where each iteration branches the tree and possibly prunes the tree until the solution is found. This is a deterministic method thus it guarantees global optimal solution.

In this work to increase the efficiency of Branch and Bound, system knowledge is incorporated. This helps in reducing the overall computational time. In the following section this will be discussed in more detail.

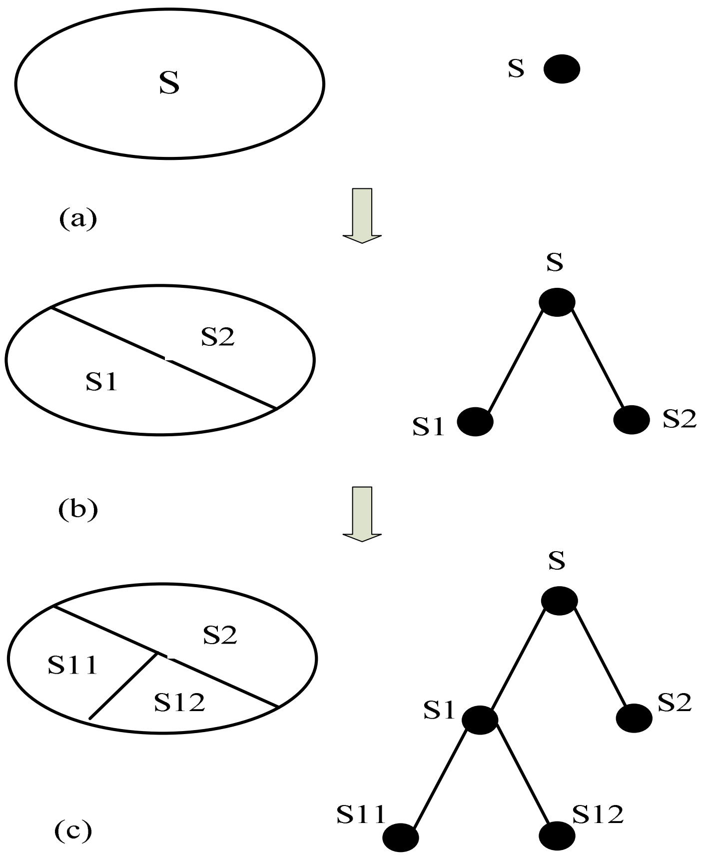

Figure 3.1 Illustration of search space by DFS algorithm of Branch and Bound.

A B&B algorithm for solving MINLP problem requires a search tree (data structure). The search tree maintains a list L of unsolved subproblems. The algorithm also maintains a record of best integer solution that has been found. The solution (x^*, w^*) is called incumbent solution. The incumbent solution gives an upper bound ub of an optimal solution to MINLP. The basic steps involved in B&B are shown in Figure 3.2 and discussed below:

1. Initialize: create list L with MINLP as initial subproblem. When integer variables are integers the problem gives an upper bound. So, if a good integer solution is known,

then initialize x^*, w^*, and ub. If there is no incumbent solution then initialize $ub = +\infty$.

2. Select next Subproblem: select an unsolved subproblem, S, from L. If L is empty then stop. If an incumbent solution exists then that solution is optimal. If no incumbent solution exists then MINLP is infeasible.
3. Solve: when integer variables are relaxed. The relaxed problem gives a lower bound. So, relax integrality constraints in S and solve the relaxed NLP. Obtain solution $\hat{x}, \hat{w}$ and lower bound lb of the subproblem.
4. Fathom Subproblem: If relaxed subproblem was infeasible, then fathom S. If $lb \geq ub$ then fathom current subproblem. So, remove S from L and go to step 2.
5. Integer solution: If $\hat{w}$ is integer, then update x^*, w^*, and ub. Remove S from L and go to step 2.
6. Branch Subproblem: At least one of the integer variables w_i takes fractional value in the solution of current subproblem. So, create two new subproblems S_1 and S_2 by adding the constraint $w_i \leq \hat{w}_i$ and $w_i \geq \hat{w}_i$ respectively. Remove S from L and add S_1 and S_2 to $L$and go to step 2.
7. Solution: When no subproblem is left in L, then optimal solution is x^*, w^*, and optimal value=incumbent.

This work explains a paradigm for the integration of engineering knowledge with the search strategy of a B&B algorithm. The optimization is fairly generic and addresses reactive power source allocation issue in power systems. The solution concerns the allocation of reactive power sources at different locations with different amounts. The system knowledge is exploited to prioritize and coordinate the optimization search or simplify the optimization effort within B&B.

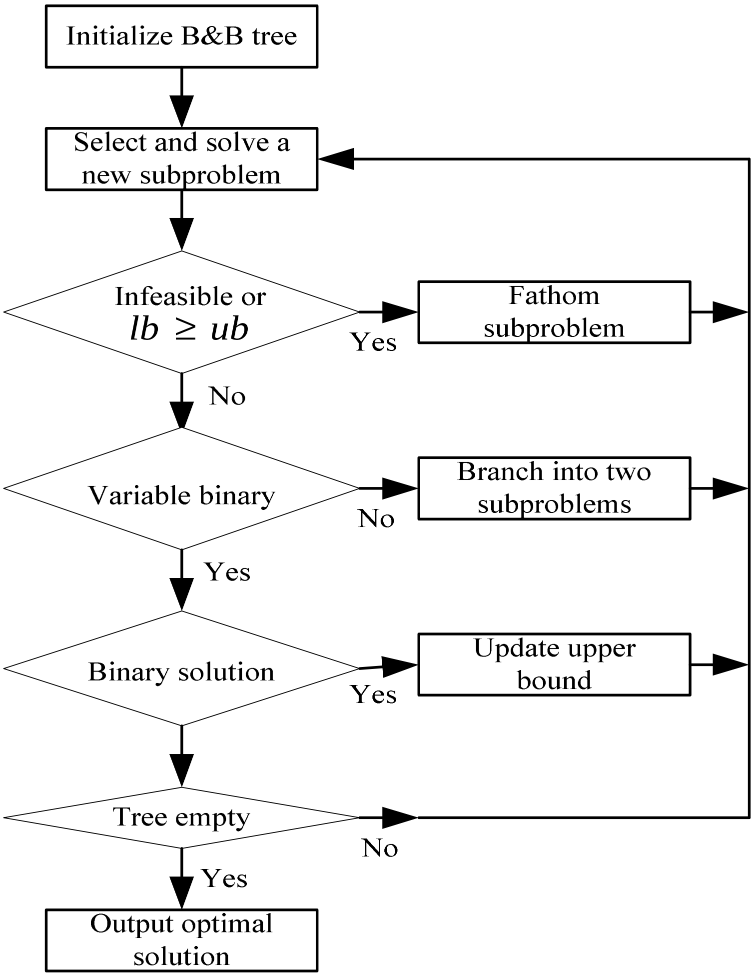

Figure 3.2 Steps involved in Branch and Bound for solving MINLP.

The main aim of developing a customized B&B is to significantly reduce the computational effort by incorporating conceptual system knowledge into the solver. The customization spans the three main aspects of B&B algorithm:

a. Node Selection

b. Branching Variable Selection

c. Upper Bound Selection

The above three selections are used and coordinated to accomplish one main aim, i.e. maximum pruning of the search tree thereby reducing the search time.

A. Node Selection

An important parameter in B&B is selection of next subproblem to be solved. In this work one of the static method i.e. Depth First Search (DFS) is used for node selection. DFS begins by expanding the initial node and generating its successors. In each subsequent step, DFS expands one of the most recently generated nodes. The nodes generated by DFS can be stored in a stack and solved as Last in First out (LIFO) order. If a node does not have any successor then the DFS backtracks to the parent and explores an alternate child. When DFS algorithm finds a solution, then the algorithm updates the current best solution. DFS B&B does not explore paths that are not guaranteed to lead to solutions better than current best solution. When DFS terminates its search then the current best solution is an optimal solution. The advantages of implementing B&B via DFS are:

a. Low node evaluation times

b. High chance of finding feasible solution quickly

c. Minimizes memory requirement, as storage requirement is linear in the depth of the state space being searched.

In DFS B&B as each node in the solution space is visited two tests are done. First, the '*isFeasible*' test is done to check whether the given node represents a feasible solution. Next, the '*getLowerBound*' test is done to determine the lower bound on the best possible solution in the given subtree. The second test determines whether this bound is less than the value of the objective function of the best solution already found. The recursive call to explore the subtree is only made if both tests succeed. Otherwise, the subtree of the solution space is pruned.

In this work, from the parent node DFS first creates the right child node by fixing w_i=0 and then the left child node by fixing w_i =1. Here, w_i is a binary variable. As the left node is stored Last in the stack so it is solved first. This approach helps in obtaining a feasible solution and a better upper bound fast. Thereby, pruning most of the nodes which have more binary variables equal to zero (i.e. w_i=0).

B. Branching Variable Selection

The efficiency of B&B heavily relies on the selection criteria of the branching variable. In the absence of specific system knowledge, use of generic branching strategy cannot guarantee better performance. A good selection of branching variable may result in elimination of large subdomains of solution space. There are several options for variable selections [88]: random, most fractional (most integer infeasible), strong branching, pseudo costs, and reliability branching.

The variable selection policy is used to choose the next variable for creating the child nodes from the bud node. Branching variable selection can make a big difference to the size of a tree search. The goal of branching variable selection is to select the variable that improves the upper bound the most.

The B&B search expands only nodes that survive the pruning test. The basic idea is to encourage early failure of nodes on the tree. The closer to the root that a node is pruned, the more tree is cut off. It is worth mentioning here that pruning rigorously does not compromise on the optimality of the solution.

In this work, the CLI information associated with each candidate control location is used. The candidate locations are ranked in descending order, which means that the candidate location which helps the system the most gets a higher rank.

Here a priority list of branching the binary variables is created. The variable corresponding to candidate control location which is most effective is branched first followed by the next most sensitive one and so on. The priority sequence of locations (binary variables) can be given as:

$w_1 > w_2 > w_3 \ldots > w_i > \ldots > w_N$

Here, binary variable w_1 is branched at tree level 1, followed by w_2 at tree level 2 and so on. Here, N is total number of binary variables.

The advantage of this approach is that it might result in massive pruning of nodes. For example when the node with $w_1=0$ is solved, it is quite likely that the lower bound of this node is greater than the best obtained upper bound, as the absence of most sensitive location will lead to higher reactive power allocation cost. This will result in pruning of that node, which is a great saving as this node is close to the root node.

C. Upper Bound Selection

A good Upper Bound is one important aspect of B&B. sometimes it takes bit of ingenuity to find a good one. Instead of waiting for DFS to find the first incumbent solution, here a heuristic approach is utilized to generate an incumbent solution even before beginning the B&B process. This is tremendously useful in pruning because many buds will never be expanded if their bounding function value is worse than the objective function value of the incumbent solution. As a heuristic, an initial incumbent solution can be obtained by selecting first half candidate locations from priority list as equal to '1' and the lower half candidate locations (with less priority) equal to '0'. This heuristic works well as the candidate locations are used one by one in descending order to meet system requirements. It is highly likely that the optimal solution will be in the neighborhood of half of the total candidate control locations.

3.4.1.2 Sequential Quadratic Programming

At every node of branch and bound tree a continuous NLP problem is solved by relaxing the binary restrictions. Thus, a general NLP problem can be written as

$$\min \quad f(x) \tag{3.3}$$

subject to

$$0 = g(x)$$

$$0 \geq c(x)$$

$$x \in R^n$$

In the NLP problem described above bounds on variables are a special case of inequality constraints. At a stationary point x^*, the first order KKT conditions are given as:

$$\nabla f\left(x^*\right) + \lambda^T \nabla g\left(x^*\right) + \mu^T \nabla c\left(x^*\right) = 0 \tag{3.4}$$

$g\left(x^*\right)=0$

$c\left(x^*\right)+s=0$

$SMe=0$

$(s,\mu)\geq 0$

Thus the solution that satisfies (3.4) is found by using Sequential Quadratic Programming (SQP) method [67]. This NLP formulation can be converted into a Lagrangian augment function $L(x,\lambda,\mu)$ form as:

$$L(x,\lambda,\mu)=f(x)+\lambda^T g(x)+\mu^T c(x) \tag{3.5}$$

where λ and μ are Lagrangian multiplier vectors for equality constraint g and inequality constraint c respectively, $e=[1,1,\cdots,1]^T$, $S=diag\{s\}, M=diag\{\mu\}$. The correspondent QP problem form can be expressed as

$$\min \quad \nabla f_k^T d_k+\frac{1}{2}d_k^T B_k d_k \tag{3.6}$$

subject to

$$\begin{aligned}\nabla g_k^T d_k+g_k&=0\\ \nabla c_k^T d_k+c_k&\leq 0\end{aligned}$$

where B_k is positive definite approximation to the Hessian matrix of the Lagrangian function $L(x,\lambda,\mu)$ of the original problem [68]-[69]. This approximation to Hessian matrix is obtained using Broyden-Fletcher-Goldfarb-Shanno (BFGS) method. BFGS method is a numerical algorithm to find optimal solution for unconstrained nonlinear problem, where it has been considered one of the most efficient approaches. BFGS belongs to quasi-newton method, which utilizes first-order gradient information to generate approximate Hessian matrix. Avoiding the calculation of exact Hessian can save significant computational cost during iteration process of optimization. Thus BFGS method can be used to update the approximate Hessian matrix as:

$$B_{k+1} = B_k + \frac{q_k^T q_k}{s_k^T q_k} - \frac{B_k s_k s_k^T B_k}{s_k^T B_k s_k} \tag{3.7}$$

Where,

$$s_k = x_{k+1} - x_k$$

$$y_k = \nabla_x L(x_{k+1}, \lambda_{k+1}, \mu_{k+1}) - \nabla_x L(x_k, \lambda_k, \mu_k)$$

$$q_k = t y_k + (1-t) B_k s_k$$

$$t = \begin{cases} 1 & \text{if } s_k^T y_k \geq 0.2 s_k^T B_k s_k \\ \dfrac{0.8 s_k^T B_k s_k}{s_k^T B_k s_k - s_k^T y_k} & \text{else} \end{cases}$$

Here q_k is obtained using the damping factor t in order to guarantee that B_{k+1} is sufficiently positive definite.

3.4.2 PHASE2: Multi-Contingency Optimization

The VAR allocation done in PHASE1 may not be optimal. One reason for this is that VAR support installed at the end of PHASE1 may obviate some of the amount installed at the beginning. Thus, PHASE2 is used to refine the solution obtained in PHASE1.

In PHASE2 all the severe contingencies of PHASE1 are considered simultaneously in the optimization framework. In this phase the VAR allocation obtained in PHASE1 is refined to find optimal VAR allocation, by considering all the severe contingencies simultaneously in the optimization model.

In PHASE2, due to consideration of contingencies simultaneously the optimization problem size becomes large. So, the size (and thereby computational) complexity of the problem is simplified by only considering relevant inequality constraints in SCOPF while dropping all equality constraints. The optimization problem in this phase is formulated as Linear Programming (LP). For solving the LP problem, SNOPT [87] solver in GAMS is used.

$$\min \quad J2 = \sum_{c \in C} \left(C_{fc} + C_{vc} \left(Q_{cc} - Q_{ic} \right) \right)$$

As the locations are fixed now, so the objective function is modified as:

$$\min \quad J2 = \sum_{c \in C} C_{vc} \left(Q_{cc} - Q_{ic} \right)$$

Subject to

$$\underline{V}_b \leq V_b^k + \sum_{c \in C} S_{v,b,c}^k \, \Delta Q_{cc}^k + \sum_{c \in C} S_{v,b,c}^k \, \Delta Q_{ic}^k \leq \overline{V_b} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON$$

$$0 \leq Q_{cc}^P + \Delta Q_{cc}^k \leq Q_{cc} \qquad \forall c \in C, \forall k \in SCON$$

$$-\Delta \overline{Q}_{cc} \leq \Delta Q_{cc}^k \leq \Delta \overline{Q}_{cc} \qquad \forall c \in C, \forall k \in SCON$$

$$0 \leq Q_{cc} \leq Q_{cc}^P + \Delta \overline{Q}_{cc} \qquad \forall c \in C$$

$$0 \leq Q_{cc}^P + \Delta \overline{Q}_{cc} \leq \overline{Q}_{cc} \qquad \forall c \in C$$

$$Q_{ic} \leq Q_{ic}^P + \Delta Q_{ic}^k \leq 0 \qquad \forall c \in C, \forall k \in SCON$$

$$-\Delta \overline{Q}_{ic} \leq \Delta Q_{ic}^k \leq \Delta \overline{Q}_{ic} \qquad \forall c \in C, \forall k \in SCON$$

$$Q_{ic}^P - \Delta \overline{Q}_{ic} \leq Q_{ic} \leq 0 \qquad \forall c \in C$$

$$\underline{Q}_{ic} \leq Q_{ic}^P - \Delta \overline{Q}_{ic} \leq 0 \qquad \forall c \in C$$

Here, Q_{cc}^P and Q_{ic}^P are capacitive and inductive VAR amount from the previous PHASE2 iteration. In the 1st iteration of PHASE2 Q_{cc}^P and Q_{ic}^P are equal to output value of VAR in

PHASE1. In the beginning of PHASE2, $\Delta\overline{Q}_{cc}$ and $\Delta\overline{Q}_{ic}$ can have big value which can be decreased slowly as the solution of PHASE2 starts getting closer to the optimal solution.

This optimization formulation does not directly involve steady state power system models. Instead, it uses the voltage sensitivity information to VAR amount, and VAR capacity constraint. So, this approach requires iterating between SCOPF with only inequality constraints and power flow to check (in)equality constraints. The process is repeated until some convergence criteria are met.

At each iteration of PHASE2, VAR amount for all contingencies is obtained. Then the network configuration is updated by including the identified VAR support for each severe contingency. The power flow simulation is carried out for each severe contingency to check if the desired voltage performance criteria is met. This step is necessary at each iteration of PHASE2 as power system model is inherently nonlinear, and the PHASE2 optimization problem is solved by using $\Delta V/\Delta Q$ linear sensitivities. This feedback process helps in identifying contingencies that have voltage violation after the VAR amount solution obtained from PHASE2 LP problem is used in the network. This feedback process also ensures that the result obtained from PHAE2 is optimal.

At each iteration of PHASE2 VAR amount can be further refined by re-computing $\Delta V/\Delta Q$ sensitivity by using the most recent network configuration for each concerned contingency. The updated sensitivity information is fed into PHASE2 optimization process and the optimization problem is solved again. The termination criteria for this iterative process is that all severe contingencies satisfy voltage performance criteria and change in VAR amount during the last few PHASE2 iterations is less than the tolerance level. The output of PHASE2 gives optimal static VAR location and amount for all severe contingencies.

3.5 Results and Discussion

3.5.1 Numerical Results

In this section, static VAR allocation results are described for the test system used in Chapter 2. In the given system much of the active power generation is in the north and west side, whilst much of the demand is in the south and east part of the network. This condition results in a predominant north to south and west to east transfer. This leads to significant reactive power losses in the line, resulting in low system voltage.

The results of PHASE1 optimization are shown in Table 3.2. From the table it can be observed that contingencies are solved in their descending order of severity. The switched shunt amount obtained after solving the present contingency is used to check which other remaining contingencies have become non-severe now for the existing VAR amount. This is shown in Table 3.3 where for example, by using the optimal amount found for contingency 18-21, contingencies 18-20, 12-18, and 12-10 become non-severe.

Table 3.1 Cost comparison of static reactive power devices at different voltage level.

Bus Voltage (KV)	Fixed Cost ($ million)	Variable Cost ($ million/100 MVAR)	Maximum Shunt Capacitance (MVAr)
115	0.07	0.41	120
138	0.10	0.41	150
230	0.28	0.41	200
345	0.62	0.41	300
500	1.30	0.41	300

Table 3.2 PHASE1: optimal allocation considering only one contingency.

No.	Line Contingency		Shunt cap. allocation (p.u.)		
	From Bus	To Bus	Bus 18	Bus 19	Bus 28
1	18	21	0.76	0.12	0.05
2	14	10	0.08	0.42	0.02
3	21	32	0.48	0.38	0.21
4	25	26	0.10	0.03	0.59

From the Table 3.3 it can be also observed that only 4 contingencies are solved in PHASE1. Thus, out of a total of 13 contingencies only 4 dominant contingencies are solved. This results in reduction of computational time and a total saving of 69.23% in PHASE1. Another significant impact is reduction in complexity of integer optimization. This shows the benefit of the methodology proposed in PHASE1.

Table 3.3 Non-severe contingencies after solving each dominant contingency.

Iteration No.	Line Contingency		Contingencies that become non-severe
	From Bus	To Bus	
1	18	21	18-20,12-18,12-10
2	14	10	21-22,19-20
3	21	32	19-21,20-22
4	25	26	28-25,28-29

The optimal allocation of switched shunt obtained at the end of PHASE1 is 0.76 pu at bus 18, 0.42 pu at bus 19,and 0.59 at bus 28. Thus, out of 6 candidate locations only 3 locations are selected as optimal locations for installing VAR source.

While solving the integer problem in PHASE1, the customized B&B was used to reach the solution faster. The depth first approach was used for node selection. Thereby the left child node where the binary variable was fixed to 1 was solved first. This approach helped in achieving the feasible and upper bound of the problem faster. The branching variable selection was predetermined based upon the sensitivity of the candidate location. Thus at each level of the tree the binary variable that needs to be branched was already fed into the program. The order in which binary variable was branched corresponds to 19, 18, 28, 21, 20 and then 26. This approach helped in pruning lot of nodes, resulting in significant computational time saving.

After PHASE1 results are obtained they are further refined in PHASE2 by considering all severe contingencies simultaneously as discussed in Section 3.4. The 3 optimal locations found in PHASE1 are fixed in PHASE2. The refinement of VAR amount is done at these selected 3 locations. This final optimal allocation of mechanically switched shunt capacitors by considering all severe contingencies simultaneously is shown in Table 3.4. The gap between the optimal solution obtained from PHASE2 and solution from PHASE1 is only 7%. This shows the usefulness of using the PHASE1 solution as the starting point in PHASE2. The total installation cost of mechanically switched shunt capacitors is $1.16 million.

Table 3.4 Optimal allocation of mechanically switched shunt VAR.

Shunt VAR location	Shunt VAR amount		Cost ($million)	Total cost ($million)
	Q_c (p.u.)	Q_i (p.u.)		
Bus 18	0.68	0.00	0.381	1.16
Bus 19	0.40	0.00	0.263	
Bus 28	0.57	0.00	0.515	

3.5.2 Discussion

One vital issue in solving the multi-contingency constrained VAR allocation problem is the huge problem size. Due to consideration of all severe contingencies simultaneously in the optimization framework the problem size becomes very big, complex to solve, and very time consuming. Sometimes, the problem may become so complex that it might be very hard to find a good solution.

One of the key factor in solving the multi-contingency VAR allocation problem is to develop a methodology which is less complex, leads to manageable problem size, and reduces overall computational time. This is highly desirable without sacrificing the accuracy of the solution.

The major reduction in the complexity and size of the problem was achieved by decomposing it into two phases. In PHASE1, instead of solving the MINLP problem for all the contingencies it was solved only for the most severe ones. Thus, the complexity of PHASE1 is independent of number of severe contingencies. This approach reduced the problem size and made it more tractable. This approach helped in determining the dominant contingencies. As the MINLP optimization was only applied to dominant contingencies the overall optimization time was significantly reduced. Also, if a location is selected for any contingency then it's retained while solving for subsequent contingencies. By fixing the already found optimal locations the number of binary variables that need to be considered while solving the subsequent contingency are reduced. This proposed approach may lead to significant reduction in the number of binary variables that need to be considered during the optimization of next dominant contingency. Thus the complexity of integer optimization in PHASE1 may reduce significantly after each contingency is processed. Some more reduction in computation time was achieved by ignoring some non-binding inequality constraints. As active power generation was pre-specified so it's operational limit constraint was ignored. Also, post-contingency bus voltages (both low and high) which were within the acceptable limit were ignored. The computational time to determine non-severe contingencies out of severe ones was reduced by solving for all the remaining severe contingencies in parallel.

The effectiveness of the PHASE1 methodology can be further refined by making use of system knowledge. The fact that reactive power is a local issue can be used in creating system equivalent of far away network for each contingency state. The reduction of part of the network by an equivalent, significantly reduces the network size and thereby problem size to be considered in optimization. It's important to understand that a system equivalent can be created for one contingency, but it may be impossible to have one system equivalent which is good for all contingency states. Thus, the optimization model developed in PHASE1 can take advantage of system equivalent (for each contingency). Although this concept is not incorporated in this work, but it is something definitely worth considering while solving for a large size power system network.

The present structure of PHASE1 can be further enhanced to obtain better results. In future as more efficient algorithms are developed which can handle large size (MI)NLP problem. The dominant contingency information obtained from PHASE1 can be utilized to further improve the results. The PHASE1 can be solved again by considering all the dominant contingencies simultaneously. This approach guarantees better PHASE1 results, but at a much reduced computational cost; as only dominant contingencies are considered simultaneously instead of all severe contingencies.

In PHASE1 to solve the MINLP problem Branch and Bound method is used. This work outlines the development of customized B&B solver and reports on the advantages observed from the customization in VAR allocation. The proposed B&B gives power system planners the flexibility of customizing the program according to their system conditions and knowledge base. The customized search engine with built-in system knowledge performs better. The capability of selecting next sub-problem to be solved and to apply branching and pruning tailored to the problem and system properties proves particularly effective. With the customized B&B less nodes have been enumerated before reaching optimality compared to search approach performed by a generic B&B. This has resulted in significant CPU time reduction. The customized product not being a black box gives users the flexibility of modifying the code to increase its performance. For example, the customized B&B can be easily extended to solve the DFS-B&B in parallelism.

After the close to optimal solution of PHASE1 is achieved the aim is to refine the installed VAR amount while considering all the contingencies. Thus, in PHASE2 all the severe contingencies are considered simultaneously. The PHASE2 optimization problem uses sensitivity information to formulate it as LP, which is suitable for large problem size. In

PHASE2, to leverage the problem size while considering all the severe contingencies simultaneously only essential constraints are considered. As in PHASE1 bus voltages which were within the acceptable limit can be ignored.

In PHASE2 only linear sensitivity information is used in the optimization. Thus, it becomes very crucial that effective region of linear sensitivity is used. It is well known from Q-V analysis that voltage and reactive power have nonlinear relationship. Thus, linear sensitivities calculated for a given amount of installed VAR is only good in close neighborhood of operating point. This means that initial VAR amount information provided in PHASE2 optimization should be close to optimal solution. To ensure that optimal solution is achieved and with less computation effort, the VAR amount obtained from PHASE1 is used as the initial operating point. Also, sensitivity information is updated after each iteration of LP optimization.

Thus, the approach developed in this work can aid power system planners to optimize the location and size of new reactive power sources on the transmission system.

CHAPTER 4. OPTIMAL ALLOCATION OF DYNAMIC VAR SUPPORT

4.1 Introduction

In recent years, full utilization of electrical equipments has been done to maximize profit. This causes overloading of some transmission lines deteriorating the stability and reliability of the system. The problem gets even more aggravated during contingencies; when system trajectories, which are the movements of state (say generator angle) and algebraic variables (say bus voltage) may violate acceptability limits. Some of these contingencies may create stability problem, while others may create power quality problem [35]. One of the main contributors to poor power quality is, abnormal low/high voltage such as unacceptable voltage dip or delayed recovery of voltage to acceptable limit. Induction generator during voltage recovery phase may absorb two or three times of reactive power than nominal value thus extending the duration of voltage dip. As penetration level of wind energy increases in future, more dynamic reactive power support may be needed to enhance low voltage ride through (LVRT) capability of wind generators and to maintain short term stability of the system [89]. During voltage dip stalling of induction motor may occur which may further delay voltage recovery. If voltage recovery is slow and there is sustained low voltage then zone 3 relay may mal-trip aggravating the problem further. Unwanted operation of protection relays, especially zone3 [37], [38] due to poor power quality should be avoided, as that can possibly lead to cascading events. Contingency during peak load may depress the voltage in fault area by 40% or more leading to voltage collapse. NERC/WECC has a voltage performance criterion which has to be respected at all times. Once severe contingencies are identified [36], the next step is to find control method to mitigate system failure due to such contingencies. Thus a control mechanism is needed to ensure post disturbance equilibrium. Also, post disturbance equilibrium should be achieved in a time frame so that the disturbance is not spread to other parts of system. The post disturbance transition process should satisfy performance constraints. Most utilities use ‘planning standards’ as a benchmark, such as the NERC/WECC [89] standard to comply with dynamic voltage performance criteria.

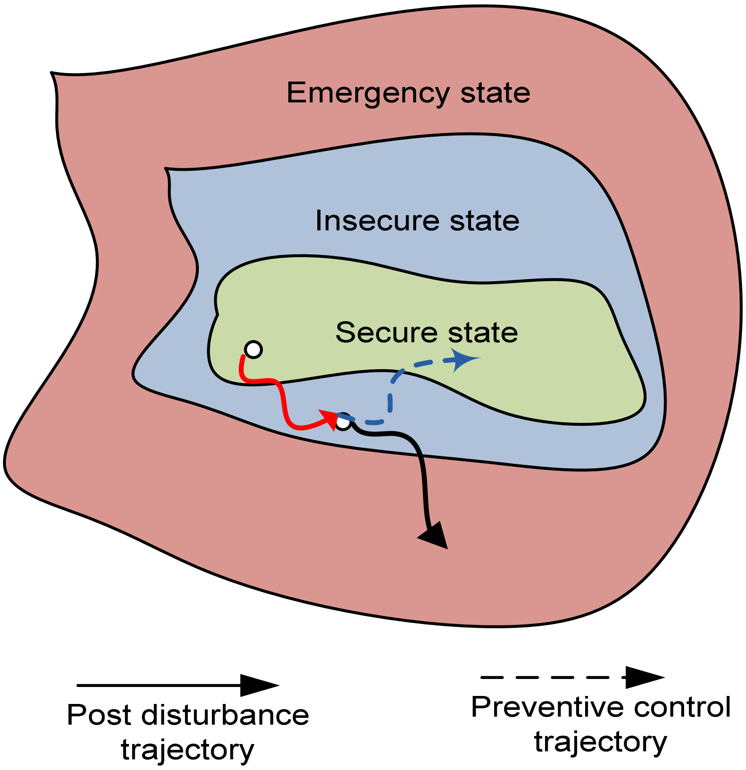

Figure 4.1 Illustration of stability region

For severe contingencies, a control mechanism is needed to confine the disturbance, satisfy performance criteria during transition process and ensure post disturbance equilibrium. There are few options to take care of transient voltage performance and short term stability. One, Under Voltage Load Shedding (UVLS) which is a slow control and may not be able to address fast voltage dynamics developed immediately after an outage. Also, shedding load is the least preferred option. Two, build new transmission lines or upgrade existing transmission lines to higher voltage level but this comes with an extra cost and usually takes 5-10 years of installation time [70]. Three, install fixed shunt capacitors but they cannot handle short term voltage problems effectively. Four, install Flexible AC Transmission Systems (FACTS) dynamic VAR devices such as static var compensator (SVC) [39]-[41]. The cost of installing FACTS range in tens of millions and can be build in 1-3 years [61]. Based upon the nature of problem addressed, dynamic VAR installation is a good option and is considered in this work. Also, dynamic VARs can help to defer transmission enhancement.

In this work, an important issue is addressed with respect to credible contingencies i.e. short term system security and power quality. Fast acting reactive power control is needed to mitigate the above problem. There are two questions regarding installation of dynamic VAR support in the system: (1) where to optimally locate VAR support? (2) what is the optimal capacity of VAR support?

In [39], [40] optimal location of dynamic VAR sources is found for enhancing power system security and power quality. Traditionally used steady state based optimal power flow which finds minimum amount of control needed to obtain required PV margin [42] do not take system dynamics into consideration. As power system is a dynamical system so it seems more realistic that dynamic system model should be used in optimization framework to obtain accurate control amount-time dependence for dynamic security.

The problem of optimal VAR allocation in dynamic framework has two subproblems: a combinatorial optimization problem and a dynamic optimization problem. This gives rise to Mixed Integer Dynamic Optimization (MIDO) problem. This is a complex optimization problem and exact solution can be obtained by complete enumeration of all feasible combinations of locations, which could be a very huge number especially for large scale system. Thus optimal allocation problem can be NP-complete. There are two approaches to solve this problem: heuristic (easy to implement, but low accuracy of result), mixed integer dynamic optimization (very difficult to implement, but high accuracy of result). Heuristic method may work fine if candidate control locations and number of severe contingencies are very few. However, if candidate control locations and number of severe contingencies are many, then this approach may give unrealistic results. The available numerical algorithms for solving MIDO problem fall into one of two categories: indirect (or variational) methods and direct (or discretization) methods.

In the direct methods MIDO problem is solved based upon discretisation of control and state variables. There are two approaches of direct method, namely sequential or control vector parameterization (only control variables are discretised), and simultaneous or direct transcription (fully discretise state and control variables). In sequential method, control variables are represented as piecewise polynomials and optimization is performed with respect to polynomial coefficients. Sequential methods are relatively easy to construct and to apply. But they require repeated numerical integration of DAE model, which may get time consuming for large scale problems. Also, sequential methods have properties of single shooting method, so they cannot handle open loop instability. Moreover, path constraints can be handled only approximately within the limits of control parameterization. Simultaneous discretisation converts MIDO problem into a finite dimensional mixed-integer non-linear problem (MINLP). The advantage of this approach is that dynamic model and optimizer constraints converge simultaneously. It also has better stability properties. For boundary value problems and optimal control problems, which need implicit solutions, this discretisation is a less expensive way to obtain accurate solution. There is one drawback however; due to discretisation the NLP problem size becomes large.

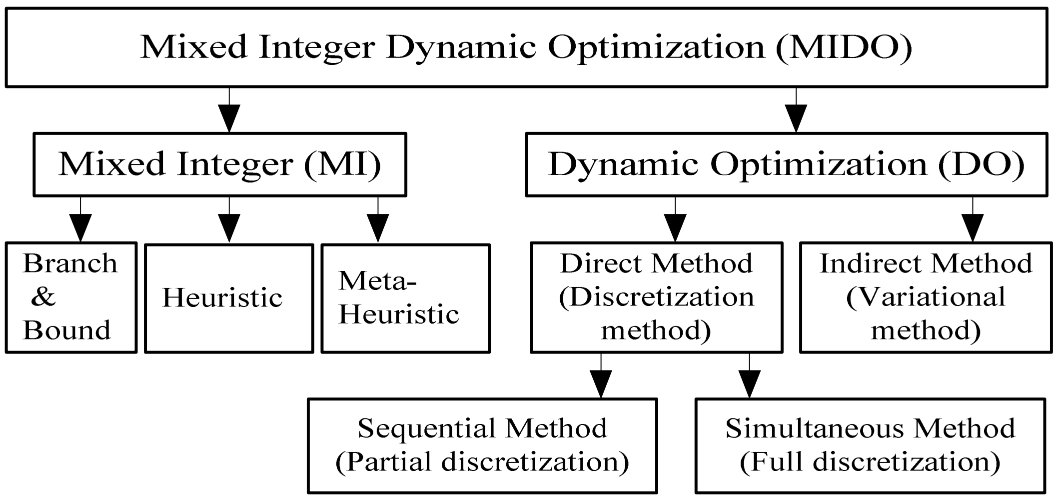

Figure 4.2 Solution approaches to MIDO problem

The MIDO algorithms in literature that utilize reduced space methods all decompose the problem into a series of primal problem where binary variables are fixed, and master problem which determines a new binary configuration for next primal problem. Thus, primal problem corresponds to continuous DO problem which gives a lower bound on final solution whereas master problem gives an upper bound on solution.

Another approach of solving DO (primal) problem is by using indirect method. The indirect approach attempts to find stationary functions via solution of Hamiltonian Maximum principle [44]-[46]. The main advantage of indirect method is high accuracy of obtained solution. In particular no approximation of controls has been undertaken, in contrast to direct methods. Indirect methods are most often applied when high accuracy of solution is crucial and enough time for obtaining the solution is available. The major disadvantage of indirect method is its inability to handle inequality constraints efficiently. If the problem requires handling of active inequality constraints, finding correct switching structure and suitable initial guesses for state and adjoint variables is often very difficult. Also, sometimes the solution may become infeasible for a given set of guessed initial conditions.

The solution approaches for solving location (master) problem can be divided into three categories:

1. Classical optimization methods: integer programming, cutting plane techniques, and branch and bound.

2. Heuristic methods: priority list.

3. Meta-Heuristic methods: expert systems, genetic algorithms, tabu search and simulated annealing.

Heuristic methods are easy to implement but only suboptimal solution can be obtained due to incomplete search of solution space. Meta-Heuristic methods are promising and still evolving. They can also handle non-convex cases, but they do not guarantee optimal solution. Also, the computational time is normally huge due to its random search process and this problem becomes more evident in case of large scale system. Classical optimization method, branch and bound is well suited for solving large scale NP-hard combinatorial problem. Branch and bound method guarantees optimal solution.

4.2 Problem Formulation

Power systems can be represented by a set of differential algebraic equations. In equation (4.1), x, y and u represent differential state variable corresponding to dynamical state, algebraic variable, and control respectively.

$$\begin{aligned} \dot{x} &= f(x, y, u) \\ 0 &= g(x, y, u) \end{aligned} \tag{4.1}$$

where, $x:[t_0, t_f] \mapsto \Re^{n_x}$ is differential variable, $y:[t_0, t_f] \mapsto \Re^{n_y}$ algebraic variable and $u:[t_0, t_f] \mapsto \Re^{n_u}$ control variable. Furthermore we assume that the derivate of the algebraic right hand side function g with respect to y, namely $\partial g/\partial y$ is regular. This guarantees that system is of index 1.

Thus a trajectory is given by:

$$T = (x, y, u) = \left\{ (x, y, u) | t \in [t_0, t_f] \right\}$$

with function x, y and u that satisfy equation (4.1).

The objective of dynamic VAR allocation problem is to find minimum dynamic VAR capacity at optimal locations that ensure dynamic security of system against severe contingencies. Thus power quality (voltage dip) and short term dynamic security problem are addressed here.

As cost of VAR device is proportional to it's rating (maximum capacity). Hence, the aim is to minimize maximum VAR support requirement over a fixed horizon. In general the optimization problem can be given as:

$$\min \quad J = IC(u, w, p) \tag{4.2}$$

subject to

DAE system

$$\dot{x}^k = f^k(x^k, y^k, u^k, w_c, p^k) \qquad \forall c \in C, \forall k \in SCON$$

$$g^k(x^k, y^k, u^k, w_c, p^k) = 0 \qquad \forall c \in C, \forall k \in SCON \tag{4.3}$$

Control, path and operational limit constraints

$$l^k(x^k, y^k, u^k, w_c, p^k) \leq 0 \qquad \forall c \in C, \forall k \in SCON \tag{4.4}$$

Initial point constraint

$$b^k\left(x_0^k, y_0^k\right) = 0 \qquad \forall k \in SCON \tag{4.5}$$

Binary constraint

$$w_c \in \{0,1\}^{n_w} \qquad \forall c \in C$$

where, $x \in \Re^{n_x}$ and $y \in \Re^{n_y}$ are vectors of differential and algebraic variables respectively; $u \in \Re^{n_u}$ is vector of time varying control variables; $p \in \Re^{n_p}$ is parameter vector such as C_v

which is, variable cost of dynamic VAR source which can vary depending upon technology. f represents dynamics of generator in form of differential equations; g represents system power balance equation in nonlinear form, furthermore it is assumed that $\partial g/\partial y$ is regular ; l represents time-invariant inequality constraints of state and algebraic variables such as minimum and maximum allowed voltage deviation during transient state condition and minimum and maximum operational capacity of different electrical devices. Power system dynamics may have system state conditions at initial time. The initial time condition is called boundary conditions. Thus, boundary conditions of system differential-algebraic equations (DAEs) are covered in b.

4.2.1 Objective Function

Dynamic VAR allocation has fixed cost associated with installation location and variable cost proportional to its rating (maximum capacity).

So, the objective is to find minimum VAR installation cost, which can ensure system security against all severe contingencies.

$$\min \quad J = \sum_{c \in C} w_c \cdot \left(C_{fc} + C_{vc} \cdot \left(Q_{cc} - Q_{ic} \right) \right) \tag{4.6}$$

In this work, fixed cost of $1.5Million and variable cost of $5Million/100Mvar is used [61].

4.2.2 Angle Stability Constraint

Voltage instability is mainly driven due to load dynamics. However, it gets influenced by the dynamics of synchronous generator which provide power and voltage to load buses [64]. Especially in short term time scale, there is no clear distinction between load driven and generator driven instability problem. Most practical voltage collapse incidents include some element of both voltage and angle instability. It is not very uncommon for voltage instability leading to angle instability [65]. As motor load proportion increases, motor terminal voltage drops more. Also, motor active power decreases leading to generation load imbalance which may deteriorate the magnitude of angular excursion and angle stability.

Similarly in short term time scale angle instability depresses voltage which may cause motor stalling thus leading to voltage instability. So in a practical system voltage instability of a load is possible due to loss of synchronism of any generator [66]. In the case of August 10, 1996 Western Interconnection breakup, PG&E and SCE experienced angular instability which left portions of SCE system operating at about 60% voltage for 10's of seconds. A rotor angle stability constraint ensures that system remains synchronized and avoids local blackout. The transient stability can be monitored through the rotor angle and its deviation from a centre of inertia reference frame. The stability constraints can be expressed as follows:

$$\rho^L \le \delta_g(t) - \delta_{COI}(t) \le \rho^U \quad \forall g, \forall t \tag{4.7}$$

This easy test of stability is sufficient to ensure an acceptable system behavior since it's combined with other time varying inequality constraints. The value of ρ is a practical threshold which can be fixed on the basis of planner experience.

where

ρ^L, ρ^U is a fixed value

$$\delta_{COI}(t) = \sum_{g=1}^{Ng} M_g \delta_g(t) \Big/ \sum_{g=1}^{Ng} M_g \qquad \forall t \tag{4.8}$$

4.2.3 Voltage Performance Constraint

It is not very uncommon for voltage problem leading to induction motor stalling. Mostly motors stall when voltage drops by 20% or more of its nominal value. Due to low voltage, motor torque falls below load torque and motor slows to standstill. This leads to large reactive power consumption further depressing voltage. Thus, it is important to maintain voltage within acceptable limits. So, transient voltage dip constraint ensures that voltage dip remains within acceptable limits and stability of the system. As low system voltage is a good indication of system instability. Thus the low voltage constraint can help in preventing voltage instability [62] and maybe angle instability as observed in [63]. During severe contingencies some generators push their voltage to high values to mitigate low voltage problem, but sometimes this maybe undesirable. Thus, by enforcing an upper limit on voltage excessive overshoot of voltage at generator bus is prevented.

$$0.75V_{0d} \le V_d(t) \le 1.25V_{0d} \qquad \forall d, \forall t \in [t_{cl}, t_s)$$

$$0.70V_{0g} \le V_g(t) \le 1.30V_{0g} \qquad \forall g, \forall t \in [t_{cl}, t_s) \tag{4.9}$$

Duration of low voltage constraint ensures that the time of low voltage does not exceed the acceptability limit so that especially the induction motors don't stall. Also, if this constraint is not violated then mal-operation of distance relays on transmission lines can be avoided.

$$0.75V_{0d} \le V_d(t) \le 0.80V_{0d} \quad \textit{for } \Delta t \le 20 cycles \qquad \forall d, \forall t \in [t_{cl}, t_s) \tag{4.10}$$

$$1.20V_{0d} \le V_d(t) \le 1.25V_{0d} \quad \textit{for } \Delta t \le 20 cycles \qquad \forall d, \forall t \in [t_{cl}, t_s)$$

Lastly voltage recovery constraint is included to ensure that system voltage recovers to an acceptable steady-state operating range within a specified time period. Transient voltage dip related inequality constraints, duration of low voltage and steady state voltage recovery inequality constraints are shown in Figure 4.3. In this work t_s is set to 3 seconds after fault clearing.

$$0.95V_{0b} \le V_b(t) \le 1.05V_{0b} \qquad \forall b, \forall t \in [t_s, t_f] \tag{4.11}$$

The optimization problem given by (4.2)-(4.5) falls under the category of Mixed Integer Dynamic Optimization (MIDO) problem. In this work, simultaneous discretisation is done to convert the MIDO problem in to MINLP problem. Then branch and bound approach is used to solve the MINLP problem. The problem is solved by relaxing or fixing the integer variables and solving a continuous NLP. The relaxed NLP problem is solved here by

Sequential Quadratic Programming (SQP) method. The overall framework of solving the problem is described in subsequent sections.

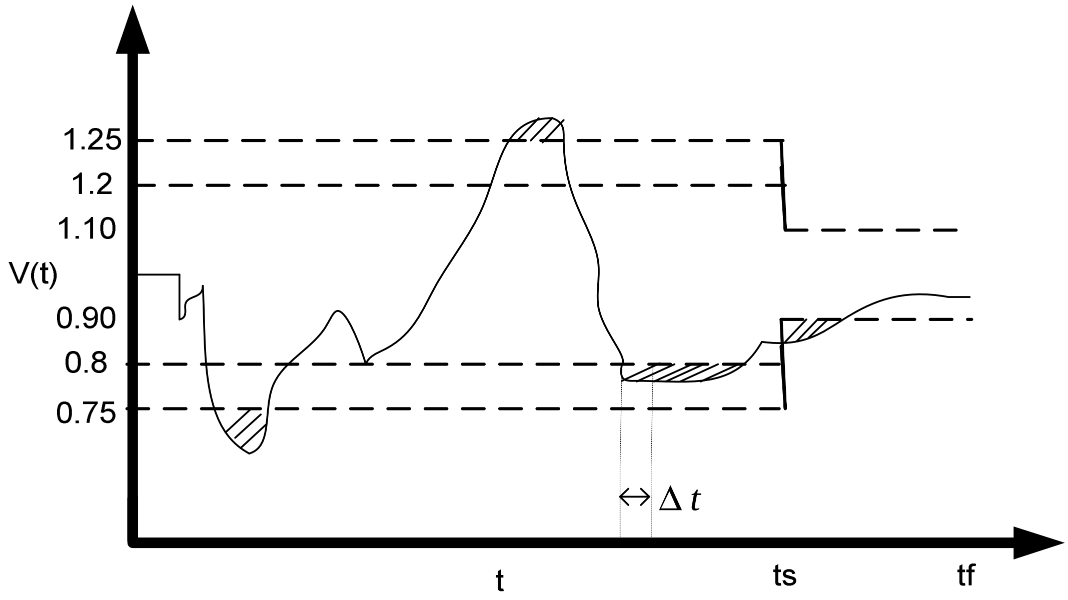

Figure 4.3 Transient voltage dip, and voltage recovery constraint.

4.3 Solution Methodology for Dynamic VAR Allocation

The aim of dynamic reactive power allocation is to determine the optimal location and amount of new reactive power sources on transmission system. The optimization is performed to ensure the security of the system and maintain system bus voltage within an acceptable range for different contingencies. This simultaneous consideration of contingencies may lead to huge problem size and large number of integer variables. This may increase the complexity of the problem exponentially. Thus, solving the problem simultaneously for a set of contingencies can be very complex.

The resultant multi-contingency constrained VAR allocation problem is too big to be implemented efficiently. So, a methodology is proposed which decomposes the overall optimization problem into two Phases. In first phase i.e. PHASE1, the optimization is performed on one severe contingency at a time, instead of optimizing all of them simultaneously. The complexity of the PHASE1 is much less than the complexity of the original problem. Also, the complexity of PHASE1 is independent of the number of severe contingencies. The concept of dominant contingencies as introduced in Section 3.3 is used to limit the number of contingencies to be processed in PHASE1. At the end of PHASE1 close to optimal VAR allocation information is obtained. The VAR allocation obtained in PHASE1 is refined in PHASE2 by considering all the severe contingencies simultaneously. The PHASE2 problem is modeled as Linear Programming (LP). The advantage of the overall proposed methodology is that large number of contingencies can be considered with an acceptable run time and memory requirement while ensuring the accuracy of the results.

4.3.1 PHASE1: Single Contingency Optimization

In PHASE1, reactive power allocation is done for a single contingency. In this Phase, there are two categories of dynamic VAR sources:

1. Existing VAR source: These VAR source location and amount are needed for any solved single contingency optimization. The VAR location and the amount already found for solved contingency is retained for subsequent optimizations in PHASE1. During subsequent optimization of PHASE1, the existing VAR amount at a previously found optimal location can only increase not decrease. This

ensures that the current VAR amount still satisfies the previously solved contingencies.

2. Candidate VAR source: These are additional VAR sources which may be needed during PHASE1 of optimization if there is insufficient existing VAR support to satisfy system security and voltage violation.

In PHASE1, optimal VAR allocation is done for one contingency at a time. The basic philosophy of solving PHASE1 here is similar to that explained in Section 3.4.1. The same problem and equations as defined in Section 4.2 are used by considering only one contingency. The information obtained from contingency ranking is used in this phase to determine the sequence in which single contingency optimization will be performed. Contingencies to be processed in PHASE1 are selected in the order of their descending severity, i.e. most severe contingency is processed first followed by less severe and so on. It is very likely that VAR allocated for a severe contingency is adequate in resolving voltage problem for a less severe contingency. Thus, solving contingencies in descending order in PHASE1 leads to better solution and speeds up the overall process.

After the result of first severe contingency is obtained, then the allocated VAR support is used to check if the remaining severe contingencies have become non-severe. This is validated by simulating the outage while utilizing the previously allocated VAR support. If for the available dynamic VAR support the bus voltages are acceptable then the particular severe contingency is tagged as non-severe.

The contingencies that become non-severe are discarded from the list of severe contingency. Contingencies that are still severe, are retained in the descending order of their severity. Then the single contingency optimization is done on the most severe contingency present in the stack. This process is repeated in PHASE1 until all contingencies have been solved.

At the end of PHASE1, two important informations are obtained: (a) the set of dominant contingencies out of severe contingencies. (b) Installed VAR location and amount for all the contingencies.

To solve the PHASE1 MIDO problem, first it is converted to MINLP problem form. The MINLP problem is then solved by the Branch and Bound (B&B) approach. The problem is solved by relaxing or fixing the integer variables and solving a continuous NLP. The relaxed NLP problem is solved here by Sequential Quadratic Programming (SQP) method.

4.3.1.1 Consideration of Location in MIDO

Immediately after the occurrence of the contingency, the system goes into dynamic (or transient) phase, which can extend from few milliseconds to few seconds. During the transient phase fact acting controllers are used to restore the system. Once the transients die out the system attains steady state which can extend for hours with the help of slow static controllers. The difference in dynamic and static behavior of the system occurs due to the consideration of dynamic and static response of the devices such as generator, and load. It is worth noting here that voltage problems are mainly driven by load location, magnitude and characteristic.

In static analysis the optimal locations found by static optimization (SO) are mainly dependent upon the location and magnitude of the load. While moving from static to dynamic analysis the location and magnitude of the load remains the same. The one thing that changes is the response (behavior) of the load. The response of the load changes from being static to dynamic. So, to control the dynamic response of the load, the VAR support with dynamic response is needed. If the VARs placed at optimal locations found by static optimization, have dynamic capability then they may be fully or partially capable of controlling dynamic performance of load. So, if the static VAR source (of right size) placed at optimal locations found in static analysis have the capability of fast and smooth ramping Up/Down and turn On/Off, then that would help in mitigating most of the problem, if not all. Ofcourse, it may not solve the problem completely, due to different motor load demand at different buses. As the motor load demand at different buses may differ, so the dynamic VAR locations and amount may vary from that of static VAR locations and amount. As static VAR sources don't have the capability of fast Up/Down smooth ramping, that leads to the use of dynamic VAR sources. However, once the system moves from transient phase to steady state phase then it is desired to bring the dynamic VAR source output back to 'zero' and let the static VAR source provide the required reactive power requirement. Also, sometimes a static VAR source which is enabled with a fast switch On/Off capability can reduce the amount of dynamic VAR support needed. Thus, static and dynamic VAR source at the same location can mutually benefit from each other.

The good news is that there is a very high correlation between optimal static VAR locations and dynamic VAR locations. The only difference is in the response characteristic of the VAR device which is mainly driven due to the response characteristic of the load. So the same optimal locations that were found in static analysis for a set of contingencies can be preferred for installing dynamic VAR sources for the same set of contingencies, ofcourse the locations may not be an optimal one for installing dynamic VAR sources. This approach couples the static analysis and dynamic analysis, which in a physical sense are also coupled. The approach developed makes use of information gathered and generated during one analysis, while solving the other. This information sharing process covers the whole spectrum of the problem, ensures better results for the whole problem, and reduces the overall computational complexity.

Thus, an approach is developed here which makes use of optimal location information obtained in static analysis. The optimal locations obtained in static analysis are given preference while solving the dynamic VAR allocation problem. This helps in either completely getting rid of integer optimization or solving it with very few candidate locations. This significantly reduces the complexity of the integer optimization part in the MIDO problem.

4.3.1.2 Discretization of DAE System

The optimization problem in PHASE1 is formulated very similar to that given in Section 4.3 and is solved for only one contingency at a time. In PHASE1 detailed power system model is considered, which helps in incorporating the system dynamic in the optimization process. Due to incorporation of system dynamics in the optimization framework the problem takes the form of MIDO.

The continuous MIDO problem is transformed to MINLP problem through a full discretization of state and control variables. There are various discretization schemes such as Imlicit Euler method, Trapezoidal method. The advantage of trapezoidal method is that its A-stable and in addition to that they have stiff decay property. Thus trapezoidal method is a good choice for the solution of stiff DAE system, which is the case in power systems. In trapezoidal method constraints are easily set at the end of each element.

Trapezoidal method is used to discretize differential algebraic equations into a set of algebraic equations. The profiles of variables are approximated by a family of polynomials on finite elements. The time interval $[t_0, t_f]$ is divided into Nt finite elements of length h_i such that $\sum_{i=1}^{Nt} h_i = t_f - t_0$, where $t = t_{i-1} + h_i \tau, \quad t \in [t_{i-1}, t_i], \quad \tau \in [0,1]$.

The differential variables are required to be continuous throughout the time horizon, while the algebraic and control variables are allowed to have discontinuities at the boundaries of elements. Thus by discretizing the differential algebraic equation, the original MIDO is transformed into MINLP form. The solution methodology of MINLP problem is same as that discussed in Section 3.4.1.

4.3.2 PHASE2: Multi-Contingency Optimization

The VAR allocation done in PHAES1 may not be optimal but its close to optimal and gives a good indication about the dynamic VAR requirement to ensure system security. The VAR allocation result obtained in PHASE1 act as a good starting point for finding optimal amount that is needed for a detailed dynamic system model. The refinement of PHASE1 result is done in PHASE2 where detailed dynamic system model and all contingencies are considered simultaneously.

In PHASE2, all the severe contingencies of PHASE1 are considered simultaneously in the optimization framework. In this Phase the VAR locations obtained in PHASE1 are fixed and the refinement is done only on the amount of VAR needed.

The problem is simplified by only considering relevant inequality constraints in SCOPF while dropping all other constraints. The optimization problem in this Phase is formulated as Linear Programming (LP).

$$\min \quad J2 = \sum_{c \in C} \left(C_{fc} + C_{vc} \left(Q_{cc} - Q_{ic} \right) \right)$$

As the locations are fixed now, so the objective function is modified as:

$$\min \quad J2 = \sum_{c \in C} C_{vc} \left(Q_{cc} - Q_{ic} \right)$$

Subject to

For low voltage dip (sensitivity has a negative value)

$$\Delta V_b^k + \sum_{c \in C} S_{v,b,c}^k \, \Delta Q_{cc}^k \leq \Delta \overline{V_b} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON$$

For duration of low voltage (sensitivity has a negative value)

$$\tau_b^k + \sum_{c \in C} S_{\tau,b,c}^k \, \Delta Q_{cc}^k \leq \overline{\tau_b} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON$$

For high voltage swell (sensitivity has a positive value)

$$\Delta V_b^k + \sum_{c \in C} S_{v,b,c}^k \, \Delta Q_{ic}^k \leq \Delta \overline{V_b} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON$$

For duration of high voltage (sensitivity has a positive value)

$$\tau_b^k + \sum_{c \in C} S_{\tau,b,c}^k \; \Delta Q_{ic}^k \le \overline{\tau_b} \qquad \forall b \in B, \forall c \in C, \forall k \in SCON$$

$$0 \le Q_{cc}^P + \Delta Q_{cc}^k \le Q_{cc} \qquad \forall c \in C, \forall k \in SCON$$

$$-\Delta \overline{Q}_{cc} \le \Delta Q_{cc}^k \le \Delta \overline{Q}_{cc} \qquad \forall c \in C, \forall k \in SCON$$

$$0 \le Q_{cc} \le Q_{cc}^P + \Delta \overline{Q}_{cc} \qquad \forall c \in C$$

$$0 \le Q_{cc}^P + \Delta \overline{Q}_{cc} \le \overline{Q}_{cc} \qquad \forall c \in C$$

$$Q_{ic} \le Q_{ic}^P + \Delta Q_{ic}^k \le 0 \qquad \forall c \in C, \forall k \in SCON$$

$$-\Delta \overline{Q}_{ic} \le \Delta Q_{ic}^k \le \Delta \overline{Q}_{ic} \qquad \forall c \in C, \forall k \in SCON$$

$$Q_{ic}^P - \Delta \overline{Q}_{ic} \le Q_{ic} \le 0 \qquad \forall c \in C$$

$$\underline{Q}_{ic} \le Q_{ic}^P - \Delta \overline{Q}_{ic} \le 0 \qquad \forall c \in C$$

Here, Q_{cc}^P and Q_{ic}^P are capacitive and inductive VAR amount from the previous PHASE2 iteration. In the 1st iteration of PHASE2 Q_{cc}^P and Q_{ic}^P are equal to output value of VAR in PHASE1. In the beginning of PHASE2, $\Delta \overline{Q}_{cc}$ and $\Delta \overline{Q}_{ic}$ can have big value which is decreased slowly as the solution of PHASE2 starts getting closer to the optimal solution.

This optimization formulation does not directly involve dynamic power system models. Instead, it uses the sensitivity of voltage dip and duration of low voltage to VAR amount, and VAR capacity constraint. So, this approach requires iterating between SCOPF with only inequality constraints and time domain simulation of detailed power system to check (in)equality constraints. The process is repeated until some convergence criteria are met.

At each iteration of PHASE2, VAR amount for all contingencies is obtained. Then the network configuration is updated by including the identified VAR support for each severe contingency. The time domain simulation is carried out for each severe contingency to check if the desired voltage performance criteria are met. This step is necessary at each iteration of PHASE2 as power system model is inherently nonlinear, and the PHASE2 optimization problem is solved by using $\Delta V/\Delta Q$ linear sensitivities. This feedback process helps in identifying contingencies that have voltage violation after the VAR amount solution obtained from PHASE2 LP problem is used in the network. This feedback process also ensures that the result obtained from PHAE2 is optimal.

At each iteration of PHASE2 VAR amount can be further refined by re-computing $\Delta V/\Delta Q$ sensitivity by using the most recent network configuration for each concerned contingency. The updated sensitivity information is fed into PHASE2 optimization process and the optimization problem is solved again. The termination criteria for this iterative process is that all severe contingencies satisfy voltage performance criteria and change in VAR amount during the last few PHASE2 iterations is less than the tolerance level. The output of PHASE2 gives optimal dynamic VAR location and amount for all severe contingencies.

4.5 Results and Discussions

4.5.1 Numerical Results

In this section, dynamic VAR allocation results are described for the test system used in Chapter 2. The results of PHASE1 optimization are shown in Table 4.1. From the table it can be observed that contingencies are solved in their descending order of severity. The SVC amount obtained after solving the present contingency is used to check which other remaining contingencies have become non-severe now for the existing VAR amount. This is shown in Table 4.2 where for example, by using the optimal amount found for contingency 19-21, contingencies 19-20, 21-22, 21-32, and 14-10 become non-severe. From the Table 4.2 it can be also observed that only 4 contingencies are solved in PHASE1. Thus, out of a total of 13 contingencies only 4 dominant contingencies are solved. This results in reduction of computational time and a total saving of 69.23% in PHASE1. While solving all the 4 dominant contingencies in PHASE1 only 3 binary variables were used instead of 6, as 3 locations had already been selected. Thus the complexity of the integer optimization was significantly reduced and so was the overall run time.

Table 4.1 PHASE1: optimal allocation of SVC considering only one contingency.

Iteration No.	Line Contingency		SVC allocation (p.u.)		
	From Bus	To Bus	Bus 18	Bus 19	Bus 28
1	19	21	1.04	1.48	0.23
2	20	22	1.17	1.60	0.31
3	25	26	1.17	1.60	0.87
4	18	21	1.20	1.60	0.87

Table 4.2 Non-severe contingencies after solving each dominant contingency.

Iteration No.	Line Contingency		Contingencies that become non-severe
	From Bus	To Bus	
1	19	21	19-20, 21-22, 21-32, 14-10
2	20	22	12-18, 12-10
3	25	26	28-29, 28-25
4	18	21	18-20

The allocation of SVC obtained at the end of PHASE1 is 1.20 pu at bus 18, 1.60 pu at bus 19, and 0.87 at bus 28.

After PHASE1 results are obtained they are further refined in PHASE2 by considering all severe contingencies simultaneously as discussed in Section 4.3. This final optimal allocation of SVC by considering all severe contingencies simultaneously is shown in Table 4.3. Thus, the total SVC installation cost is $22.69 million.

Table 4.3 Optimal allocation of SVC.

SVC location	SVC amount		Cost ($million)	Total cost ($million)
	Q_c (p.u.)	Q_i (p.u.)		
Bus 18	1.189	0.00	7.445	22.69
Bus 19	1.584	0.00	9.419	
Bus 28	0.866	0.00	5.829	

Figure 4.4 shows voltage response of bus 19 and bus 119 due to line contingency 19-21 with and without SVC. From the bus voltage response with SVC it can be observed that after the fault is cleared there is no voltage dip and delayed voltage recovery problem. The

presence of dynamic VAR device (SVC), leads to fast voltage recovery which in turn significantly reduces the absorption of reactive power by the load as shown in Figure 4.5.

From Figure 4.5 it can be observed that due to the presence of SVC the reactive power demand of load returned to its pre-fault level at 0.7secs, whereas without the SVC it took 1.7 secs. The reduced reactive power demand, results in less motor speed deviation as shown in Figure 4.6.

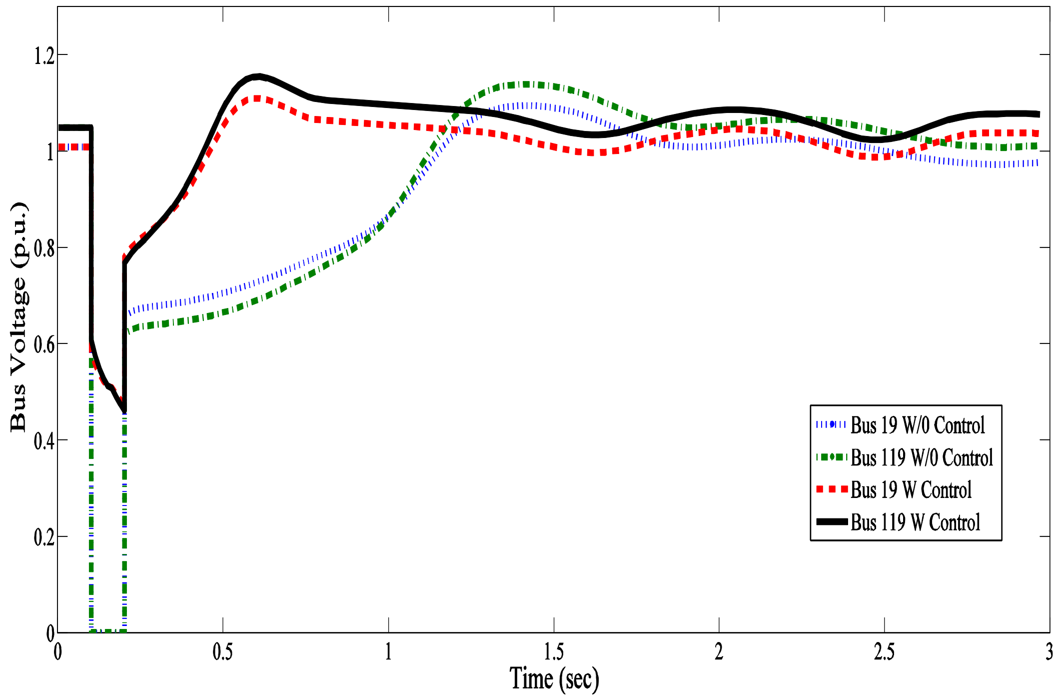

Figure 4.4 Bus voltage response due to line contingency 19-21 with and w/o SVC.

From Figure 4.6, where it can be clearly observed that with the presence of SVC the speed deviation is 0.02pu less than that of without SVC and the speed recovers to its pre-fault level at 0.7secs whereas it took 1.2secs to recover to its pre-fault level without SVC.

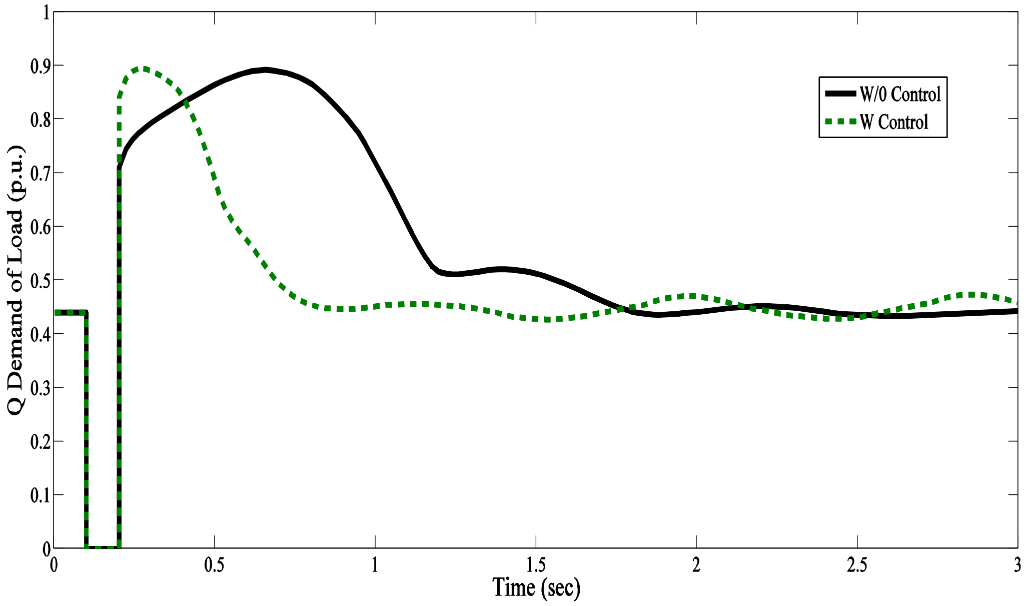

Figure 4.5 Q demand @bus 119 due to contingency 19-21 with and w/o SVC.

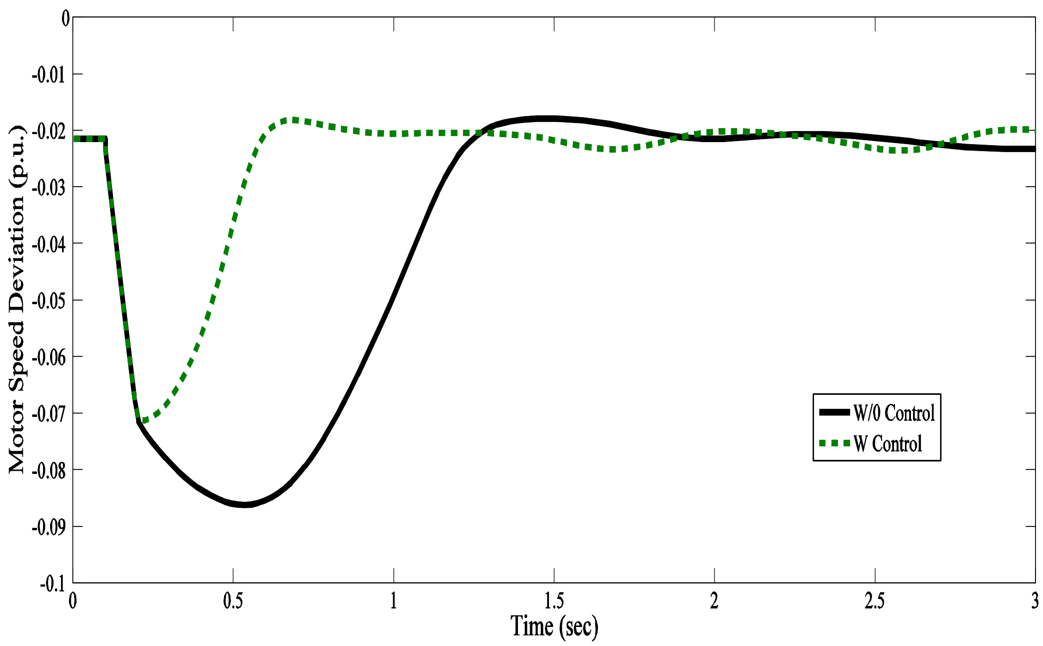

Figure 4.6 Motor speed dev. @bus 119 due to contingency 19-21 with and w/o SVC.

4.5.2 Discussion

One vital issue in solving the multi-contingency constrained dynamic VAR allocation problem is the huge problem size. The huge problem size arises due to consideration of system dynamics and multiple contingencies simultaneously in the dynamic optimization framework.

One of the key factor in solving the multi-contingency dynamic VAR allocation problem is to develop a methodology which is less complex, leads to manageable problem size, and reduces overall computational time. This is highly desirable without sacrificing the accuracy of the solution.

The major reduction in the complexity and size of the problem was achieved by decomposing it into two phases. In first phase i.e. PHASE1, instead of solving the problem for all the contingencies it was solved only by considering one contingency at a time. Thus the complexity of PHASE1 is independent of the number of severe contingencies. The contingencies are solved in their decreasing order of severity. This approach immensely helped in identifying dominant contingencies that need to be solved, and non-severe contingencies that can be ignored. The information obtained from static VAR allocation is used while solving for dynamic VAR allocation. By giving preference to the optimal locations obtained for static VARs, the number of binary variables that need to be considered while solving the contingencies in PHASE1 are reduced. Thus, the complexity of integer optimization in PHASE1 was significantly reduced. In PHASE1 as only one contingency was solved at a time so the VAR amount obtained at the end may not be accurate. The rough estimate of dynamic VAR amount obtained in PHASE1 is further refined in PHASE2 by considering all severe contingencies simultaneously.

The PHASE2 optimization problem uses sensitivity information to formulate it as LP, which are suitable for large problem size. In PHASE2, to leverage the problem size due to consideration of full dynamic model while considering all the severe contingencies simultaneously only essential constraints are considered. In PHASE2 only linear sensitivity information is used in the optimization. Thus, it becomes very crucial that effective region of linear sensitivity is used. This means that initial VAR amount information provided in PHASE2 optimization should be close to optimal solution. To ensure that optimal solution is achieved and with less computation effort, the VAR amount obtained from PHASE1 is used as the initial operating point. Also, sensitivity information is updated after each iteration of LP optimization by using the full dynamic model and the most updated dynamic VAR amount.

Thus, the approach developed in this work can aid power system planners to optimize the location and size of new dynamic reactive power sources on the transmission system.

CHAPTER 5. CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

This dissertation represents a significant contribution to the highly identified need of system planners in better allocation of reactive power source. In this work a tool has been developed for optimal allocation of static and dynamic VAR source. The tool finally offers an answer to planner's long awaited question of optimally allocating dynamic VAR sources while considering system dynamics for a set of severe contingencies being considered simultaneously. The approach that is developed here bridges the static and dynamic VAR allocation problem. This results in maximizing the benefit of installed static and dynamic VAR sources at minimum investment cost.

In the restructured environment, all users and planners of power system expect appropriate voltage level and system security after a contingency. Static VAR allocation is done to ensure acceptable steady state system voltage and system stability. To ensure system dynamic security and restore system performance to acceptable limits within admissible time dynamic VAR allocation is considered in this work. Thus a framework is needed for power system static and dynamic monitoring and for maintaining static and dynamic security.

Although static VAR allocation problem has been an active research area, but there is no industry grade tool to address this important issue. Further, very limited research has been done by academic and industrial researchers for optimal allocation of dynamic VAR sources. Mostly, dynamic VAR planning is structured mainly by static analysis of the system. Thus by static optimization based analysis; dynamic performance among different VAR devices, and their post-contingency impact on system gets ignored. So, dynamic optimization is needed to optimally allocate VAR sources based upon their dynamical behavior and realistic system response due to their presence.

This work provides a framework with state of the art computational method for power system dynamic security assessment and enhancement. Time domain simulation is performed to capture and realize the realistic dynamical behavior of system. A tool for dynamic VAR allocation has been developed completely in time domain framework to ensure that system trajectories remain within acceptable state space domain.

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

1. Development of a systematic methodology by integrating the information obtained from static and dynamic analysis for optimally allocating static and dynamic VAR sources. This results in optimal allocation of static and dynamic VAR sources and enables coordinated use of static and dynamic VAR sources. This minimizes the overall amount of installed VAR sources and maximizes their overall utilization.
2. Developed an approach to reduce the optimization problem size by considering only a smaller but relevant set of severe contingencies and focusing on areas prone to voltage problem. To do this, *severity indices* based upon static and dynamic voltage response has been proposed and used. The *severity indices* were used to rank severe contingencies given by Contingency Severity Index (CSI), and rank vulnerable buses given by Bus Vulnerability Index (BVI).

3. Developed a methodology to reduce the complexity of location (integer) problem. First, out of all plausible locations in the network only few but most effective candidate locations are selected and used in the integer optimization. Second, the integer problem is solved by the well known Branch and Bound (B&B) method. To increase the efficiency of B&B while solving the integer problem, customization of the solver is done. The proposed B&B gives power system planners the flexibility of customizing the program according to their system conditions and system knowledge base. The customized solver guides the search process more efficiently and reduces the computational time significantly. Furthermore, the customized product not being a black box gives user an option of modifying the code to increase it's performance, such as but not limited to solving DFS-B&B in parallelism.
4. To address the issue of VAR allocation for multiple severe contingencies, an optimization framework is proposed which solves the problem in two phases. In first phase i.e. PHASE1 the optimization problem is formulated as MINLP and is solved only for one contingency at a time. The result of PHASE1 gives a sense of system response and VAR requirement. The output of PHASE1 gives near optimal solution, which is fed into second phase i.e. PHASE2. The close to optimal solution obtained from PHASE1 is further refined in PHASE2 to get optimal solution by considering all the contingencies simultaneously. As Q-V relationship is non-linear so a close to optimal solution of PHASE1 is very good starting point for PHASE2. As the starting point of PHASE2 is near optimal solution of PHASE1, thus the optimal

solution can be achieved faster. The PHASE2 problem is formulated as a LP problem and solves all severe contingencies simultaneously. As the optimization formulation is linear in PHASE2, it is fast, even though all the severe contingencies are considered simultaneously.

5. In PHASE1, knowledge of problem domain is incorporated in the approach to reduce the complexity of the problem. In PHASE1, there are three ways by which the problem complexity and overall computational time is significantly reduced. First, in PHASE1 as only one contingency is considered at a time so the complexity of PHASE1 is independent of the number of severe contingencies. Second, the concept of dominant contingency is introduced and used in PHASE1. Thus, instead of solving for all the severe contingencies in PHASE1 only very few dominant contingencies are solved. Third, the optimal locations obtained after solving a dominant contingency are fixed and used while solving subsequent contingencies. This reduces the number of binary variables to be considered while solving subsequent contingencies. Thus, the overall complexity and computational time of integer optimization is significantly reduced by the proposed approach.
6. Developed an approach for dynamic VAR allocation completely in dynamic framework where the problem is formulated as mixed integer dynamic optimization. To solve the DO problem efficient numerical techniques are implemented. To efficiently handle path (inequality) constraints simultaneous discretization approach is implemented. By using simultaneous discretization

the DO problem is transformed into NLP form. The resulting NLP is solved by the state of the art gradient based nonlinear solver.

5.2 Future Work

The research work presented in this dissertation has not only made a significant contribution in the field, but has also opened new areas for future research. In the future work following issues will be worth considering:

1. Coordinated control of static and dynamic VAR device i.e. to co-ordinate their response time and amount. This kind of study may require some EMTP based analysis to better understand the impact of switching these devices in/out on transient voltage.
2. Each power network is different and so are the solutions. Even the output characteristics of each dynamic VAR device are slightly different. So, it would be good idea to do a benefit-cost analysis thereby comparing performance of different dynamic VAR devices against their cost.

BIBLIOGRAPHY

[1] G. S. Vassell, "Northeast Blackout of 1965," IEEE Power Engineering Review, vol. 11, pp. 4-8, Jan. 1991.

[2] U.S.-Canada Power System Outage Task Force, "Final Report on the August 14, 2003, Blackout in the United States and Canada: Causes and Recommendations," U.S. Department of Energy, Washington, D.C. April 2004.

[3] P. Fairley, "The unruly power grid," IEEE Spectrum, vol. 41, pp. 22-27, August 2004.

[4] P. Kundur, J. Paserba, V. Ajjarapu, G. Andersson, A. Bose, C. Canizares, N. Hatziargyriou, D. Hill, A. Stankovic, C. Taylor, T. Van Cutsem, and V. Vittal, "Definition and classification of power system stability IEEE/CIGRE joint task force on stability terms and definitions," IEEE Transactions on Power Systems, vol. 19, pp. 1387-1401, 2004.

[5] X. Wang, and J. R. McDonald, Modern power system planning, New York: McGraw Hill, 1994.

[6] Western Electricity Coordinating Council. NERC/WECC planning standards. [Online].Available:http://www.wecc.biz/documents/library/procedures/CriteriaMaster .pdf (Date accessed: Mar. 9, 2007)..

[7] IEC 61000-4-30 "Electromagnetic Compatibility (EMC) – Part 4-30: Testing and Measurement Techniques – Power Quality Measurement Methods," Feb. 2003.

[8] A. Hammad and M. El-Sadek, “Prevention of transient voltage instabilities due to induction motor loads by static VAr compensators,” IEEE Trans. Power Syst., Vol. 4, pp. 1182– 1190, Aug. 1989.

[9] D. J. Shoup, J. J. Paserba, and C. W. Taylor, "A survey of current practices for transient voltage dip/sag criteria related to power system stability," in Proc. of the IEEE Power Engineering Society Power Systems Conference and Exposition, Oct. 2004, pp. 1140-1147.

[10] M. Ni, J. D. McCalley, V. Vittal, and T. Tayyib, “Online risk-based security assessment,” IEEE Trans. Power Syst., vol. 18, no. 1, pp. 258–265, Feb. 2003.

[11] B. Venkatesh, G. Sadasivam, and M. A. Khan, “Optimal reactive power planning against voltage collapse using the successive multiobjective fuzzy LP technique,” Proc. Inst. Elect. Eng., Gen., Trans., Distrib., vol. 146, no. 4, pp. 343–348, Jul. 1999.

[12] T. Jain, L. Srivastava, and S. N. Singh, “Fast voltage contingency screening using radial basis function neural network,” IEEE Trans. Power Syst., vol. 18, no. 4, pp. 1359–1366, Nov. 2003.

[13] C.D. Vournas, and E.G. Potamianakis, “Induction Machine Short-term Voltage Stability and Protection Measures”, IEEE PSCE, pp: 993 – 998, Oct. 29-Nov. 1 2006.

[14] J.A. Diaz de Leon II, and C.W. Taylor, “Understanding and solving short-term voltage stability problems”, IEEE PES, Vol. 2, pp: 745-752, June 2002.

[15] V. Stewart, and E.H. Camm, “Modeling of stalled motor loads for power system short-term voltage stability analysis”, IEEE PES, Vol. 2, pp: 1887-1892, June 2005.

[16] B. Koeunyi, and J.S. Thorp, “An importance sampling application: 179 bus WSCC system undervoltage based hidden failures and relay misoperations”, Thirty-First Hawaii International Conference on System Sciences, Vol.3, pp: 39-46, 1998.

[17] Geun-Joon Lee, M.M. Albu, and G. T. Heydt, “A power quality index based on equipment sensitivity, cost, and network vulnerability” IEEE Trans. on Power Delivery, Vol. 19, Issue 3, July 2004 pp:1504-1510.

[18] C. W. Taylor, Power System Voltage Stability, EPRI/McGraw Hill, 1994.

[19] J.W. Shaffer, “Air conditioner response to transmission faults”, IEEE Trans. on Power Systems, Vol. 12, Issue 2, May 1997, pp:614 – 621.

[20] V. Brandwajn, “Efficient bounding method for linear contingency analysis,”IEEE Trans. Power Syst., vol. 3, no. 1, pp. 38–43, Feb. 1988.

[21] F. D. Galiana, “Bound estimates of the severity of line outages in power system contingency analysis and ranking,” IEEE Trans. Power App. Syst., vol. 103, no. 9, pp. 2612–2624, Sep. 1984.

[22] T. Smed, “Feasible eigenvalue sensitivity for large power systems,” IEEE Trans. Power Syst., vol. 8, no. 2, pp. 555–561, May 1993.

[23] H. K. Nam, Y. K. Kim, K. S. Shim, and K. Y. Lee, “A new Eigen-sensitivity theory of augmented matrix and its applications to power system stability analysis,” IEEE Trans. Power Syst., vol. 15, no. 1, pp. 363–369, Feb. 2000.

[24] A. C. Zambroni, “Identifying a vanishing eigenvalue in voltage collapse analysis with consideration of limits,” Proc. Inst. Elect. Eng., Gen., Trans., Distrib., vol. 148, no. 2, pp. 263–267, Mar. 2001.

[25] D.J. Tylavsky, A. Bose, et al, "Parallel Processing in Power Systems Computation", IEEE Transactions on Power Systems, Vo1.7, no.2, pp. 629-638, May 1992.

[26] G. Aloisio, M.A. Bochicchio, M. La Scala, and R. Sbrizzai, “A distributed computing approach for real-time transient stability analysis”, IEEE Transactions on Power Systems, Vo1.12, no.2, May 1997, pp. 981-987.

[27] D. Yang, and V. Ajjarapu, “A decoupled time-domain simulation method via invariant subspace partition for power system analysis”, IEEE Trans. on power systems, Vol. 21, no. 1, Feb. 2006.

[28] P.W. Sauer, and M.A. Pai, “Power system dynamics and stability” Englewood cliffs, NJ: Prentice-Hall, 1998.

[29] P. Kundur, “Power system stability and control” New York: McGraw-Hill, 1994.

[30] Z. Feng, V. Ajjarapu, and B. Long, “Identification of voltage collapse through direct equilibrium tracing,” IEEE Trans. Power Syst., Vol. 15, no.1, pp.342-349, Feb. 2000.

[31] C.F. Henville, “Power quality impacts on protective relays-and vice versa”, IEEE PES, vol. 1, Jul.2001, pp: 587-592.

[32] K. Bae, and J. S. Thorp, “An importance sampling application: 179 bus WSCC system under voltage based hidden failures and relay misoperations”, System Sciences, HICSS Proc., vol. 3, Jan. 1998, pp: 39-46.

[33] S. Gerbex, R. Cherkaoui, and A.J. Germond, “Optimal location of FACTS devices to enhance power system security”, IEEE Proc., Power Tech. Conference, vol. 3, Jun. 2003.

[34] B. Mahdad, T. Bouktir, and K. Srairi, “Strategy of location and control of FACTS devices for enhancing power quality”, IEEE MELCON, May 2006, pp: 1068-1072.

[35] D. J. Shoup, J. J. Paserba, and C. W. Taylor, “A survey of current practices for transient voltage dip/sag criteria related to power system stability” IEEE PSCE, vol.2, pp. 1140-1147, Oct. 2004.

[36] A. Tiwari, and V. Ajjarapu, “Contingency assessment for voltage dip and short term voltage stability analysis" presented at 7th Bulk Power System Dynamics and Control, Aug. 2007.

[37] C. F. Henville, “Power quality impacts on protective relays-and vice versa”, IEEE PES, vol. 1, pp. 587-592, Jul. 2001.

[38] K. Bae, and J. S. Thorp, “An importance sampling application: 179 bus WSCC system under voltage based hidden failures and relay misoperations”, System Sciences, HICSS Proc., vol. 3, pp. 39-46, Jan. 1998.

[39] S. Gerbex, R. Cherkaoui, and A. J. Germond, “Optimal location of FACTS devices to enhance power system security”, IEEE Proc., Power Tech. Conference, vol. 3, Jun. 2003.

[40] B. Mahdad, T. Bouktir, and K. Srairi, “Strategy of location and control of FACTS devices for enhancing power quality”, IEEE MELCON, pp. 1068-1072, May 2006.

[41] Y. T. Hsiao, C. C. Liu, H. D. Chiang, and Y. L. Chen, “A new approach for optimal VAr sources planning in large scale electric power systems”, IEEE Trans. Power Systems, vol. 8, no. 3, pp. 988-996, Aug. 1993.

[42] C. Y. Chung, Y. C. Chan, X. J. Lin, T. S. Chung, and C. W. Yu, “Cost analysis of reactive power support with consideration of voltage stability margin and contingency”, in Proc. 2003 Advances in power system control, operation and management, vol. 2, pp. 607-612.

[43] O. von Stryk and R. Bulirsch, “Direct and indirect methods for dynamic optimization”, Annals of Operation Research, vol. 37, pp. 357-373, 1992.

[44] A. E. Bryson, and Y. C. Ho, “Applied optimal control: optimization, estimation, and control”, New York: Hemisphere Pub. Corp., 1975.

[45] A. C. Chiang, “Elements of dynamic optimization”, Waveland Press, 2000.

[46] D. Yang, “Power system dynamic security analysis via decoupled time domain simulation and dynamic optimization,” Ph.D. dissertation, Dept. Elect. Eng., Iowa State Univ., Ames, 2006.

[47] C.A. Canizares, and Z.T. Faur, “Analysis of SVC and TCSC controllers in voltage collapse,” IEEE Trans. on Power Systems, Vol. 14, no. 1, Feb. 1999, pp. 158 – 165.

[48] Y. L. Chen, “Weak bus oriented optimal multi-objective VAR planning,” IEEE Trans. on Power Systems, Vol.11, no.4, Nov. 1996, pp. 1885-1890.

[49] F. Capitanescu, and T. Van Cutsem, “Unified sensitivity analysis of unstable or low voltages caused by load increases or contingencies,” IEEE Trans. on Power Systems, Vol.20, no.1, Feb. 2005, pp. 321 – 329.

[50] D. Mader, S. Kolluri, M. Chaturvedi, and A. Kumar, “Planning and implementation of large synchronously switched shunt capacitor banks in the Entergy system,” IEEE Power Engineering Society Summer Meeting, Vol. 4, 16-20 Jul. 2000, pp. 2045 – 2050.

[51] S. Kolluri, A. Kumar, K. Tinnium, and R. Daquila, “Innovative approach for solving dynamic voltage stability problem on the Entergy System,” IEEE Power Engineering Society Summer Meeting, Vol. 2, 25-25 Jul. 2002, pp. 988 – 993.

[52] V.S. Kolluri, and S. Mandal, "Determining reactive power requirements in the southern part of the entergy system for improving voltage security - a case study," IEEE Power Systems Conference and Exposition, Oct. 29-Nov. 1 2006, pp. 119 – 123.

[53] B. B. Chakrabarti, D. Chattopadhyay, and C. Kumble, "Voltage stability constrained VAr planning-a case study for New Zealand," Large Engineering Systems Conference on Power Engineering, 11-13 Jul. 2001, pp. 86 – 91.

[54] J. R. S. Mantovani, and A. V. Garcia, "A heuristic method for reactive power planning," IEEE Trans. Power Syst., vol. 11, no. 1, pp. 68–74, Feb. 1996.

[55] Y. L. Chen, and Y. L. Ke, "Multi-objective Var planning for large scale power systems using projection-based two-layer simulated annealing algorithms," IEE Proc. Generation, Transmission and Distribution, vol. 151, no. 4, pp. 555–560, Jul. 11, 2004.

[56] B. Cova *et al.*, "Contingency constrained optimal reactive power flow procedures for voltage control in planning and operation," IEEE Trans. Power Syst., vol. 10, no. 2, pp. 602–608, May 1995.

[57] V.S. Kolluri, and S. Mandal, "Determining reactive power requirements in the southern part of the entergy system for improving voltage security - a case study," IEEE Power Systems Conference and Exposition, Oct. 29-Nov. 1 2006, pp. 119 – 123.

[58] P. Pourbeik, R. J. Koessler, W. Quaintance, and W. Wong, "Performing comprehensive voltage stability studies for the determination of optimal location, size and type of reactive compensation," IEEE Power Engineering Society General Meeting, 18-22 Jun. 2006.

[59] V.S. Kolluri, and S. Mandal, "Determining reactive power requirements in the southern part of the Entergy system for improving voltage security - a case study," IEEE Power Systems Conference and Exposition, Oct. 29-Nov. 1 2006, pp. 119 – 123.

[60] J.G. Singh, S.N. Singh, and S.C. Srivastava, "An Approach for Optimal Placement of Static VAr Compensators Based on Reactive Power Spot Price," IEEE Trans. on Power Systems, Vol. 22, no. 4, Nov. 2007, pp. 2021 – 2029.

[61] H. Liu, "Planning reactive power control for transmission enhancement," PhD dissertation, Iowa State University, 2007.

[62] Y. Mansour, E. Vaahedi, A. Y. Chang, B. R. Corns, B. W. Garret, K. Demaree, T. Athay, and K. Cheung, "B.C. Hydro's on-line transient stability assessment (TSA)

model development, analysis, and post-processing," IEEE Trans. on power systems, vol.10, no.1, pp. 241-253, Feb. 1995.

[63] A. B. R. Kumar, V. Brandwajn, A. Ipakchi, and R. Adapa, "Integrated framework for dynamic security analysis," Proc. Of IEEE of 20th Int. Conf. on Power Industry Computer Applications, pp. 260-265, May 11-16, 1997, Columbus, Ohio.

[64] C. D. Vournas, P. W. Sauer, and M. A. Pai, "Relationships between voltage and angle stability of power systems," International journal of Electrical Power and Energy Systems, Vol. 18, no. 8, pp. 493-500, 1996.

[65] E. G. Potamianakis, and C. D. Vournas, "Short-term voltage instability: effects on synchronous and induction machines," IEEE Trans. on Power Syst., vol. 21, no. 2, pp. 791-798, May 2006.

[66] Y. Xue, T. Xu, B. Liu, and Y. Li, "Quantitative assessments for transient voltage security," IEEE Trans. on Power Syst., vol. 15, no. 3, Aug. 2000.

[67] S. Leyffer, "Integrating SQP and Branch-and-Bound for Mixed Integer Nonlinear Programming," Computational Optimization and Applications, Vol. 18, no. 3, Mar. 2001.

[68] C. Schmid, and L. T. Biegler, "Quadratic programming methods for reduced Hessian SQP," Computers and Chemical Engineering, vol. 18, no. 9, pp. 817–832, Sep. 1994.

[69] L. T. Biegler, J. Nocedal, and C. Schmid, "A reduced Hessian method for large-scale constrained optimization," SIAM J. on Optim. , vol. 5, no. 2. pp.314–347, 1995.

[70] Siemens PTI – "PSS®E Rev. 32 Program Application Guide".

[71] V. K. Krishnan, "Coordinated static and dynamic reactive power planning against power system voltage stability related problems," MS dissertation, Iowa State University, 2007.

[72] H. Liu, L. Jin, J. McCalley, R. Kumar, V. Ajjarapu, and N. Elia, "Planning Reconfigurable Reactive Control for Voltage Stability Limited Power Systems," IEEE Trans. on Power Syst., vol. 24, no. 2, pp. 1029-1038, May 2009.

[73] V. Krishnan, H. Liu, and J. D. McCalley, "Reactive power planning against power system steady state voltage instability," in Proc. 2008 North American Power Symposium, Sep. 2008.

[74] V. Krishnan, H. Liu, and J. D. McCalley, "Coordinated reactive power planning against power system voltage instability," in Proc. 2009 IEEE systems conference and exposition, Mar. 2009.

[75] L. Hang, A. Bose, and V. Venkatasubramanian, “A fast voltage security assessment method using adaptive bounding,” IEEE Trans. Power Syst., vol. 15, no. 3, pp. 1137-1141, Aug. 2000.

[76] Reliability Test System Task Force of the Application of Probability Methods Subcommittee – “The IEEE Reliability Test System – 1996”, IEEE Trans. on PWRS, vol. 14, no. 3, pp. 1010-1020, Aug. 1999.

[77] PSS®E test system for voltage collapse analysis. [Online]. Available: http://www.pti-us.com/pti/company/enewsletter/2009july/PSSE_System_Test_for_Voltage_Collapse_Analysis.html.

[78] E. Hirst. (2004). U.S. Transmission Capacity: Present Status and Future Prospects. [Online]. Available: http://www.eei.org/industry_issues/energy_infrastructure/transmission/USTransCapacity10-18-04.pdf.

[79] R. Piwko, N. Miller, J. Sanchez-Gasca, X. Yuan, R. Dai, and J. Lyons, “Integrating Large Wind Farms into Weak Power Grids with Long Transmission Lines,” in Proc. 2005 IEEE Power Engineering Society Transmission and Distribution Conf. and Exhibition, Dec. 2005.

[80] W. Zhang, F. Li, and L. M. Tolbert, “Review of reactive power planning: objectives, constraints, and algorithms,” IEEE Trans. Power Syst., vol. 22, no. 4, pp. 2177 - 2186, Nov. 2007.

[81] K. Iba, H. Suzuki, K. I. Suzuki, and K. Suzuki, “Practical reactive power allocation/operation planning using successive linear programming,” IEEE Trans. Power Syst., vol. 3, no. 2, pp. 558-566, May 1988.

[82] K. Aoki, M. Fan, and A. Nishikori, “Optimal Var planning by approximation method for recursive mixed-integer linear programming,” IEEE Trans. Power Syst., vol. 3, no.4, pp. 1741-1747, Nov. 1988.

[83] K. Y. Lee and F. F. Yang, “Optimal reactive power planning using evolutionary algorithms: A comparative study for evolutionary programming, evolutionary strategy, genetic algorithm, and linear programming,” IEEE Trans. Power Syst., vol. 13, no.1, pp. 101-108, Feb. 1998.

[84] A. Brooke, D. Kendrick, A. Meeraus, and R. Raman, “GAMS: A user’s guide,” GAMS development corporation, 1998. [Online]. Available: www.gams.com.

[85] SBB, “GAMS-the solver manuals: SBB,” GAMS development corporation, Washington, DC, USA.

[86] P. E. Gill, W. Murray, and M. A. Sanders, "SNOPT: An SQP algorithm for large-scale constrained optimization," SIAM journal on Optimization, vol. 12, no.4, pp. 979-1006, 2002.

[87] D. Applegate, T. Koch, and A. Martin, "Branching rules revisited," Operations research letters, vol. 33, no. 1, pp. 42-54, Jan. 2005.

[88] M. Molinas, J. A. Suul, and T. Undeland, "Low Voltage Ride Through of Wind Farms With Cage Generators: STATCOM Versus SVC," *IEEE Trans. Power Electronics*, vol. 23, no. 3, pp. 1104-1117, May 2008.

[89] Western Electricity Coordinating Council, (2003, Apr.), NERC/WECC Planning Standards. [Online]. Available: http://www.wecc.biz/documents/library/procedures/planning/WECC-NERC_Planning%20Standards_4-10-03.pdf.

[90] M. K. Pal, "Voltage stability: analysis needs, modeling requirement, and modeling adequacy," IEE Proc. Gen., Trans. and Dist., vol. 140, no.4, pp. 279-286, Jul. 1993.

LIST OF PUBLICATIONS

A. Tiwari, and V. Ajjarapu, "Optimal allocation of dynamic VAR support using Mixed Integer Dynamic Optimization," IEEE Trans. on Power Systems, vol. 26, no. 1, pp. 305-314, Feb. 2011.

A. Tiwari, V. Van Acker, P. Nieuwesteeg, and Kwok Cheung, "A pricing and dispatch engine for wholesale electricity market using quadratic programming," Deregulation and Restructuring and Power Technologies (DRPT), pp. 329-334, May 2008.

A. Tiwari, and V. Ajjarapu, "Optimal allocation of dynamic VAR for enhancing stability and power quality," IEEE PES General Meeting, Aug. 2008.

A. Tiwari, and V. Ajjarapu, "Event Identification and Contingency Assessment for Voltage Stability via PMU," North American Power Symposium, pp. 413-420, Dec. 2007.

A. Tiwari, and V. Ajjarapu, "Contingency Assessment for Voltage Dip and Short Term Voltage Stability Analysis," Bulk Power System Dynamics and Control-VII, Dec. 2007.

A. Tiwari, and V. Ajjarapu, "Reactive power cost allocation based on modified power flow tracing methodology," IEEE PES General Meeting, Jul. 2007.

A. Tiwari, and V. Ajjarapu, "Modified methodology for tracing power flow," North American Power Symposium, pp. 317-322, Sep. 2006.