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Decision making under uncertainty in power system using Benders decomposition

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Decision making under uncertainty in power system using Benders decomposition

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DEDICATION

I would like to dedicate this thesis to my wife Ying Wu and to my parents without whose understanding and support I would not have been able to complete this work.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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ABSTRACT

Decision-making for operations, maintenance, and investment planning of electric power systems must handle a great deal of uncertainty.

In the work described here, the enhanced risk index is used to describe these uncertainties, and the Benders decomposition algorithm plays the role of integrating three components of the decision making problem: economy, reliability, and risk.

A decomposed security-constrained optimal power flow is developed to demonstrate the significant speed enhancement of the chosen algorithm. The risk-based optimal power flow, risk-based unit commitment problem, risk-based transmission line expansion, and risk-based Var resource allocation are formulated and demonstrated.

A general Benders decomposition structure is developed to cover most of the decision making problems encountered in everyday use within the power industry. In order to facilitate this algorithm, a service oriented architecture (SOA) is introduced and a Benders decomposition and SOA based computation platform is designed.

CHAPTER 1 INTRODUCTION

Electric power, natural gas, oil, ground and air transportation, communications, and water reservoirs are critical national infrastructures, each of which has a large number of distributed, interdependent, capital-intensive physical assets that can fail in catastrophic ways. The common asset management challenge is a set of decision problems related to operation, maintenance, and planning of those assets where decision-makers must identify alternatives and for each one, assess costs, benefits, and risks. Quality of resulting decisions depends on quality of information used in the assessments and how that information is processed. Central, and essential, are information characterizing the health, or condition, of the assets. Often-used indicators of asset condition are age and time since the last inspection and maintenance, so “nameplate ”data and maintenance histories have always been highly influential in the decision process. Condition data from manual inspections are also incorporated if available. It has been only recently, however, that sensing, communication, and database technology has evolved to the point where it is feasible for decision-makers to access operating histories and asset-specific real-time monitoring data. Creative use of this data via processing, fusion, assessment, and decision algorithms can significantly enhance the quality of the final actions taken and decision-maker confidence, and, for even one of the aforementioned industries, result in very large national impact in terms of more economic and reliable system performance.

A rough estimate of the numbers of power transformers and circuit breakers comprising the US transmission system (138-765 kV) are 150,000 and 600,000, respectively; in addition, there are 254,000 miles of high voltage transmission lines. Total replacement value of the lines alone (excluding land) is conservatively estimated at over $100 billion dollars [1] and triples when including transformers and circuit breakers. Investment in new transmission equipment has significantly declined over the past 15 years. Some of the equipment is well beyond intended life, yet is operated under increasing stress, as load growth, new generation, and economically motivated transmission flows push equipment beyond nameplate limits.

Economic operation, and ultimately electric energy price, is heavily influenced by transmission equipment availability, because transmission forced outages require utilization of more expensive generation. Maintaining acceptable electric transmission system reliability and delivering electric energy at low energy prices requires innovations in sensing, diagnostics, communications, data management, processing, algorithms, risk assessment, decision-making (for operations, maintenance, and planning), and process coordination. Among these asset management problems, the data-driven electric power industry has made strides in sensing and diagnostics. Yet there has been less progress in (a) communications, (b) data management, information processing and associated algorithms, (c) risk assessment methods, and (d) decision-making paradigms, and progress has been almost nonexistent in (e) process coordination. This dissertation will focus on the latter three of these by developing and linking multi-timescale stochastic decision algorithms.

There are three interconnected electric power transmission grids in North America: the eastern grid, the western grid, and Texas, with each being comprised of assets which include transmission lines, support structures, transformers, power plants, and protection equipment. Within each grid, power supplied must equal power consumed at any instant of time; also, power flows in any one circuit depend on the topology and conditions throughout the network. This interdependency means that should any one element fail, repercussions are seen throughout the interconnection, affecting system economic and engineering performance. Overall management requires decision in regards to how to operate, how to maintain, and how to reinforce and expand the system, with objectives being risk minimization and social welfare maximization. The three decision problems share a common dependence on equipment health or propensity to fail; in addition, their solutions heavily influence future equipment health. As a result, they are coupled, and optimality requires solution as a single problem. However, because network size (number of nodes and branches) together with number of failure states is so large, such a problem, if solved using traditional optimization methods, is intractable. In addition, the three decision problems differ significantly in decision-horizon, with operational decisions implemented within minutes to a week, maintenance decisions within weeks to a couple of years, and investment decisions within 2-10 years. Therefore, excepting the common dependence and effect on equipment health, the coupling is sequential, with solution to latter-stage problem depending on solution to former-stage problems. Because of this, the industry has solved them separately, with the coupling represented in a very approximate fashion via human communication mechanisms. It should be the case, then, that traditional solutions are suboptimal.

The objective of this work is to design and develop a system for integrating decision algorithms associated with power system risk-reliability-economy decision problems. Doing so will improve all decisions. In accomplishing this objective, we perform a decomposition of the essential decision problems and we provide a solution algorithm for each of them. The various decision problems are then tied together using Benders decomposition, and a service orientated software architecture is designed to support these decision problems.

An assumption made in this dissertation is that the failure probabilities of the components are known. It is recognized, however, that obtaining probabilities accurately reflecting equipment state for a given type of decision problem is a non-trivial problem, but it is one that is left to others in order to limit the scope of this work. The decision models developed in this work are intended to operate interactively, so that decision in each time frame utilizes information from decision within other time frames.

1.1 Asset Management Decision Problems

Asset management decision problems are classified into one of 4 types which all involve resource allocation with the objective to minimize cost and risk. These specific asset management decision problems include (a) Operations, (b) Short-term maintenance selection and scheduling, and long-term maintenance planning, and (c) Facility planning. These problems differ primarily in their time scale but are linked by a common focus on the interactions between the condition of equipment and the decisions taken. The work of this dissertation will focus on the operations and the facility planning problems.

The operations problem is to allocate supply in the next hour-to-week to meet the demand while minimizing risk (exposure to failure consequences); the decision variables are the generation levels at the power plants. There are two levels of this problem. The first is the unit commitment (UC) problem. The second is the optimal power flow (OPF) problem. OPF is actually a UC sub-problem, but UC is typically solved on a weekly basis, resulting in identification of which units are connected at each hour, with a simplified version of OPF. OPF is solved on at least an hourly basis, to find the allocation of energy among the connected units, given the UC solution.

In the OPF, the objective is to minimize the generation cost of supplying a specified system power demand subject to power flow equations (based on the Kirchoff's laws governing the power flowing in the network) together with hard constraints on system and asset capabilities [2]. The security-constrained OPF (SCOPF) is the OPF with additional operational constraints for each of some identified network contingencies. The UC is an integer program (IP) to select, for each hour of a week, the units to be connected to the grid. The literature is rich in work on this problem, with [3, 4] providing good summaries. Yet little work has been done on the integration of UC and transmission reliability, with [5, 6] being exceptions that model security as hard constraints rather than as an objective to be achieved. The security-constrained UC (SCUC) is the UC with additional operational constraints for each of some identified network contingencies.

The long term transmission planning problem under uncertainty, to allocate financial resources over a time horizon on the order of a decade to provide adequate transmission facilities, can be formulated as a stochastic program [7]. As in [8], it is typical to employ a DC load flow approximation to obtain a more tractable linear model. The closely related reactive power planning will be formulated as a nonlinear stochastic program.

1.2 Solution Approach

J. F. Benders [9] proposed the Benders decomposition in 1962 and A. M. Geoffrion [10] extended it in 1972, following which it began to find applications in power system decision-related problems. The basic idea underlying Benders decomposition is to solve large-scale problem via a sequence of smaller ones. This provides that Benders is well-suited to integrating the various power system asset management decision algorithms.

This dissertation is not the first work to utilize Benders for power system decision problems, and in fact it has up to now experienced the following three stages with respect to the power system area.

I. Mathematical development stage (1960's and early 1970's): This stage includes the invention of Benders decomposition method in 1962 and further development in 1972.

II. Early application in power systems (1980's and 1990's): This stage resulted in some good applications of Benders decomposition to power systems including hydrothermal coordination, corrective security-constrained optimal power flow, maintenance scheduling, generation, transmission, and Var planning are developed.

III. Present application in power system (late 1990's until now). Most works focus on SCUC during this period, and maintenance scheduling, and planning are reformulated for competitive market systems.

References [11, 12] give solutions to the dispatch and scheduling of hydrothermal system and give good explanations of the Benders method. The generation planning problem is solved in [13, 14, 15, 16, 17, 18]. CSCOPF (corrective security-constrained optimal power flow) is proposed in [19]. Reference [20] is a good summary: the Benders decomposition is reviewed and the applications to CSCOPF, transmission planning, Var allocation, and parallel computation are described. Var planning is described in [21, 22, 23] and in [24, 25] voltage stability is considered. References [26, 27, 28, 29, 30] use Benders to solve the transmission planning problem. It is also used to address composite generation-transmission planning in [31, 32, 33]. It is used to address the maintenance problem in [34, 35, 36, 37, 38, 39]. ATC is calculated using Benders in [40]. References [41, 42, 6, 43, 44, 45, 46, 47, 48, 49, 50] use Benders to solve the unit commitment problem considering network and security constraints. Reference [51] is another good summary of Benders applications in power systems. References [52, 53, 54, 55] use Benders to integrate risk into the OPF, SCUC, and planning.

The application of Benders decomposition in this dissertation is unique, relative to that of the literature, in that the risk index [56] is integrated to address the uncertainty and that the economy, reliability, and the risk management are systematically integrated in each decision problem addressed. In addition, the use of Benders is facilitated by the service-oriented programming approach used to develop certain kinds of software systems today.

1.3 Decision-making under Uncertainty and Risk Index

Operating and planning bulk interconnected electric power systems are complex activities. Conflicting issues such as economy and reliability have to both be considered when making the appropriate decisions. Although economic competition is emphasized in the restructured power market environment, reliability remains the principal core value of the power industry. How to make a particular decision in a *economic* manner while maintaining *reliability* under *uncertainty* remains an important power industry problem.

Generally the decision variables can be placed into two categories:

1. Amount of control that should be applied for available resources;

2. Whether existing components should be maintained or replaced or whether new components should be added.

Both these decision variables categories apply to economic related decisions.

Both integer and continuous decision variables are involved in decision-making problems. The problems could be specified in the form of the linear programming (LP), nonlinear programming (NLP), mixed integer linear programming (MILP) and mixed integer nonlinear programming (MINLP). The objective functions of these decision-making problems are typically economic benefits such as cost, investment and social welfare. The constraints are typically expressed as power flow equation, flow limits, and system parameter limits. These problems could be very complex.

Decision-making without considering uncertainty is impractical in most situations especially as the time span increases. All network-related decision making in power systems must consider the unexpected failures of power system components and load fluctuations. The risk index is used in this work to describe these uncertainties.

1.3.1 Risk Index

Risk is defined as the product of probability and severity [56], shown in (1.1):

$$R = P \times Sev \tag{1.1}$$

where, R is the risk index, P is the probability with respect to future load scenarios and outages, and Sev is the severity of the future situation.

As shown in Fig.1.1, decision makers have to deal with the following situation: they make a decision *now* and suffer the corresponding impact in the *future*. So pursuing the single objective of lowering cost could result in huge future risk. Alternatively, avoiding all future risk definitely will make the cost too high. The role of the risk index is therefore to serve as **an indicator which biases the decision conservatively when risk is too high and optimistically when risk is comparatively low, according to the given information**.

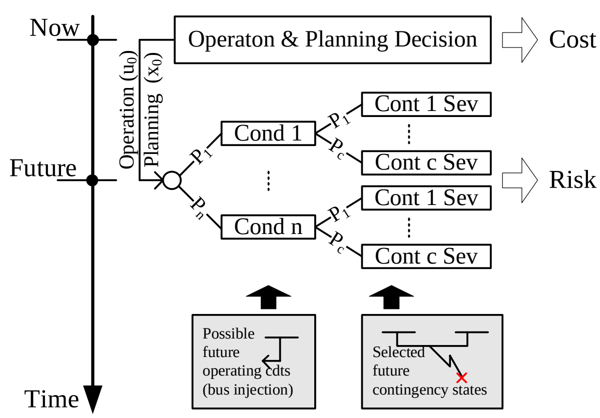


Figure 1.1: Illustration of risk index and decision-making

In Fig.1.1, the decision variables for now can be put into two categories as introduced before. Although the severity might also have economic consequences, they are restricted in this dissertation to power system reliability consequences in this dissertation such as over flow and load shedding.

1.3.2 Enhanced Risk Index

The risk index defined in [56] is a pure expectation index that provides a very good indication of the current decision. When risk index is integrated within the optimal decision problem to facilitate the decision making, the risk can be managed through the adjustment of the candidate decisions. For example, placing a heavier weight on the risk part could lead to a more conservative and higher cost decision to reduce the risk. At the same time, in the optimization procedure both aspects of the risk index can be managed respectively. For example, the probability of component failure can be reduced by appropriate maintenance [57]. More important, in power system reliability-related decision-making, some level of management of the severity is highly needed in the decision-making process.

As shown in Fig.1.2, situation C outperforms A and B in both expectation and variance, and A has a smaller expectation but larger variance. C is the most preferred situation. If a severity tolerance is set, situation B should be chosen in favor of avoiding huge severity between A and B. But if it is known that the severity can be relieved, A will be chosen.

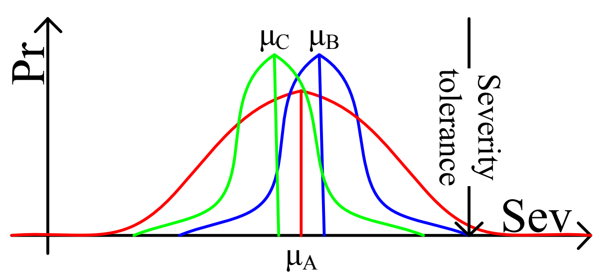


Figure 1.2: Probability density function plot of the risk

In this dissertation, two types of severity management are provided.

- *Controllability* represents the situation that after an event, the severity can be mitigated by available control resources.

- *Acceptability* means that if a particular events happens, just how much severity should be allowed to happen.

Other situations may also occur. Sometimes the controllability may not be sufficient to provide complete mitigation of the severity, resulting in existence of a certain level of tolerance for the severity.

After the management of severity is integrated into the risk index, it is renamed the enhanced risk index. In this dissertation, the enhanced risk index is used in almost all the cases and it will still be called simply the risk index.

Under uncertainty, decision-making problems such as those described will become more complex and remains a hot topic in the power industry. In the deregulated environment, decision-making under uncertainty has become more attractive due to both economic motivation and computational development of the modern computer. This dissertation aims to provide systematic answers for these decision-making problems.

1.4 Software System Integration

When applying decomposition techniques to the real practical large scale problems, how the parallel computation is performed, how these smaller problems interact with each other, how the security is ensured, how the user can interface with these problems become an essential problem. The need for a structure, a protocol, or a diagram is needed. The information technology is also evolving. The structured programming, objective oriented programming and service oriented architecture (SOA) recently and finally. The service oriented architecture provides a level of modularity and autonomy that is attractive for decision algorithms encountered in power systems.

The spirit of Benders decomposition is to decompose the large and complex problem into loose coupling small and easy problems. All the decomposed problems are autonomic problems and typically independent with each other. At the same time, these subproblems are stateless and composible. These characteristics are similar to the principles of the SOA.

Based on these facts, a Benders decomposition and SOA based decision making diagram, BenSOA, is proposed in this dissertation. In this design, the subproblems of Benders decomposition will be the services of SOA. The SOA infrastructure will facilitate the communication between subproblems and realize the decision making process.

1.5 Organization of dissertation

The rest of this dissertation is organized as follows: Chapter 2 introduces the background of power industry, basic principles of the power system engineering, and decision-making under uncertainty, Chapter 3 describes Benders decomposition algorithm, Chapter 4 discusses the decomposed security-constrained optimal power flow, the improved corrective security-constrained optimal power flow, and the risk-based optimal power flow, Chapter 5 proposes the risk-based unit commitment, Chapter 6 addresses risk-based transmission system expansion planning, Chapter 7 proposes risk-based Var allocation, Chapter 8 proposes the general Benders decomposition structure and introduces the design of the Benders decomposition and service oriented structure integrated platform, and chapter 9 provides conclusions and suggestions for future work.

CHAPTER 2 POWER SYSTEM PRINCIPLES

2.1 Introduction

An understanding of the structure of the power industry and the basic conceptions of power system reliability will facilitate decision making. Meanwhile the power system modeling and analysis play an important role in the decision making problems because all the decision makings in power system area must consider the reliability issue. The linear sensitivity analysis and simultaneous feasibility test (SFT) used in power system is introduced, which can be thought as a simple mimic form of Benders decomposition. In this chapter, these basic principles will be introduced and some of these will be used in the later chapters.

2.2 Background and Basic Conceptions

2.2.1 Electric Power Industry

In the traditional power industry, vertically integrated electric utilities managed three main power system components: generation, transmission, and distribution within its own territorial monopoly. In the restructured power industry, these three main components are unbundled and the new entities such as the generation company, the transmission company, and the load service entity, take charge in the three components respectively and represent their own individual interests. A new entity, typically called an independent system operator (ISO), also emerges to operate the system and to maintain system reliability.

An electric market is created through the basis of the unbundling of the principal components of the power industry. The market has a much larger territory than that of the traditional utility. Two kinds of economic entities are created: the players and the ISO. The players include the generation company, the transmission company, the load service entity, the broker, etc. These players each represent themselves and pursue their own benefit in the electric market. The ISO represents society and tries to simultaneously maximize social welfare and maintain power system reliability.

2.2.2 Power System Reliability

The NERC's definition of the electric system reliability [58] is:

> **Reliability**—The degree of performance of the elements of the bulk electric system that results in electricity being delivered to customers within accepted standards and in the amount desired. Reliability may be measured by the frequency, duration, and magnitude of adverse effects on the electric supply (or service to customers).

According to the NERC's definition, reliability can be addressed by considering two basic and functional aspects of the electric system—adequacy and security:

> **Adequacy**—The ability of the bulk electric system to supply the aggregate electrical demand and energy requirements of customers at all times, taking into account scheduled and reasonably expected unscheduled outages of system components.

> **Security**—The ability of the bulk electric system to withstand sudden disturbances such as electric short circuits or unanticipated loss of system components or switching operations.

In plain language, adequacy implies that sufficient generation and transmission resources are available to meet projected needs plus reserves for contingencies. Security implies that the power system will remain intact even after outages or equipment failures. One of the main aspects of system security is so-called steady-state security [59]. This is defined as the ability of the system to operate steady-state-wise within the specified limits of safety and supply quality following a contingency, in the time period after the fast-acting automatic control devices have restored the system load balance, but before the slow-acting controls, e.g. transformer tappings and human decisions, have responded. This dissertation focuses on steady-state security for power systems operation and planning.

2.2.3 N-1 Criteria

Generally the security represents the so-called N-1 criteria. "N "is the total number of transmission "elements "in the system and "N-1 "is the total system with one element out of service. The 'minus one' could be a generation unit, a transmission line or a transmission transformer. The basic idea is that even if one component is lost, the system should still satisfy the load requirements without operating violation.

Transmission line and transformer failures generally cause changes with respect to the flows and voltages on the transmission equipments still remaining connected to the system. Generation failures can also cause flows and voltages to change in the transmission system, with possible addition of dynamic problems involving system frequency and generator output. In this dissertation, the security assessment will use this criteria.

2.3 Power System Analysis

Modern power systems have become increasingly complex and interconnected over the past one hundred years. These systems, however, are evolved from some very basic theories developed by some scientific giants more than one hundred years ago and these basic theories remain the unchanged bases of the power system analysis. Higher level layers have of course been added to the power systems in the past and will be in the future. Some basic modeling and analysis methods will be introduced in this section as preparation for the work discussed in the later chapters.

2.3.1 Power Flow

In power flow analysis the transmission system is modeled as a set of buses or nodes interconnected by transmission links. Generators and loads, connected to various nodes of the system, inject and withdraw power from the transmission system. The compact form of the power flow equations is as follows:

$$g(x) = 0 \tag{2.1}$$

In the equation (2.1), algebraic variables x represent the solution of power flow. Algebraic equations g represent network equations. At each bus of the power system, power injection is balanced.

2.3.1.1 AC Power Flow

For AC power flow, the network equations (2.1) can be expanded into nonlinear forms representing both real power and reactive power balance.

$$\begin{cases} P_{gi} - P_{li} - P_{ti} = 0 \\ Q_{gi} - Q_{li} - Q_{ti} = 0 \end{cases} \tag{2.2}$$

where P_{gi} is real power generation at bus i, P_{li} is real power load at bus i, P_{ti} is net real power injection at bus i, Q_{gi} is reactive power generation at bus i, Q_{li} is reactive power load at bus i, and Q_{ti} is net reactive power injection at bus i.

The real and reactive power generations are determined by the inherent characteristics of the generator. The real and reactive loads are determined by the load characteristics. The net real and reactive power injections are constrained by the physical characteristics, which are represented by the following equations:

$$\begin{cases} P_{ti} = \sum_{j=1}^{N} V_i V_j \left[G_{ij} cos(\theta_i - \theta_j) + B_{ij} sin(\theta_i - \theta_j) \right] \\ Q_{ti} = \sum_{j=1}^{N} V_i V_j \left[G_{ij} sin(\theta_i - \theta_j) - B_{ij} cos(\theta_i - \theta_j) \right] \end{cases} \tag{2.3}$$

where θ_i and θ_j are the phase angles at buses i and j respectively, V_i and V_j are the bus voltage magnitudes respectively, and $G_{ij} + jB_{ij} = Y_{ij}$ is the ij term in the Y_{bus} matrix of the power system.

The variables V and θ are bus voltage and angle respectively, and these variables belong to the unknown variables x in (2.1). Generally if V is given the correspondent reactive power balance equation will be removed from (2.1) and if θ is given the correspondent real power balance equation will be removed from (2.1).

2.3.1.2 DC Power Flow

DC power flow, which is quite fast to analyze and therefore permits determination of a large series of power flows within a reasonable time frame, is a good approximation to AC power flow under normal load situations. The following assumptions are made for DC power flow:

- All branch resistances are equal to zero.
- All voltage magnitudes are constant.
- The differences of phase angles between voltages at the ends of any branch are within normal loading range (where the errors are not very high).

Under these assumptions, there are no losses in the system (no resistance) and a real power solution can be obtained without solving simultaneously for reactive power.

Using nomenclature of DC power flow, the B matrix of DC power flow is:

$$B = r \cdot y \cdot r^T \tag{2.4}$$

where r is the reduced node-branch incidence matrix.

The DC power flow is formulated simply as follows (reference bus removed):

$$P = B \cdot \theta \tag{2.5}$$

where θ is the bus angle vector (reference bus not included), and the P is the bus injection vector (reference bus not included).

The line flow is as follows:

$$p_{ij} = y_{ij} \cdot (\theta_i - \theta_j) \tag{2.6}$$

where y_{ij} is the admittance between bus i and j.

The vector form of line flow is as follows:

$$P_{ij} = y \cdot r^T \cdot B^{-1} \cdot P = H \cdot B^{-1} \cdot P = H \cdot \theta \tag{2.7}$$

Although the reference bus voltage angle is known and will not appeared in vector θ, all the line flow can be obtained using equation (2.7) due to the characteristics of DC flow.

DC power flow is useful for rapid calculations of real power flows and is very useful in security analysis studies.

2.3.2 Linear Sensitivity Analysis

There are two types of linear sensitivity analysis: linear sensitivity coefficients and linear sensitivity factors corresponding to AC power and DC power flow respectively. These sensitivities will be used in the simultaneous feasibility test process. One important observation is that the idea of the linear sensitivity analysis is very similar to Benders decomposition used in power system area. Both linear sensitivity analysis and Benders decomposition use the gradient or Lagrange information to adjust the tentative results.

2.3.2.1 Linear Sensitivity Coefficients

Linear sensitivity coefficients give an indication of the change in one system quantity (e.g., MW flow, MVA flow, bus voltage, etc.) as another system quantity (e.g., generator MW output, transformer tap position, etc.) is varied. One important assumption is that as the adjustable variable is changed the power system reacts so as to keep all of the power flow equations solved [3].

One example deriving linear sensitivity coefficients of an AC network model is given here. The power flow equation is repeated as:

$$g(x, u) = f(x) - u = 0 \tag{2.8}$$

where x is the state vector of voltages and phase angle and u is the vector of control variables. For simplicity, the control variable here is defined as the generator MW output.

From the current operating point x and u, a small enough adjustment Δ occurs and before and after power flow is solved, yielding:

$$
\begin{aligned}
&g(x+\Delta, u+\Delta) = g(x,u) + g'(x,u)\cdot[\Delta x, \Delta u]^T = 0\\
&g'(x,u)\cdot[\Delta x, \Delta u]^T = [f'(x), -1]\cdot[\Delta x, \Delta u]^T = 0\\
&f'(x)\cdot\Delta x = \Delta u\\
&J_{fx}\cdot\Delta x = \Delta u
\end{aligned}
$$

Transmission system dependent variables, h, are assumed, which can be MVA flows, load bus voltages, etc, and can be expressed as a function of the state and control variables. We try to find their sensitivity with respect to changes in the control variables.

Around the current operating point, we have:

$$
\begin{aligned}
\Delta h &= J_{hx}\Delta x + J_{hu}\Delta u \Rightarrow\\
\Delta h &= [J_{hx}\cdot J_{fx}^{-1} + J_{hu}]\Delta u
\end{aligned}
$$

According to the above derivation, we get

$$\Delta h = J\cdot\Delta u \tag{2.9}$$

where J is the linear sensitivity coefficients matrix between h and u around the operating point.

One important characteristic of the linear sensitivity coefficients is that the value is only good for small adjustment and the sensitivities must be recalculated often [3].

2.3.2.2 Linear Sensitivity Factors

Similar to DC power flow, determination of network linear sensitivity factors is another fast approximation method used in power flow problems. There are several kinds of sensitivity factors, including generation shift factors and line outage distribution factors [3]. Only generation shift factors are described in this example.

The GSF (generation shift factors) are designated α_{li} and have the following definition:

$$\alpha_{li} = \frac{\Delta f_l}{\Delta P_i} \tag{2.10}$$

where l is the line index, i is the bus index, Δf_l is the change in megawatt power flow on line l when a change in generation, ΔP_i, occurs at bus i, and ΔP_i is the change in generation at bus i.

It is assumed in this definition that the change in generation, ΔP_i, is exactly compensated by an opposite change in generation at the reference bus, and that all other generators remain fixed. The GSF at the reference bus is zero. The generation shift factors are linear estimates of the change in flow resulting from a change in power at a bus. The effects of simultaneous changes on several generating buses can be calculated using superposition.

A special situation with respect to the generation shift factor is the so called PTDF (power transfer distribution factor), describing the situation when the change in generation is not compensated by a reference bus. PTDF determines a change in the power flow at each line when one (1) MW is transferred from one bus of the network to another.

We reformulate (2.7) here again as follows:

$$f = y \cdot r^T \cdot B^{-1} \cdot P = H \cdot B^{-1} \cdot P = H \cdot \theta = A \cdot P \Rightarrow \Delta f = A \cdot \Delta P \tag{2.11}$$

where A is the matrix of generation distribution factor.

From the above derivation, we can see that the linear sensitivity vector is equivalent to that of DC power flow. It is very easy to obtain the PTDF via superposition given the direction of the transfer.

$$PTDF = A \cdot D = A \cdot [0, ..., 1, ..., -1, ...0]^T \tag{2.12}$$

where, D is the direction vector (PTDF can also be extended to zonal transfer usage by changing the direction vector to direction matrix) 1 is the injection, and -1 is the withdrawal.

2.3.2.3 Simultaneous Feasibility Test

The SFT (Simultaneous Feasibility Test) is widely used in SCED and SCUC [60, 61, 62]. SFT is a Contingency Analysis process. The objective of SFT is to determine violations in all post-contingency states and to produce *generic constraints* to feed into economic dispatch or unit commitment, where a *generic constraint* is a transmission constraint formulated according the linear sensitivity coefficients/factors introduced in section 2.3.2.

Due to the fast speed and simple application, the SFT procedure is widely used in power industry. The common flowchart is as follows:

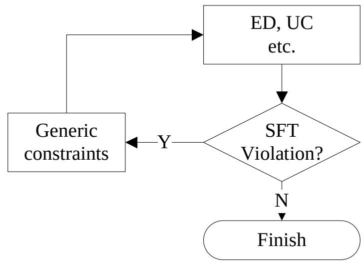


Figure 2.1: SFT flowchart

The ED or UC is first solved without considering network constraints and security constraints. The results are sent to perform the security assessment in a typical power flow. If there is an existing violation, the new constraints are generated using the sensitivity coefficients/factors and are added to the original problem to solve repetitively until no violation exists.

2.3.3 Optimal Power Flow

The optimal power flow of OPF has had a long history in its development. It was first discussed by Carpentier in 1962 and took a long time to become a successful algorithm that could be applied in common use [3].

The general form of the OPF is as follows:

$$\begin{aligned} Min \quad & f(x,u,z) & \\ s.t. \quad & g(x,u,z) & = 0 \\ & h(x,u,z) & \leq h^{max} \end{aligned} \tag{2.13}$$

where g are power flow constraints, h are operation constraints.

u are decision variables that can be:

- Generator voltage magnitude & real power
- Voltage magnitude & angle at slack bus

- Real power flow through DC lines
- Phase angles across phase-shifting transformers
- Turn ratios of tap-changing transformers
- Admittances of variable reactors and switched capacitor banks
- Breaker positions by which the network can be reconfigured

x are the state (dependent) variables that can be:

- Real & reactive power at reference bus
- Reactive power & angle at PV buses
- Voltage magnitudes & angles at PQ buses

z are the exogenous variables (specified) that can be:

- Real & reactive demands at load buses
- Tie line flows
- Admittance matrix

The above is the general form, Next we will give the detailed formulation to be used in this work (we will delete the z in the formulation for simplicity purpose).

In the following three formulations: f_0 models the cost of preventive control actions, and, for the kth system configuration ($k = 0$ corresponds to the pre-contingency configuration, while $k = 1, \ldots, c$ correspond to the c post-contingency configurations), x_k is the vector of state variables, u_k is the vector of preventive and corrective control variables. Equality constraints $g_k(\bullet) = 0$ is the bus power balance equations and the inequality constraints $h_k(\bullet) \leq h_k^{max}$ concerns physical limits of equipments (e.g., bounds on: generators active/reactive powers, transformers equipped with tap-changer ratios, shunt reactance, phase shifters angle, etc.) and operational limits (e.g., limits on branch currents and voltage magnitudes). Δ_k^{max} is the vector of maximally allowed variations of control variables between the base case and kth post-contingency state.

The formulation of OPF is as follows,

$$
\begin{aligned}
Min \quad & f_0(x_0, u_0) & \\
s.t. \quad & g_0(x_0, u_0) & = 0 \\
& h_0(x_0, u_0) & \leq h^{max}
\end{aligned}
\tag{2.14}
$$

To check the steady-state security of the power system, security constraints are added to problem (2.14) to form the security-constrained optimal power flow (SCOPF) [59].

$$
\begin{aligned}
Min \quad & f_0(x_0, u_0) & \\
s.t. \quad & g_k(x_k, u_0) = 0 & k = 0, 1 \cdots, c \\
& h_k(x_k, u_0) \leq h_k^{max} & k = 0, 1 \cdots, c
\end{aligned}
\tag{2.15}
$$

In this formulation, all security constraints are presented at the same time. Sometimes the security-constrained optimal power flow also called preventive security-constrained optimal power flow (PSCOPF), and in this dissertation we denote it simply as SCOPF. Compared to the SCOPF, the corrective security-constrained optimal power flow (CSCOPF) was proposed in 1987 [19] and is formulated as follows

$$
\begin{aligned}
Min \quad & f_0(x_0, u_0) & \\
s.t. \quad & g_k(x_k, u_k) = 0 & k = 0, 1 \cdots, c \\
& h_k(x_k, u_k) \leq h^{max} & k = 0, 1 \cdots, c \\
& |u_k - u_0| \leq \Delta_k^{max} & k = 1, 2 \cdots, c
\end{aligned}
\tag{2.16}
$$

Compared with SCOPF, the CSCOPF does not require that the system state variables are within limit before and after contingencies. Instead the CSCOPF permits the corrective control to bring the state variables back to the limit after a contingency. In the market environment, the demand bids can also be added to the objective function without changing the structure of the problem.

CHAPTER 3 BENDERS DECOMPOSITION

Benders decomposition will be used as a principal technique in this dissertation, so a comprehensive introduction of this methodology will be given in this chapter.

3.1 Introduction of the Problem Structure

J.F. Benders introduced the Benders decomposition (BD) algorithm for solving large-scale, mixed-integer linear programming problems (MILP), which partition the problem into a programming problem (which may be linear or non-linear, and continuous or integer) and a linear programming problem [9]. A.M. Geoffrion generalized this method, which is generalized Benders decomposition (GBD) and made it applicable to nonlinear problems [10].

Problems for which Benders can be applied are those that have the following structure:

$$Min \qquad z = c(x) + d(y) \tag{3.1a}$$

$$s.t. \qquad A(x) \geq b \tag{3.1b}$$

$$E(x) + F(y) \geq h \tag{3.1c}$$

Constraint (3.1c) is referred to as the *coupled constraint* and $E(x)$ is called the *coupler* in this dissertation.

In Benders decomposition [9], the second part problem is required to be a linear programming problem, which is convex and dual theory can be applied to. Although in [10] all the objective function and constraints can be completely nonlinear functions, a so called "**P** property" is preferred for better performance, which means that the decision variables are partitioned explicitly in the objective function and constraints. Even if the **P** property holds, the second part problem could be still nonconvex with only weak duality applied, indicating that a dual gap exists. When GBD is mentioned in this dissertation, the **P** property is applied implicitly.

From the literature review (section 1.2), it is observed that most successful applications of generalized Benders decomposition is linear coupled, which means that in addition to the **P** property the coupler in the coupled constraint is a linear function. We name the linear coupled generalized Benders decomposition as LGBD. LGBD is actually GBD with additional the requirements of **P** property and linear coupling.

Table 3.1: Problem Formulation Summary for BD, GBD and LGBD

Num	d(y) & F(y)	coupler E(x)
BD	linear	linear
GBD	linear/nonlinear	linear/nonlinear
LGBD	linear/nonlinear	linear

3.2 Outline of the Methodology

We repeat problem (3.1a) here again and put it into the BD form, which means that all the objective and constraints are linear. For simple explanation, the coupler is put into explicitly linear form. This form is called the standard form in this dissertation.

$$Min \qquad z = c(x) + d(y) \tag{3.2a}$$

$$s.t. \qquad A(x) \geq b \tag{3.2b}$$

$$E \cdot x + F(y) \geq h \tag{3.2c}$$

This problem can be decomposed into three subproblems [20]: master problem, feasibility subproblem, and optimality subproblem.

- **Master Problem**

  Decide on a feasible x^* considering only constraint (3.2b) via what is referred to as the master problem:

$$\begin{aligned} Min \quad & \underline{z} = \; c(x) + \alpha(x) && (3.3a) \\ s.t. \quad & A(x) \geq b && (3.3b) \end{aligned}$$

where $\alpha(x)$ is a piecewise function of the optimality subproblem optimal value as a function of the master problem decision variable x. $\underline{z}$ is a lower bound of the whole problem and will be updated iteratively by the optimality subproblem.

- **Feasibility Subproblem**

In order to check whether (3.2c) is satisfied based on x^* given in the master problem, a slack vector is introduced and the corresponding subproblem is formulated as:

$$\begin{aligned} Min \quad & \nu = 1^T \cdot s && (3.4a) \\ s.t. \quad & F(y) + s \quad \geq h - E \cdot x^* && (3.4b) \end{aligned}$$

Here, 1^T is the vector of ones, and $\nu > 0$ means that violations occur in the subproblem. In order to eliminate the violations, the feasibility cut (3.5) is added to the master problem:

$$\nu + \lambda E(x^* - x) \leq 0 \tag{3.5}$$

where λ is the Lagrangian multiplier vector for inequality constraints (3.4b). This problem is called *feasibility check subproblem* or *feasibility problem* for short.

- **Optimality Subproblem**

Decide on a feasible y^* considering constraint (3.2c) given x^* from the master problem.

$$\begin{aligned} \omega = Min \quad & d(y) && (3.6a) \\ s.t. \quad & F(y) \quad \geq h - E \cdot x^* && (3.6b) \end{aligned}$$

where ω is the value of $\alpha(x)$ at x^*.

If the solution is not optimal, the optimality cut (3.7) is added to the master problem:

$$\omega + \pi E(x^* - x) \leq \alpha \tag{3.7}$$

where π is the Lagrangian multiplier vector of inequality constraints (3.6b). This subproblem is called the *optimality check subproblem* or *optimality problem* because it is used to check the optimality of the master problem according to the *Benders Rule*.

Benders rule: The partition theorem for mixed-variables programming problems [9] provides an important optimality rule on which Benders decomposition is based. The optimal solution $(\underline{z}^*, x^*)$ from the master problem and the optimal solution y^* from the optimality subproblem are obtained. If the upper bound $\bar{z} = c(x^*) + d(y^*)$ is equal to the lower bound $\underline{z}^*$ from the first-stage problem, then the triplet $(\underline{z}^*, x^*, y^*)$ is the optimal solution for the complete problem. In other words, the problem is optimal only when its subproblems are also optimal.

The process of Benders decomposition is a learning process (try-fail-try-inaccurate-try--solved) as shown in Fig.3.1. This process is called the Benders process and is described as follows.

1. Solve the master first and then send the optimal solution x^* to the two subproblems;

2. Check if the optimal solution from the master problem is feasible. If it is not feasible, the feasibility check subproblem will send a feasibility cut back to the master problem so that the master problem can remove this infeasible solution set.

3. Use Benders rule to check if the estimation of the optimality subproblem optimal value from the master problem is accurate enough. If Benders rule is not met, an update estimation of $\alpha(x)$ is sent to the master problem by an optimality cut. If the Benders rule is met, the problem is solved.

This process is easily expanded to stochastic programming. The optimal value from the master problem is sent to the multi-scenario optimality problem. The process is exactly the same as in the deterministic case, except that all the optimality cuts and the optimal value from the optimality problem are weighted by the probability of the scenario. The more complicated case would be the scenario tree.

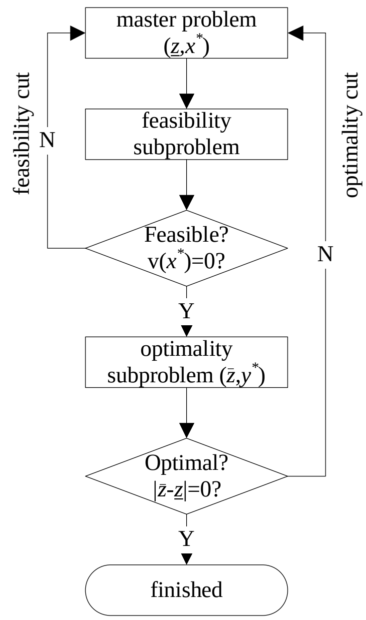


Figure 3.1: Benders process

A typical procedure using Benders decomposition is illustrated in Fig.3.2. First, a large-scale and complex problem, which is hard or impossible to solve as a whole, is studied to decide how to formulate the master problem, feasibility subproblem and optimality subproblem. During this step, the coupled constraints need to be carefully determined. Second, the solution algorithms or solvers for different subproblems should be decided. Although different subproblems can utilize different algorithms or solvers, the requirement is that the algorithms or solvers for the feasibility and optimality subproblem need to provide Lagrange multipliers. Third, the Benders process and Benders rule are used to obtain the final solution.

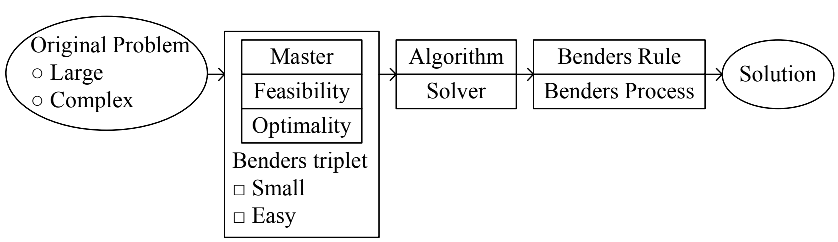


Figure 3.2: Benders procedure

3.3 Derivation of the Benders Decomposition Principle

The feasibility problem/cut and optimality problem/cut is very meaningful,both mathematically and physically [20] and they will be derived in this section.

3.3.1 Derivation of the Optimality Problem and Cut

The optimality cut is used to update the estimation of the function $\alpha(x)$ in problem (3.3a), as reproduced below [20]:

$$\begin{aligned} Min \quad & c(x) + \alpha(x) \\ s.t. \quad & A(x) \geq b \end{aligned} \tag{3.8}$$

where $\alpha(x)$ is the solution of the optimality problem (3.6a). This problem is reproduced below as (3.9):

$$\begin{aligned} \omega = Min \quad & d(y) \\ s.t. \quad & F(y) \geq h - E \cdot x \end{aligned} \tag{3.9}$$

The Benders decomposition principle can be derived as follows: the dual of the optimality problem (3.9) can be written as

$$\begin{aligned} Max \quad & \pi(h - E \cdot x) \\ s.t. \quad & \pi F \leq d \end{aligned} \tag{3.10}$$

Note that the feasible region of problem (3.10), defined by $\pi F \leq d$, does not depend on the master problem decision x. The region is a convex polyhedron, and can be characterized by the set of its extreme points (or vertices) $\Pi = \left\{\pi^1, \pi^2, \cdots, \pi^p\right\}$ where p is the number of vertices. So we can conclude that the solution of problem (3.10) will be the maximum vertex. At the same time, it will be the optimal solution of problem (3.9) due to duality. Furthermore, we can write the master problem as:

$$\begin{aligned} Min \quad & c(x) + \alpha \\ s.t. \quad & A(x) \geq b \\ & \alpha \geq max\left\{\pi(h - Ex)\right\} \end{aligned} \tag{3.11}$$

We know ω is the optimal solution value of the optimality problem (3.9) for a given master problem solution x^*. Because the optimal solution values of the primal and dual problems coincide, we can say that $\omega = \pi^*(h - Ex^*) \Rightarrow \pi^* h = \omega + \pi^* E x^*$. Substituting $\pi^* h$ into the expression of the Benders cut $\pi^j(h - Ex)$, we obtain

$$\omega + \pi^* E(x^* - x) \leq \alpha \tag{3.12}$$

The optimality cut ($\alpha \geq \pi^i(h - Ex)$) can be added one at a time to further reduce the size of the master problem by number of the constraints. But it should be noticed that this size reduction will result in multiple iterations.

3.3.2 Derivation of the Feasibility Problem and Cut

The solution x from master problem could result in an infeasible solution to the original problem because only a subset of the constraints are considered. With the introduction of the slack variable, the problem (3.4a) will be always feasible.

In solving (3.4a), if the objective function is nonzero, implying that the original problem is not feasible, the feasibility cut ($\nu + \lambda E(x^* - x) \leq 0$) is generated. The physical meaning of this cut is as follows: moving x around the x^* along the direction of the gradient (λE) to make the ν to be zero. For better understanding, the feasibility cut can be put into the form of Newton method (the $\leq$ is changed to $=$), as $x = x^* + (\lambda E)^{-1}\nu(x^*)$, which is for solving $\nu(x) = 0$. The graph to describe this is shown in Fig.3.3.

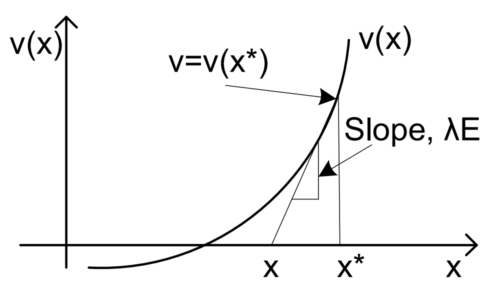


Figure 3.3: Graph description of feasibility cut

The above derivation (slack variable approach) is used mostly in power system area and another kind of derivation (extreme ray approach) can be seen in [63]. If (3.9) is infeasible, then the dual (3.10) is unbounded. Then an *extreme ray* need to be obtained to generate the feasibility cut. Compared with this one, the slack variable derivation we introduced earlier is easier to understand and apply to the practical problem in power system area. Although the derivation is different, the basic purpose is to make the optimality subproblem feasible.

3.3.3 An Example of Benders decomposition

The problem is put into the standard form introduced earlier as follows:

$$\begin{aligned} Min \quad & (-5)x + (-4)y_1 + (-3)y_2 \\ s.t. \quad & (-1)x + (-0)y_1 + (-0)y_2 \geq -20 \\ & (-1)x + (-2)y_1 + (-3)y_2 \geq -12 \\ & (-3)x + (-2)y_1 + (-1)y_2 \geq -12 \end{aligned} \tag{3.13}$$

where x,y_1, and y_2 are greater or equal to zero. x is an integer.

The master problem will be formulated as follows:

$$\begin{aligned} Min \quad & (-5)x + \alpha \\ s.t. \quad & (-1)x + (-0)y_1 + (-0)y_2 \geq -20 \end{aligned} \tag{3.14}$$

α will be set to a very small number in the first iteration and will be updated in subsequent iterations.

The feasibility check problem is formulated as follows:

$$\begin{aligned} Min \quad & (-0)y_1 + (-0)y_2 + (+1)s_1 + (+1)s_2 \\ s.t. \quad & (-2)y_1 + (-3)y_2 + (+1)s_1 + (+0)s_2 \geq -12 - (-1)x \\ & (-2)y_1 + (-1)y_2 + (+0)s_1 + (+1)s_2 \geq -12 - (-3)x \end{aligned} \tag{3.15}$$

where y_1, y_2, s_1, and s_2 are greater or equal to zero.

The optimality check problem is formulated as follows:

$$\begin{aligned} Min \quad & (-4)y_1 + (-3)y_2 \\ s.t. \quad & (-2)y_1 + (-3)y_2 \geq -12 - (-1)x \\ & (-2)y_1 + (-1)y_2 \geq -12 - (-3)x \end{aligned} \tag{3.16}$$

where y_1 and y_2 are greater than or equal to zero.

The dual problem of the optimality check problem is as follows:

$$\begin{aligned} Max \quad & (-12+x)\pi_1 + (-12+3x)\pi_2 \\ s.t. \quad & (-2)\pi_1 + (-2)\pi_2 \leq -4 \\ & (-3)\pi_1 + (-1)\pi_2 \leq -3 \end{aligned} \tag{3.17}$$

where π_1 and π_2 are greater than or equal to zero.

After solving this problem, the following cuts are obtained from different iterations:

$$\begin{aligned} 4x &\leq 24 \quad \textit{feasibility cut} \\ 3x &\leq 12 \quad \textit{feasibility cut} \\ 9x-\alpha &\leq 36 \quad \textit{optimality cut} \\ 2x-\alpha &\leq 24 \quad \textit{optimality cut} \\ 5x-\alpha &\leq 24 \quad \textit{optimality cut} \end{aligned}$$

From the feasibility cut, it is easy to find that $x \leq 4$. The procedure is further explained in Fig.3.4. The left part is the feasible region of the dual problem (3.17), which will not be affected by the results of the master problem according to (3.10). But when the master problem sends different results, the objective function is different, which causes the optimal value of the optimality problem to jump among all the three candidate vertexes. In the right plot, the estimation of the α as a function of x is plotted according the right plot. After this procedure the master problem becomes a mixed integer programming problem that only depends on x. Due to the non-convexity of the integer problem this problem has multiple solutions.

From the optimality cuts information we can obtain the same results as shown in Table.3.2. The underlined values are correponding to the square point in Fig.3.4

The core part of Benders decomposition is to obtain $\alpha(x)$, which is based on dual theory. One brilliant aspect of this algorithm is that the dual problem has a constant feasible region and the optimal value of the optimality problem has to on one of the vertexes of this constant region.

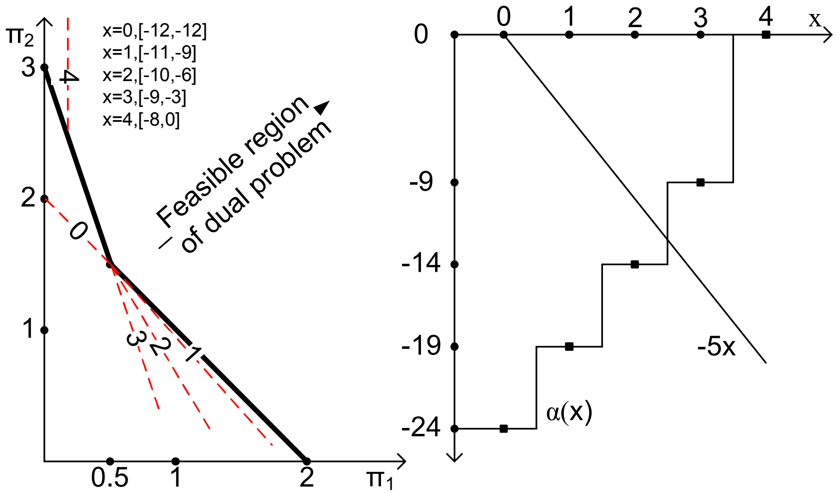


Figure 3.4: Example of the Benders decomposition

Table 3.2: Estimation of the $\alpha(x)$

x	0	1	2	3	4
$\alpha \geq 9x - 36$	-36	-27	-18	-9	0
$\alpha \geq 2x - 24$	-24	-22	-20	-18	-16
$\alpha \geq 5x - 24$	-24	-19	-14	-9	-4

3.3.4 Some Special Forms of Benders Decomposition

The above introduction is the full version of Benders decomposition. Some special forms also exits.

No optimality problem. Although there is no y in the objective function of the original problem (3.2a), y still exit in the constraints. This form is very common and possibly one of the most used forms of Benders decomposition, such as SCUC in [47].

No feasibility problem. In some situations, the optimality problem will be always feasible. So the feasibility problem is not necessary.

Dual-role feasibility and optimality problem. In some applications, the feasibility and optimality problem can be the same problem.

The original form and the above special forms will be used in this dissertation.

3.4 Advantages and Limitations of Benders Decomposition

Benders decomposition is a very powerful algorithm, with the following advantages:

a) De-scaling the problem. For a very large scale problem, the Benders decomposition algorithm can decompose the problem into a certain number of small scale problems, achieving better computational efficiency because computation complexity of most problem is not linear.

b) Flexibility. After the optimization problem is decomposed, each subproblem can be solved by any appropriate algorithm/tool.

c) Parallel computing. Most of the subproblems of Benders decomposition are independent of each other, and this characteristic can facilitate the possibility of using parallel computing.

d) Stochastic programming. For complex stochastic programming problem, Benders decomposition can be a very good solution method.

These advantages make Benders decomposition very attractive. But in order to use Benders decomposition, some requirements must be met.

I Mathematically the formulation of the original problem must be staircase as shown in the standard form and convexity assumption must be met for the subproblems. The staircase insures that the problem can be decomposed easily and the convexity assumption ensures that the problem converges to a real optimal solution.

II Physically the problem can be time-decomposed and/or function-decomposed. Time-decomposition means that the relationship between subproblems are sequential. Function-decomposition represents a situation in which each subproblem performs different function independently.

CHAPTER 4 RISK-BASED OPTIMAL POWER FLOW

In the first part of this chapter, a decomposed security-constrained optimal power flow is proposed to show the speed enhancement capability obtained through applying Benders decomposition. In the second part an improved corrective security-constrained optimal power flow is proposed to avoid possible catastrophic consequence of the corrective security-constrained optimal power flow. In the third part, a risk-based optimal power flow is described, which can improve economic benefit while guaranteeing system reliability.

4.1 Decomposed Security-constrained Optimal Power Flow

4.1.1 Introduction

Security-constrained optimal power flow (SCOPF) problem is computationally intensive if implemented using a full AC power flow and with numerous contingencies. The computational bottleneck of the SCOPF is due to the scale caused by the number of contingencies. In this work, we target this issue via application of Benders decomposition, to decompose the problem into subproblems associated with each contingency. The proposed formulation is referred to as the decomposed SCOPF, or DSCOPF.

4.1.2 Problem Formulation and Solution Method

The formulation of the SCOPF is [59]:

$$Min \quad f_0(x_0, u_0) \tag{4.1a}$$

$$s.t. \quad g_k(x_k, u_0) = 0 \qquad k = 0, \cdots, c \tag{4.1b}$$

$$h_k(x_k, u_0) \leq h^{max} \qquad k = 0, \cdots, c \tag{4.1c}$$

where f_0 models the cost of control actions, and, for the kth system configuration ($k = 0$ corresponds to the pre-contingency configuration, while $k = 1, , c$ correspond to the c post-contingency configurations), x_k is the vector of state variables, and u_0 is the vector of preventive control variables.

In [19], by setting the corrective control to zero, security-constrained optimal power flow is decomposed, but subproblems no longer have OPF structure as shown in (4.1a), and as a result, the numerical tests showed that the computation time is more sensitive to the number of buses of the system than when they have OPF structure. Reference [48] solves the optimal power flow master problem, then minimize the real and reactive power injected by fictitious sources in subproblems, resulting in a very large number of decision variables for large systems. The approach presented in this work is similar to these two approaches in that the master problem is an optimal power flow, but it differs in that the subproblems minimize adjustment of the preventive controls in subproblems. This is advantageous because decision variables in the subproblem include only control variables of the complete problem, reducing computation effort. In addition, the subproblems retain the optimal power flow structure and therefore have similar computation complexity. This section explains why this decomposition increases computational efficiency for the SCOPF and illuminates our approach via three examples.

The problem is decomposed for solution via Benders decomposition method and for this problem, the no optimality subproblem special form will be used. In the Benders approach [20] to solving DSCOPF, the master problem finds an optimal solution under normal constraints.

$$\begin{aligned} Min \quad & f_0(x_0, u_0) & \\ s.t. \quad & g_0(x_0, u_0) & = 0 \\ & h_0(x_0, u_0) & \leq h^{max} \end{aligned} \tag{4.2}$$

The c contingency sub-problems are then:

$$\begin{aligned} Min \quad & 1^T \cdot \epsilon_k \\ s.t. \quad & g_k(x_k^0, u_0 + \epsilon_k) = 0 \\ & h_k(x_k^0, u_0 + \epsilon_k) \leq h^{max} \end{aligned} \tag{4.3}$$

where 1^T is the vector of ones, ϵ_k is the vector representing the preventive control adjustment, and superscript 0 represents that the state variables are different from the normal condition.

The purpose of this subproblem is to eliminate these adjustments by passing 'cuts' (constraints) back to the master when the subproblem is infeasible. λ is the Lagrangian multiplier vector of constraints. u_0^* is the fixed control from the master problem. In order to eliminate the violations, the feasibility cut (4.4) is added to the master problem [20]:

$$1^T \cdot \epsilon_k + \lambda(u_0^* - u_0) \leq 0 \tag{4.4}$$

As shown in Fig.4.1 the optimal power flow (master) is solved first. The resulting control variables are sent to a power flow solver to determine if there is any violation under each credible contingencies. If there is violation, these control variables are sent to the contingency subproblems to generate the Benders cut. All subproblems are independent and can be solved in parallel. The overall problem solution is found when all control provided by the master problem is acceptable for the entire post-contingency situation.

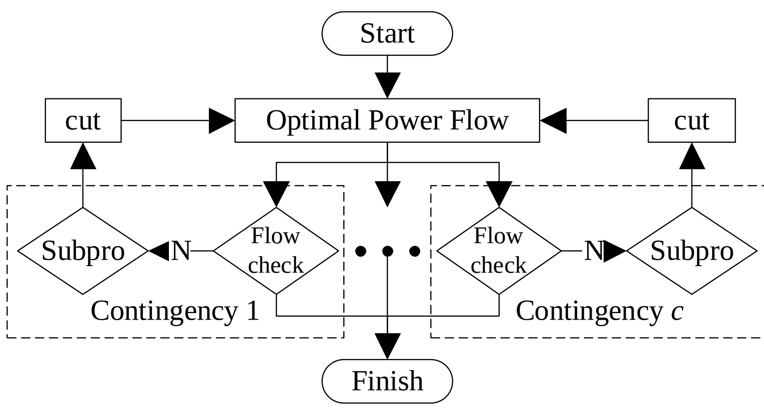
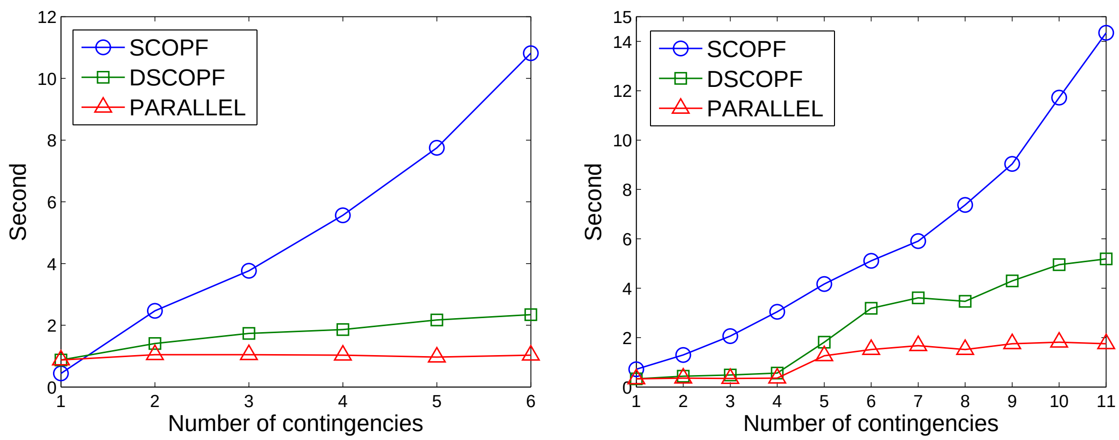


Figure 4.1: The flowchart to solve SCOPF parallel with Benders Decomposition

4.1.3 Illustration

The approach is illustrated on two 6-bus test systems A6 [49], B6 [3], and on the 24-bus RTS96 [64]. Computing time for three different strategies are given in Fig. 4.2. In all three strategies, the basic OPF solver is the same (run via MATLAB v. R2007a on Dell PC with

2.80GHz, 3.75 GB RAM), the contingencies are randomly drawn, and the initial values for nonlinear OPF solver are the same. The parallel case represents an ideal situation which assumes all subproblems can be solved simultaneously without considering communication time. Actual parallel computing times would be slightly more than this ideal case. A solution obtained for a specific number of contingencies using SCOPF is the same as that obtained using DSCOPF in all cases.



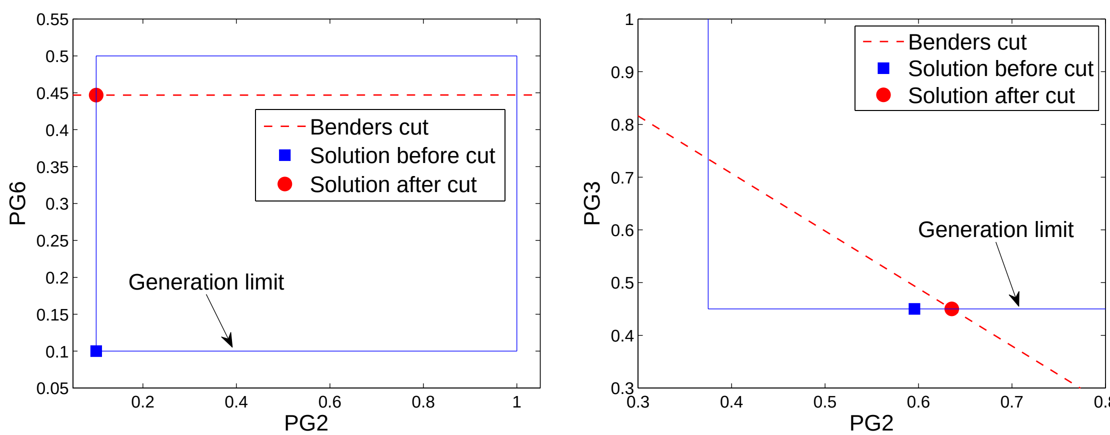
(a) Test system A6 (b) Test system B6

Figure 4.2: Computation time comparison of 6-bus test system

We observe that computing time of SCOPF increases quadratically with increase in number of contingencies. In contrast, computing time of DSCOPF increases linearly. The same comparison is performed on RTS 96 with 1, 2, and 3 contingencies, and two typical cases (random contingencies) are shown in Table 4.1, which shows the DSCOPF is faster, accurate and stable than SCOPF under same numerical tolerances; the comparison is consistent with that of the 6-bus systems. We provide a complexity analysis to support these observations.

Suppose the OPF problem has k preventive control variables, l state variables, and m constraints. With n contingencies, the SCOPF will have k preventive control variables, $l \times n$ state variables, and $m \times n$ constraints. The numerical optimization generally uses the gradient based method which requires computation of the Jacobian. When we calculate the Jacobian, because the number of variables is about "$2 * n$ "times original OPF problem, the computation time is about "n^2 "times. So compared to the OPF problem, we estimate computation complexity of the SCOPF as nearly $O(n^2)$ and some of the constraints are inequality constraints which make the complexity even worse. In contrast, the complexity of DSCOPF is only $O(n)$, because it only solves a certain number of problems of similar size to the OPF problem. If computed in parallel the complexity of DSCOPF is even less.

Figure 4.3 provides insight into the Benders algorithmic process. Case I is line 2-3 outage of the A6 test system, and Case II is line 1-2 outage of the B6 test system.



(a) Test system A6 (b) Test system B6

Figure 4.3: Computation evolution of DSCOPF

In case I, unit 1 of the A6 test system is much less costly than the other two, so the OPF will give a result residing at the square point in Fig.4.3a. Then the contingency pushes it to the round point which results in less generation from unit 1.

In case II, a similar situation happens and due to network constraints the square point is

Table 4.1: Computing speed and results using different strategies of RTS96

#	Speed(Second)						Results(+30000$)			
	SCOPF		DSCOPF		PARA.		SCOPF		DSCOPF	
	i	ii	i	ii	i	ii	i	ii	i	ii
1	79	-	11	6	11	6	515	-	512	512
2	2k	17	17	19	13	18	680	676	656	655
3	-	-	17	23	13	18	-	-	1082	1082

not at the minimum of unit 2 as shown in Fig.4.3b.

4.1.4 Conclusion

In this section, Benders decomposition is applied to decompose the traditional SCOPF, and the underlying computational complexity is analyzed. This approach results in significantly better computing speed without sacrificing accuracy for both serial and parallel computing strategies.

4.2 Improved Corrective Security-constrained Optimal Power Flow

4.2.1 Introduction

CSCOPF extends the feasible solution region of SCOPF by considering the available controllability of the power system. However the system could face voltage collapse and/or cascading overload right after a contingency before the corrective action is taken. So the constraints to avoid these catastrophic situations are applied [65], resulting in what we call the improved CSCOPF (ICSCOPF) here. We use the Benders decomposition method to solve ICSCOPF.

4.2.2 Problem Formulation and Solution Procedure

The compact form of ICSCOPF is as follows [65]:

$$
\begin{aligned}
Min \quad & f_0(x_0, u_0) && && (4.5)\\
s.t. \quad & g_k(x_k, u_k) = 0 && k = 0, 1 \cdots, c\\
& g_k^0(x_k^0, u_0) = 0 && k = 1, 2 \cdots, c\\
& h_k(x_k, u_k) \le h^{max} && k = 0, 1 \cdots, c\\
& h_k^0(x_k^0, u_0) \le p_k h^{max} && k = 1, 2 \cdots, c\\
& |u_k - u_0| \le \Delta_k^{max} && k = 1, 2 \cdots, c
\end{aligned}
$$

where p_k is a scalar value modeling how much the constraints just after the contingency application are relaxed with respect to the permanent limits.

Compared with CSCOPF, for each contingency equality constraints $g_k^0(x_k^0, u_0) = 0$ and inequality constraints $h_k^0(x_k^0, u_0) \leq p_k h^{max}$ impose the existence and viability of the intermediate state reached just after contingency occurrence and before application of corrective control actions. The problem is decomposed as follows.

The master problem finds an optimal solution under normal constraints, which is actually an OPF formulation, as follows:

$$\begin{aligned} Min \quad & f_0(x_0, u_0) \\ s.t. \quad & g_0(x_0, u_0) = 0 \\ & h_0(x_0, u_0) \leq h^{max} \end{aligned} \tag{4.6}$$

The controllability check sub-problem is as follows:

$$\begin{aligned} Min \quad & 1^T \epsilon_k \\ s.t. \quad & g_k(x_k, u_k) = 0 && k = 1, 2 \cdots, c \\ & h_k(x_k, u_k) \leq h^{max} && k = 1, 2 \cdots, c \\ & |u_k - u_0^*| - \epsilon_k \leq \Delta_k^{max} && k = 1, 2 \cdots, c \end{aligned} \tag{4.7}$$

In minimizing the weighted summation of the control slack variable ϵ, if it is zero, it means the corrective control can bring the system back to normal after a contingency happens.

The collapse and cascading failure check subproblem is:

$$\begin{aligned} Min \quad & 1^T \varpi_k \\ s.t. \quad & g_k^0(x_k^0, u_0 + \varpi_k) = 0 && k = 1, 2 \cdots, c \\ & h_k^0(x_k^0, u_0 + \varpi_k) \leq p_k h^{max} && k = 1, 2 \cdots, c \end{aligned} \tag{4.8}$$

where ϖ_k is the vector representing the adjustment of the preventive control.

The physical meaning of this subproblem can be explained as follows. Supposing that when the contingency happens, all the controls of the system are frozen. Then the following phenomenon could occur: 1) no **severe**(cascading overload and voltage collapse) constraint violation; 2) severe low voltage, which could lead to low voltage protection action; 3) voltage collapse, equality condition fails; 4) cascading overload, which could lead to line tripping. If the optimal value of this subproblem is not zero, meaning that the preventive control must be adjusted in some way, situation 2), 3) and/or 4) could happen. The flowchart is shown in Fig. 4.4.

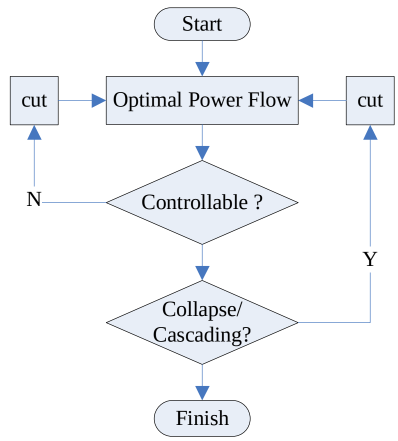


Figure 4.4: Flowchart to solve ICSCOPF with Benders Decomposition

4.2.3 Illustration

This approach can be tested using a modified 6-bus test system A6 [49]. In this case, the generator outputs are the only control variables. Voltage magnitude is within [0.90 1.10] (p.u.) and line active power limits are [2, 1, 1, 1, 1, 1, 1] (p.u.). The re-dispatch considers the ramp rates and re-dispatch time to obtain the Δ. For example, if the ramp rate is .5 and corrective time is 1, then $\Delta = 0.5 * 1 = 0.5$. Case I represents the situation CSCOPF is safe and the re-dispatch effect on voltage collapse is shown in case II, and its effect on cascading overload flow is shown in case III. The dispatch's effect on voltage is not very significant in this case and is not studied here.

Case I. No severe constraints violation: The contingency set is branch [1 2 3 4 5 6 7] outage. The post contingency voltage is [0.90 1.10] p.u., and line active power limits are expanded to 1.4 times the original. A 12-minute limit is applied to re-dispatch. No severe constraints are violated in the post-contingency, and thus the CSCOPF solution is feasible.

Case II. Voltage collapse: The contingency set is branch [1 2 4 5 6 7] outage. The post contingency voltage is [0.80 1.10] p.u., and line active power limits are expanded by 2.0 times that of original. A 72-minute limit is applied to re-dispatch (This situation is only used to create a voltage collapse and has no practical meaning here). The outage of branch 1 will create a voltage collapse situation which results in a higher cost than the CSCOPF. When this collapse happens, the outputs of generators 2 and 3 are 0.1 and 0.2 respectively. The collapse and cascading failure check subproblem generated a cut which forces the output of generators 2 and 3 to change to 0.1 and 0.2857 respectively, and the voltage collapse is avoided. In this situation, the corrective control time is extended which results in better economic benefit but a risk of voltage collapse.

Case III. Cascading overload: The contingency set is branch [1 2 3 4 5 6 7] outage. The post contingency voltage is [0.90 1.10] p.u., and line active power limits are expanded by 1.2 times those of the original. A 24-minute limit is applied to re-dispatch. The outage of the branch 1 will result in too much overload in branch 2 which could cause cascading protection actions. At this time the outputs of generators 2 and 3 are 0.3912 and 0.4197 respectively. The collapse and cascading failure check subproblem generated a cut which forces the output of generators 2 and 3 to change to 0.3952 and 0.4954 respectively, and the cascading overload is avoided.

Table 4.2: Results of different strategies

CASE	SCOPF	CSCOPF	ICSCOPF
I	$4652.21	$4443.59	$4443.59
II	$4652.21	$3576.80	$3613.63
III	$4652.21	$4235.64	$4273.22

The above three cases shows that the CSCOPF can obtain economic benefit but faces the risk of voltage collapse and cascading overload, and the ICSCOPF can avoid these risks.

The contingency set is branch [1 2 3 4 5 6 7] outage. In Fig. 4.5, the x-axis is the relaxation rate of the line limit and y-axis is cost in $. From Fig.4.5 we can see that more relaxation rate and longer re-dispatch time results in less cost. But this trend has a marginal effect, that is,

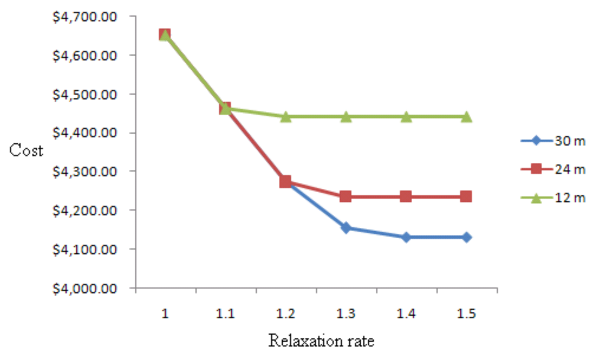


Figure 4.5: Sensitivity analysis

after some value it will stop improving.

4.2.4 Conclusion

In this section, Benders decomposition has been used successfully to solve the ICSCOPF ensuring existence and viability of the short-term equilibrium point using a constant power model after a contingency is applied and before corrective controls may take place. This work could make the CSCOPF not only economically attractive but also practically feasible and it could draw more attention in a market environment which wants to utilize the existing asset more efficiently.

4.3 Risk-based Optimal Power Flow

4.3.1 Introduction

Optimal power flow is a fundamental computation in the power industry as an essential tool for market coordinators and owners of multiple generation units. Algorithmic improvements have resulted in significant benefits. To this end, there have been two "extremes" proposed. The first was the preventive optimal power flow [59], heavily biased towards security. The second was corrective optimal power flow [19] heavily biased towards economy. However, there is concern that the preventive optimal power flow is too costly, and that the corrective optimal power flow is too risky. Although there has been additional work to mitigate this concern by, for example, including voltage collapse and cascading overload constraints in the corrective optimal power flow [65], it is still not clear that the approach maintains an appropriate balance between economy and security. We address this by proposing the risk-based optimal power flow, which is based on the following strategy: if the risk is relatively small, the operation will be in corrective mode; if the risk is relatively large, the dispatch will move toward preventive mode. The risk plays a role to adjust the dispatch according the predicted near-future situation. The approach requires contingency probabilities. All further discussion is referenced to an identified list of contingencies, such that use of the word “contingency ”assumes it is one on the identified list. Normally, the list includes all N-1 contingencies.

Traditionally the system operating state is divided into three states: normal state, emergency state and restore state [66]. References [67][68][69] also developed similar classifications with minor differences. In order to explain the relationship of preventive, classical corrective, improved corrective, and risk-based optimal power flow, in this work, these three states are further divided as shown in Figure 4.6. Here, the emergency state is divided into two sub-states: 1) controllable emergency: If system falls into this sub-state, it can be drawn back to the normal state by the corrective control; 2) uncontrollable emergency: no corrective control can be done to return the system back to normal without load curtailment. The normal state is divided into three sub-states: 1) preventive security state: the system remains within the normal state following occurrence of any contingency; 2) corrective security state: there exists at least one contingency whose occurrence will cause the system to transfer into the controllable emergency state; 3) insecure state: there exists at least one contingency for which occurrence will cause the system to transfer to the uncontrollable emergency state and the system will therefore be forced into a restore state in which load curtailment must take place.

The traditional preventive SCOPF [59] is designed to control the system so that it always operates the system in the preventive security state. The corrective SCOPF [19] is designed to improve economic benefit by operating the system in the classical corrective security state (comprised of the corrective security state and part of the insecure state), which exposes the system to the possibility of load curtailment. The improved corrective SCOPF [65] avoids this

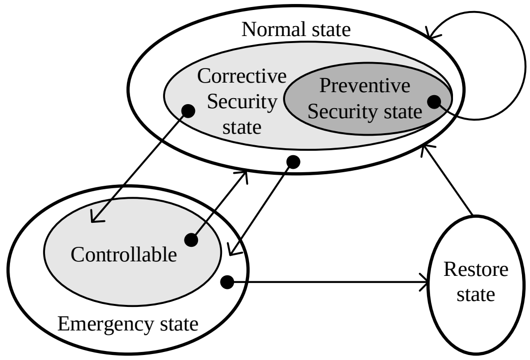


Figure 4.6: The system operation state

exposure by constraining operation to only the corrective security state (as we have defined it), which eliminates that part of of the classical corrective state that is exposed to the uncontrollable emergency state. Risk-based optimal power flow will use the improved corrective strategy to obtain better economic benefit, subject to additional control on the expected distance of the post contingency operation point to the insecure normal state. This expected distance is a measure of risk.

4.3.2 Modeling of Severity Function

Only steady state security is considered in this work, i.e.,no dynamic issue will be considered. So our implementation of risk-based optimal power flow includes overload security (flow violations and cascading overloads) and voltage security (voltage magnitude violations and voltage instability).

We view the extreme case of flow violation is cascading overload, and the extreme case of voltage magnitude decrease is voltage collapse. The severity is thus categorized into two types: hard and soft constraints. Hard constraints include cascading overload and voltage collapse, and will not be permitted. Soft constraints include overload and undervoltage; these can be relaxed in some situations. For the two hard-constrained cases, special treatment, which will be described in this work, is performed to eliminate exposure to them. For the soft constraints, the severity is modeled as the distance from the post-contingency operation point to the nearest feasible operating point. This can be represented by several kinds of parameters, such as direct violation, load shedding, and so on. Here we choose the minimum amount of the corrective control (re-dispatch in this section), needed to be applied to return the system to the normal state.

4.3.3 Problem Formulation and Solution Method

We first provide the complete problem formulation including all constraints. Then we provide the alternative formulation necessary to apply the proposed Benders decomposition solution method to our problem.

4.3.3.1 Complete Problem Formulation

The formulation is as follows,

$$
\begin{aligned}
Min \quad & f_0(x_0, u_0) + \beta R(x_0, u_0) && && (4.9a) \\
s.t. \quad & g_k(x_k, u_k) = 0 && k = 0, \cdots, c && (4.9b) \\
& g_k^0(x_k^0, u_0) = 0 && k = 1, \cdots, c && (4.9c) \\
& h_k(x_k, u_k) \leq h^{max} && k = 0, \cdots, c && (4.9d) \\
& h_k^0(x_k^0, u_0) \leq p_k h^{max} && k = 1, \cdots, c && (4.9e) \\
& |u_k - u_0| \leq \Delta_k^{max} && k = 1, \cdots, c && (4.9f) \\
& g_k^1(x_k^1, u_0 + s_k) = 0 && k = 1, \cdots, c && (4.9g) \\
& h_k^1(x_k^1, u_0 + s_k) \leq h^{max} && k = 1, \cdots, c && (4.9h) \\
& R(x_0, u_0) = \sum_{k=1}^{c} Pr_k \cdot s_k && k = 1, \cdots, c && (4.9i)
\end{aligned}
$$

where β is the weight of risk, f_0 models the cost of preventive control actions, and, for the kth system configuration ($k = 0$ corresponds to the pre-contingency configuration, while $k = 1, \ldots, c$ corresponds to the c post-contingency configurations), x_k is the vector of state variables, u_k is the vector of control variables and s_k is the severity. Equality constraints (4.9b) and inequality constraints (4.9d) impose the feasibility of the pre-contingency and corrected post-contingency states. On the other hand, equality constraints (4.9c) and inequality constraints (4.9e) impose, for each contingency, the existence and viability of the intermediate state reached just after contingency occurrence and before application of corrective control actions. Equality constraints (4.9b) and (4.9c) are the AC bus power balance equations, while the inequality constraints (4.9d) and (4.9e) account for the physical limits of equipment (e.g., bounds on: generators active/reactive powers, transformers equipped with tap-changer ratio, shunt reactors, phase shifter angles, etc.) and operational limits (e.g., on branch currents and bus voltage magnitudes). Note that p_k is a scalar value modeling how much the constraints, just after occurrence of the contingency, are relaxed with respect to the emergency limits. Inequalities (4.9f) are "coupling "constraints between the base case and post-contingency values of control variables aimed at preventing unrealistic values of corrective control variables; Δ_k is the vector of maximal allowed variations of control variables between the base case and kth post-contingency state. Equations (4.9g) and (4.9h) are the severity evaluation constraints, which represent the relief of the severity by re-dispatch. Equation (4.9i) gives the evaluation of the risk index. The superscript $(0, 1)$ represents different set of flow equations, state variables and limit constraints under post contingency short-term situation and post correction situation respectively.

4.3.3.2 Problem formulation in Benders decomposition

In this subsection, we describe the application of Benders decomposition to the problem of subsection 4.3.3.1.

The master problem finds an optimal solution under normal constraints, which is an ordinary OPF formulation.

$$\begin{aligned} Min \quad & f_0(x_0, u_0) & \\ s.t. \quad & g_0(x_0, u_0) & = 0 \\ & h_0(x_0, u_0) & \leq h^{max} \end{aligned} \tag{4.10}$$

The controllability check subproblem is used to minimize the weighted summation of the control slack variable ϵ. If it is zero, it means the corrective control can bring the system back to the normal state after occurrence of any contingency. The controllability check sub-problem is as follows.

$$
\begin{aligned}
Min \quad & e^T \cdot \epsilon_k && && (4.11)\\
s.t. \quad & g_k(x_k, u_k) = 0 && k = 1, 2 \cdots, c \\
& h_k(x_k, u_k) \le h^{max} && k = 1, 2 \cdots, c \\
& |u_k - u_0^*| - \epsilon_k \le \Delta_k^{max} && k = 1, 2 \cdots, c
\end{aligned}
$$

where e is the weighting vector, reflecting preference of action.

The collapse and cascading failure check subproblem is used to assure the *existence* and *viability* of the post-contingency short-term equilibrium and avoid extreme flow violations. Its formulation is as follows:

$$
\begin{aligned}
Min \quad & a^T \cdot \varpi_k && && (4.12)\\
s.t. \quad & g_k^0(x_k^0, u_0 + \varpi_k) = 0 && k = 1, 2 \cdots, c \\
& h_k^0(x_k^0, u_0 + \varpi_k) \le p_k h^{max} && k = 1, 2 \cdots, c
\end{aligned}
$$

where ϖ_k is the vector representing the preventive control adjustment (For generator output, it represented by the combination of positive dummy real injection and positive dummy load), and a is the weighting vector.

The physical meaning of this subproblem can be explained as follows. Supposing when the contingency occurs, all the controls of the system are frozen. Then either power is balanced and no *severe* (within relaxation) constraint violations occur, or one or more of the following occur: 1) severe low voltage, which could lead to operation of low voltage protection; 2) voltage collapse; 3) cascading overload, which could lead to protection action. If the optimal value of this subproblem is not zero, it means the preventive control must be adjusted in some way, otherwise situation 1), 2) and/or 3) could happen.

The risk minimization subproblem is

$$
\begin{aligned}
Min \quad & R(x_0, u_0) = \sum_{k=1}^{c} Pr_k \cdot s_k && k = 1, 2 \cdots, c && (4.13)\\
s.t. \quad & g_k^1(x_k^1, u_0 + s_k) = 0 && k = 1, 2 \cdots, c \\
& h_k^1(x_k^1, u_0 + s_k) \le h^{max} && k = 1, 2 \cdots, c
\end{aligned}
$$

where s is the vector representing the adjustment of the preventive control, which is the measurement of the severity.

Of the above three subproblems, the controllability check (4.11) subproblem and the collapse and cascading failure check subproblem (4.12) are both *feasibility check subproblems* and as such will generate *feasibility cut* to return to the master problem. On the other hand, the risk minimization subproblem (4.13) is the *optimality check subproblem* and will generate *optimality cut* to return to the master problem.

4.3.3.3 Solution procedure

In an earlier section, the original problem is decomposed into one master problem and several subproblems. How these subproblems work together will be described here. The flow chart is shown in Figure 4.7.

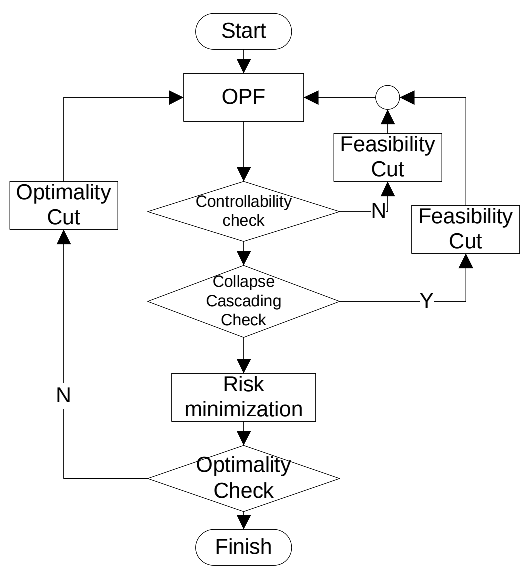


Figure 4.7: Solution procedure of RBOPF using Benders decomposition

Step 1. An ordinary OPF problem (4.10) is solved first and a raw guess of risk is made (in the first iteration, the risk guess is zero).

Step 2. Check the controllability of the system relative to each credible contingency using (4.11). If there is just one contingency for which it is not possible to use corrective

From	To	R(pu)	X(pu)	Limit(MW)
1	2	0.005	0.170	200
1	4	0.003	0.258	100
2	3	0.000	0.037	100
2	4	0.007	0.197	100
3	6	0.000	0.018	100
4	5	0.000	0.037	100
5	6	0.002	0.140	100

Table 4.3: Circuit parameters

control to bring the system back to the normal state, then a feasibility cut is sent back to the master problem; return to step 1.

Step 3. Check if the given dispatch will cause collapse or cascading overload for each credible contingency using (4.12). If any of the defined catastrophic situations can occur, a feasibility cut is sent back to the master problem and return to step 1.

Step 4. Minimize the risk using the probability of the contingency and the severity evaluation model introduced earlier in this paper. If the Benders rule is not met, then an optimality cut is sent back to the master problem; return to step 1.

Step 5. Output the results.

The risk-based optimal power flow is a high level integration of the security-constrained optimal power flow [59], corrective security-constrained optimal power flow [19], improved corrective security-constrained optimal power flow [65] and risk evaluation.

4.3.4 Illustration

This approach is illustrated by a simple 6-bus test system A6 modified from [49]. The predefined contingency list consists of N-1 failure of each circuit. The average failure rate is adapted from data characterizing the IEEE reliability test system [64].

Bus	$	$/MWh	$/MW^{2}h	Ramp(MW/h)
1	176.9	13.5	0.0004	80
2	129.9	32.6	0.001	50
6	137.4	17.6	0.005	20

Table 4.4: Generation unit information

Bus	G(MW)	Q(MVAR)	PLoad	QLoad
1	[100 220]	[-32 68]	-	-
2	[10 100]	[-16 59.5]	-	-
3	-	-	65	27.6
4	-	-	65	23.8
5	-	-	79.7	25.3
6	[10 50]	[-16 42.5]	-	-

Table 4.5: Bus information

4.3.4.1 Case study

First, the optimal power flow result is calculated, in which no security constraints are considered, and the cost is $3533.48.

Case 1 Security-constrained optimal power flow:

In this case, the ordinary security-constrained optimal power flow problem is solved and the cost is $4652.28.

Case 2 Security-constrained optimal power flow with post-contingency corrective rescheduling:

In this case, the optimal power flow problem is calculated and the post-contingency reschedule has to be finished within a 12-minute interval. The cost is $4443.60.

Case 3 Security-constrained optimal power flow with post-contingency corrective rescheduling avoiding collapse and cascading:

In this case, the risk minimization part is not integrated and the problem is solved with the emergency operating limit 1.1 times that of the normal thermal limit and operating time for less than 12 minutes. The cost is $4462.41.

Case 4 Risk-based optimal power flow

In this case, based on Case 3, the risk minimization part is added to assess the possible impact. The cost is $4572.60.

In the above four cases, the feasible region of Case 1 corresponds to the preventive security state, the feasible region of Case 2 corresponds to the classical corrective security state, and the feasible region of Case 3 and Case 4 corresponds to the corrective security state.

With respect to optimal cost, we can also observe that: Case 1 > Case 4 > Case 3 > Case 2. Case 1 is the most costly because it is the most secure. Case 2 is least costly, but it is exposed to the possibility of collapse or cascading overload. Case 3 is less costly than Case 1 because of the corrective control, and Case 3 is more costly than Case 2 because it avoids the cascading overload. Case 4 is less costly than Case 1 because of the corrective control and Case 4 is more costly than Case 3 because it considers the possible impact.

After we solve the above four cases, we can numerically plot the system operation states as shown in Figure 4.8. The preventive security state is plotted according the information from Case 1, and the corrective security state uses the information from Case 3. The classical corrective security state, which does not consider collapse or cascading consistent with the approach of [19], is plotted for comparison from results of Case 2. The generation unit output limit, which is the large rectangle, corresponds to the normal state.

In Figure 4.9, the solutions of all the cases are plotted. All uncommented lines in Figure 4.9 have the same meaning as in Figure 4.8. From Table 4.4, we know that unit 1 is the least costly unit and unit 3 is the most costly unit. So when the optimal power flow is solved, the output of units 2 and 3 are at their minimum. In Case 1, the operating point is pushed to the square point by the Benders cuts (security constraints); in Case 2, it is forced to the diamond point by the controllability check subproblem's Benders cuts, which are the classical corrective security constraints; in Case 3, it is moved to the upper triangle point by the collapse and cascading failure check subproblem's Benders cuts (improved corrective security constraints); in Case 4, compared with Case 3, it is further pushed to the right triangle point by the risk minimization subproblem's Benders cuts (risk).

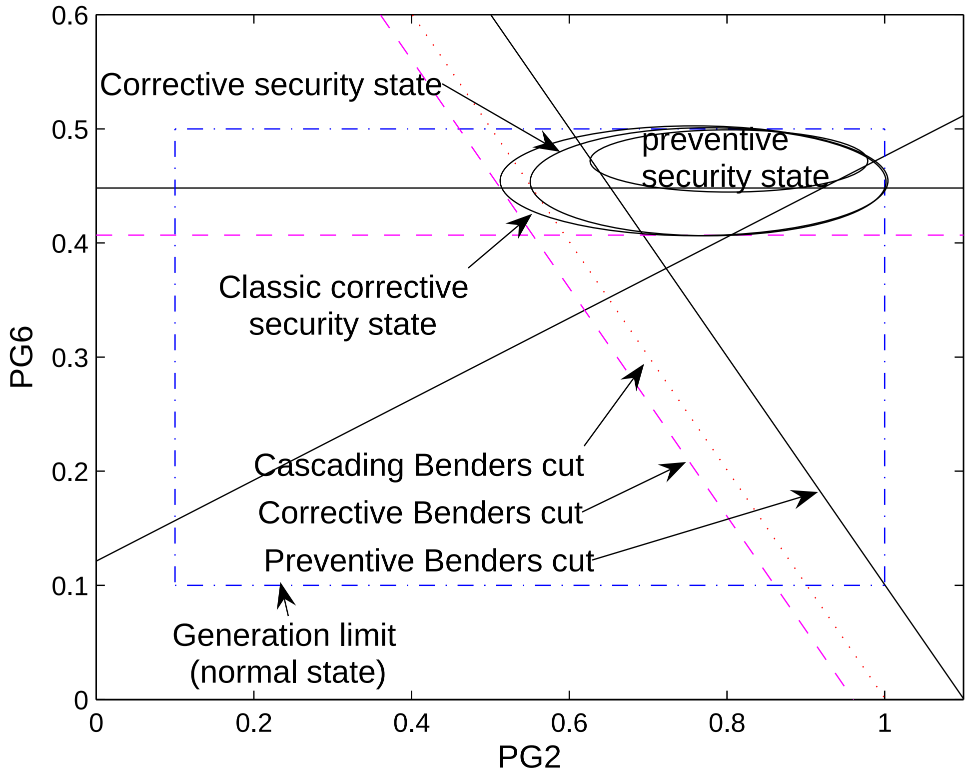


Figure 4.8: The system operation state cut by Benders cut

4.3.4.2 Sensitivity analysis

The purpose of the risk index is to function as *an indicator which biases decisions conservatively when risk is too high and optimistically when risk is comparatively low, according to the information given.*

In Figure 4.10, we observe that the solution of risk-based optimal power flow problem will move to security-constrained optimal power flow problem (Case 1) if the contingency probability is too high, and move to the Case 3 solution to obtain better objective value if the contingency probability is too low resulting in a higher security level.

The risk under different weight is shown in Figure 4.11. Here, we observe that risk increases under smaller weight. This is reasonable because if we put more weight on the risk, we prefer a more conservative operating pattern and a smaller risk will be obtained.

Compared with the deterministic method, the risk-based optimal power flow provides an auto-steering decision-making strategy which can obtain better economic benefit without sac-

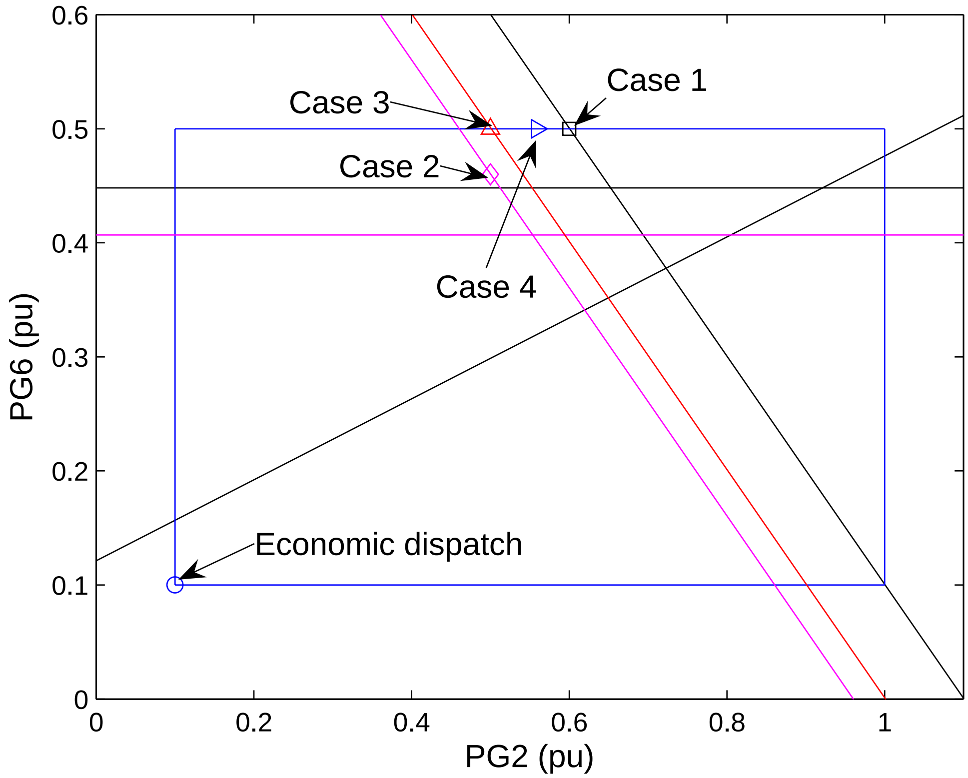


Figure 4.9: The solutions of all the cases

rificing reliability.

4.3.5 Conclusion

In this work, a refined system operation state model is introduced first. The relationship between the sub-states and different optimal power flow strategies is described. Based on this model, the risk-based optimal power flow is proposed and the solution method is given. This approach is illustrated using a test system and the results are satisfying. At the same time the proposed system operation state model is plotted numerically.

4.4 Conclusion

The decomposed security-constrained optimal power flow demonstrated the speed enhancement capability of the chosen algorithm: Benders decomposition. The improved corrective security-constrained optimal power flow showed the capability of Benders decomposition to

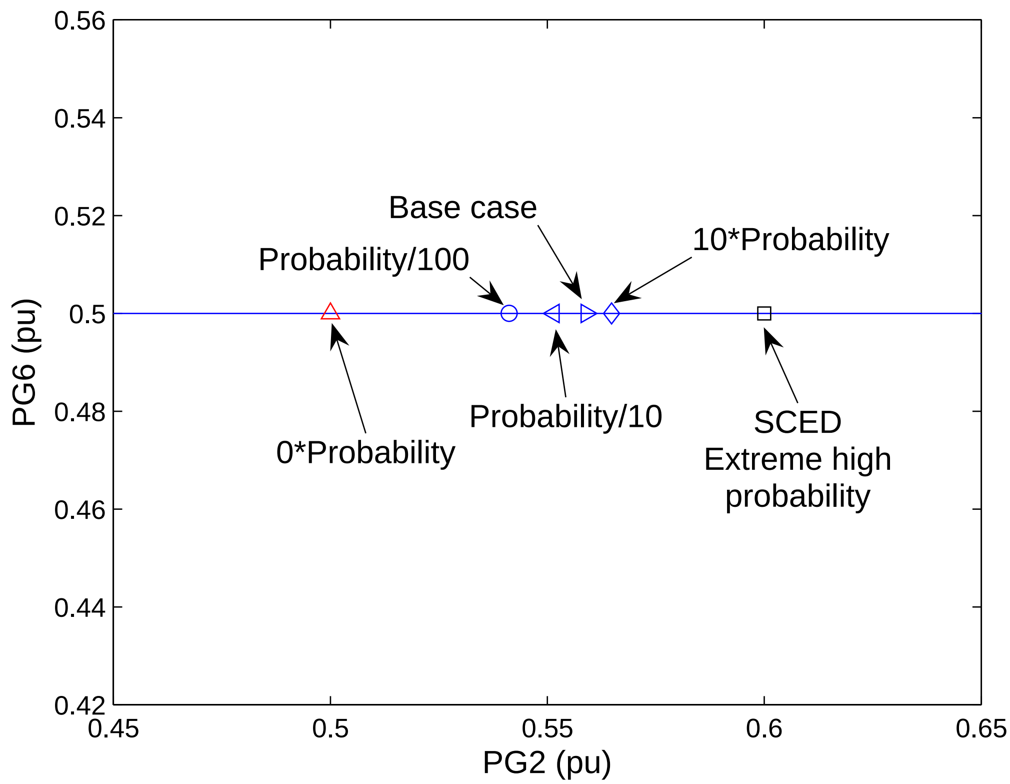


Figure 4.10: Sensitivity analysis of the risk-based optimal power flow

avoid the voltage collapse and cascading overload. Based on these two approaches, risk-based optimal power flow is proposed. This approach can obtain the better economic benefit through reasonable exposure to the risk, and at the same time avoid the catastrophic severity.

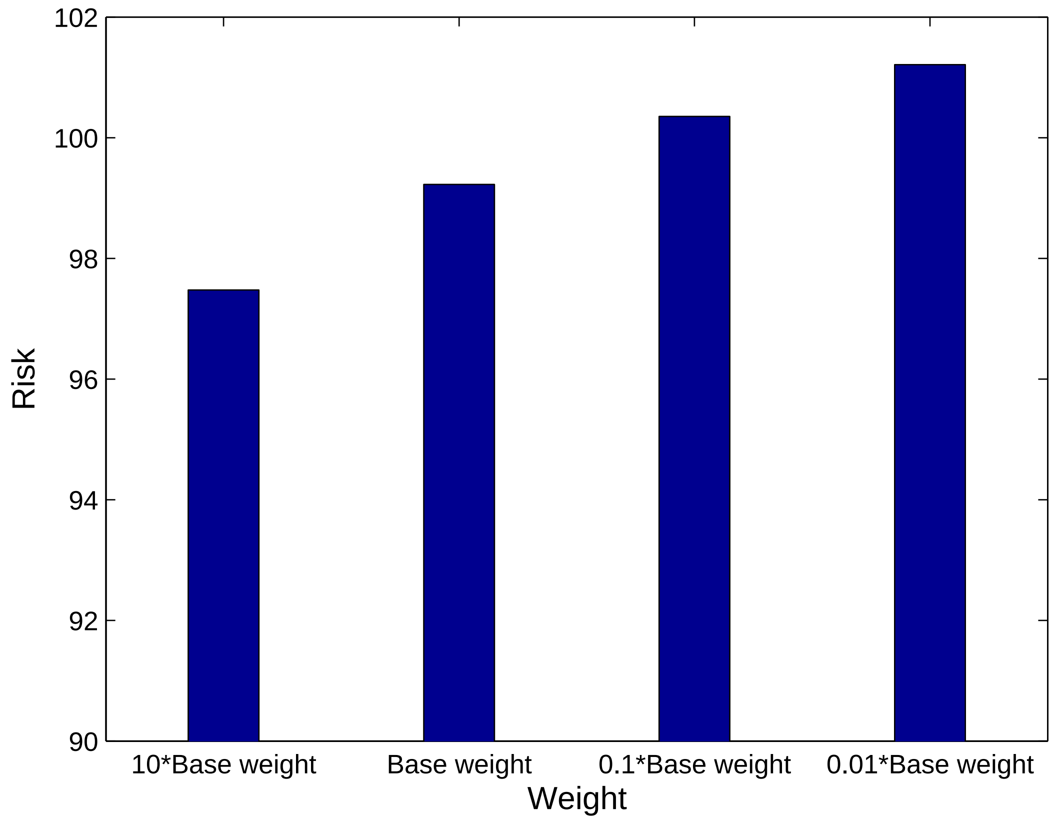


Figure 4.11: Sensitivity analysis of the risk-based optimal power flow

CHAPTER 5 RISK-BASED UNIT COMMITMENT

Economic benefit and reliability are competing objectives in the power industry. Unit commitment, generally performed by the ISO, should identify economically efficient and reliable solutions. In addition, the decision of the unit commitment should also provide a price signal to GENCOs and TRANSCOs to keep their units or network reliable.

This chapter reports on the risk-based unit commitment formulation and solution procedure. We assume that the unit commitment is performed for a day-ahead 24 hour period based on supplier offers and system component average failure probabilities. Solution of the problem is obtained via a three-stage stochastic program based on Benders decomposition where unit commitment is performed in stage 1, dispatch is performed in stage 2, and risk minimization is performed in stage 3.

5.1 Problem Formulation and Solving Procedure

The problem is formulated using a DC power flow model. The objective function is formulated as follows:

$$
\begin{aligned}
Min \quad \sum_{t=1}^{T}\sum_{i=1}^{N} \quad & st_i\alpha_{it} + sd_i\beta_{it} && \textit{Unit commitment} \\
& +c_i p_{it} && \textit{Economic dispatch} \\
& +\textstyle\sum_{j=1}^{c} Pr_{jt}\cdot Sev_{jt} && \textit{Risk evaluation}
\end{aligned}
\tag{5.1}
$$

where, T is the period for performing the unit commitment, $N$is the number of the units, C is the number of the predefined contingencies, st_i is the starting cost of unit i, α_{it} is unit i start at time t, sd_i is the shut down cost of unit i, β_{it} means unit i shut down at time t, c_i is output cost of unit i, p_{it} is the output of unit i at period t, Pr_{jt} is the probability of contingency j at period t, and Sev_{jt} is the severity of contingency j at period t, characterizing load curtailment.

Equation (5.1) is written in three lines to show the three stages explicitly, which are unit commitment, economic dispatch and risk evaluation (minimum load curtailment). We will set forth the explicit problem formulation for each stage in the following development. In each case, only the basic constraints are identified, and other constraints can be added as desired without affecting the approach.

The first stage problem is as follows:

$$\begin{aligned} Min \quad & \textstyle\sum_{i=1}^{T} \sum_{n=1}^{N} (st_i \alpha_{it} + sd_i \beta_{it}) & \\ s.t. \quad & \alpha_{it} - \beta_{it} & = I_{it} - I_{i(t-1)} \\ & \textstyle\sum_{n=1}^{N} P_{imax} I_{it} & \geq D_t + R_t \\ & \textstyle\sum_{n=1}^{N} P_{imin} I_{it} & \geq D_t \end{aligned} \tag{5.2}$$

where, I_{it} is the state of unit i at period t, P_{imax} is the maximum output of unit i, P_{imin} is the minimum output of unit i, D_t is the load at time t, and R_t reservation at time t.

The first stage feasibility check problem (minimum load curtailment problem) is as follows, which is run for all time periods.

$$\begin{aligned} Min \quad & d^r r & \\ s.t. \quad & p_{it} & \leq P_{imax} I_{it} \\ & -p_{it} & \leq -P_{imin} I_{it} \\ & a_0(p+r) & \leq b_0 \\ & a_1(p+r) & \leq b_1 \end{aligned} \tag{5.3}$$

where, r is load curtailment vector, d^r is load curtailment penalty factor vector, a_0 is power flow equations and bounds of flows under normal condition, $a1$ is power flow equations and bounds of flows under contingency condition, and p is generation output vector.

The second stage problem is as follows:

$$
\begin{aligned}
Min \quad & \textstyle\sum_{i=1}^{T}\sum_{n=1}^{N}(c_i p_{it}) && (5.4)\\
s.t. \quad & p_{it} \leq P_{imax} I_{it} \\
& -p_{it} \leq -P_{imin} I_{it} \\
& a_0(p_{it}) \leq b_0
\end{aligned}
$$

The second stage feasibility check problem is as follows.

$$
\begin{aligned}
Min \quad & d^r r + d^s s && (5.5)\\
s.t. \quad & a_1(p + r) \leq b_1 \\
& |p - p^*| - s \leq \Delta
\end{aligned}
$$

where, s is the vector of penalty variables for set of coupling constraints, d^s is the positive cost vectors, p^* is the generation output vector given as a known parameter from second stage problem, and Δ is the vector representing the range of the redispatchability of units. The third stage problem is as follows:

$$
\begin{aligned}
Min \quad & \textstyle\sum_{j=1}^{C} Pr_{jt} \cdot Sev_{jt} && (5.6)\\
s.t. \quad & Sev_{jt} = \sum_{m=1}^{B} F \cdot V \\
& a_1(p + V - v) \leq b_1 \\
& V + f - v = d - p^*
\end{aligned}
$$

where, V is the load curtailment vector, v is the dummy load needed to balance the whole system, p^* is the generation injection vector computed by stage 2, f is the network injection vector, d is the bus load vector, F is the penalty factor vector of load curtailment, and B is the bus number.

A flow chart of the solution procedure is given in Fig. 5.1 and described as follows:

Step 1. A pure unit commitment problem (without considering the network constraint) is solved.

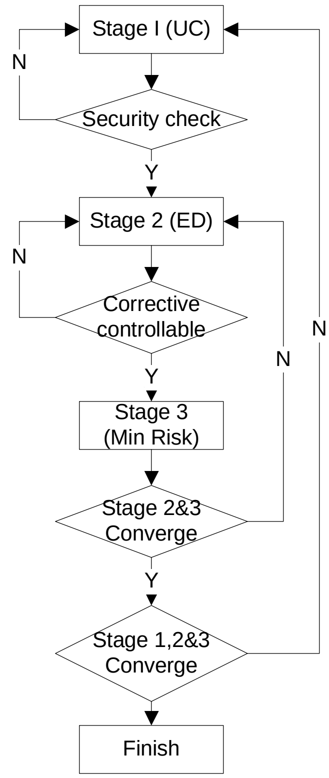


Figure 5.1: Flowchart of Solving RBUC using Benders decomposition

Step 2. The feasibility check is performed for the normal condition and the predefined contingencies. If infeasible, a Benders cut is generated and returned to step 1. Otherwise, go to step 3.

Step 3. Solve a economic dispatch problem without considering contingencies.

Step 4. The feasibility check is performed for the predefined contingencies. If infeasible, a Benders cut is generated and returned to step 3. Otherwise, go to next step.

Step 5. Solve the risk minimization problem.

Step 6. Check if the stage 2 and stage 3 problems converge according the Benders optimal policy. If it has not converged, then return to step 3. If it converges, go to next step.

Step 7. Check if the whole problem is converged according the Benders optimal policy. If it is not converged, then return to step 1. If it converges, stop.

5.2 Illustration

The A6 test system is used here, and a condition monitor is installed in circuit 6. The problem is converged after 4 iteration, as shown in Fig. 5.2. We can see the learning process of Benders decomposition. The lower part is the guessing of the optimal value and the upper is a feasible solution. When the two are equal, that is, when the Benders optimality rule is met, the problem is solved.

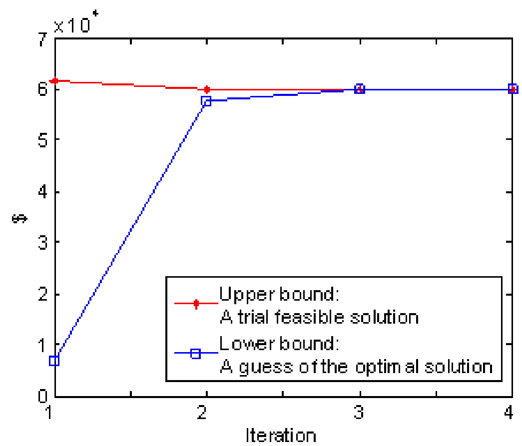


Figure 5.2: The convergence of the three-stage RBUC

In Fig. 5.3, we see that the risk of contingency 1 is much higher then others, because circuit 1 carries most of the inexpensive power from unit 1. So an additional line between bus 1 and bus 2 is suggested. We also can see that in some times the risk is almost zero, and maintenance can be done in these time slots without introducing high risk.

We will also see the effect of a real-time condition monitor which can provide a more accurate failure probability. Suppose the monitor installed in circuit 6 provides information that the circuit 6 failure probability should be increased by a factor of 100. From Fig. 5.4a, we see that after obtaining a high failure probability of circuit 6, the flow on circuit 6 decreases. And after the circuit 6 outage, its flow will be picked up by circuit 3. If we use the average failure probability, there will be a violation on circuit 3 after the circuit 6 outage, but after we know a high failure probability of circuit 6, the violation of circuit 3 is avoided or reduced, as shown in Fig. 5.4b.

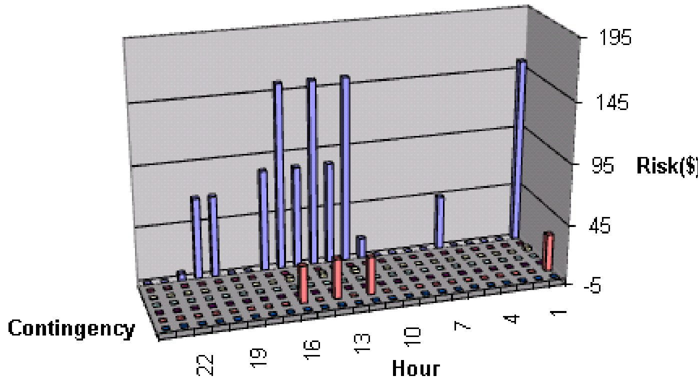
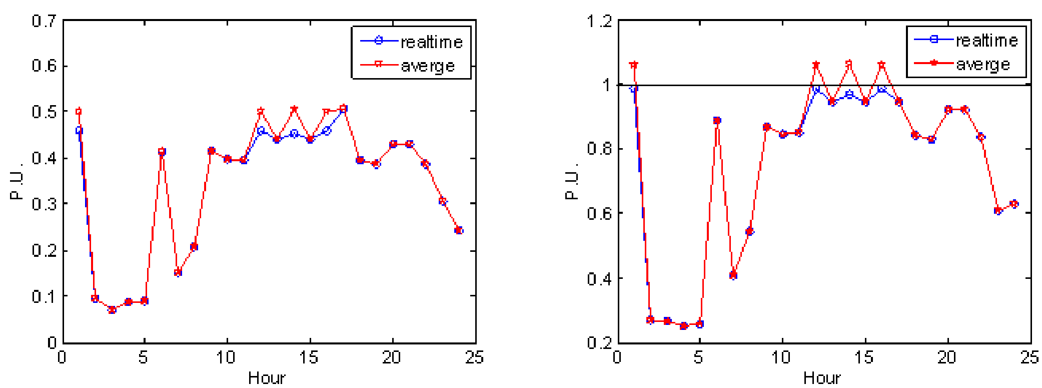


Figure 5.3: Risk of next 24 hours for 7 contingencies



(a) flow of circuit 6 before circuit 6 outage (b) flow of circuit 3 after circuit 6 outagee

Figure 5.4: The effect of a real-time failure probability

5.3 Conclusion

In this chapter, a risk-based unit commitment approach is introduced, which can be used for day-ahead market. And the risk-based economic dispatch, which is a part of RBUC's stage 2 and 3, can also be used for the real-time market. A three-stage stochastic programming approach is proposed to solve the problem. The result is illustrated on a 6-bus test system. The proposed approach is the only illustration for a multiple-stage Benders decomposition application in this dissertation and is very meaningful.

CHAPTER 6 RISK-BASED TRANSMISSION LINE EXPANSION

For several years now the pace of transmission investment has lagged behind the rate of load growth and generating capacity additions. Given this situation, under deregulation an increased interest in transmission expansion has occurred. Generally the expansion of the transmission has three purposes: adequacy: to meet future load under normal conditions; security: to meet future load under contingency conditions; risk: to reduce (or eliminate) the need to operate lines at their thermal limits. The third purpose results in relieving congestion in electricity markets that operate based on locational marginal price (LMPs). Transmission expansion planning is not a new area in power system, but it has not been developed in a way that algorithmically couples with operational decision problems so the approach described in this chapter will facilitate this via systematic consideration of adequacy, security, and risk.

6.1 Risk Index for Line Expansion

Severity assessment provides a quantitative evaluation of what would happen to the power system in the specified condition in terms of severity, impact, consequence, or cost. When the line expansion study is performed, the post contingency consequence to be considered is how much the line flow is approaching the limiting capacity. The plan should be developed in such way that post-contnigency flow margin is maintained. We define the severity function for overload as (6.1).

$$Sev = M \times \epsilon \tag{6.1}$$

where ϵ is the vector measuring how closely the line flow approaches the rating and M is the penalty vector for the specific operating violation.

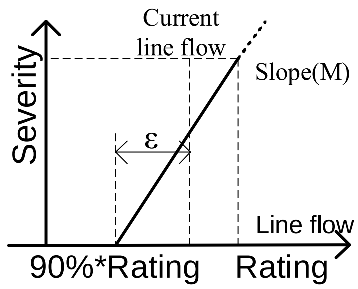


Figure 6.1: The illustration of the overload severity function

6.2 Problem Formulation and Solution Procedure

6.2.1 DC flow model and decision variable decomposition

As discussed in [70] the transmission solution method suited for solving power system planning problem uses the linear (dc) load flow model because:

a. It can be solved by a standard linear programming methods.

b. It requires only active power, MW forecasts, and

c. The error introduced by using the linear load flow approximation is acceptable in long-range planning studies.

The decomposed DC flow model with decision variable x, representing whether to install the line or not, is given as follows [20].

$$f_{ij}/(\theta_i - \theta_j) = \acute{\gamma}_{ij} \cdot x \tag{6.2}$$

where $\acute{\gamma}$ is the candidate line susceptance, i and j are both bus indices, θ is the bus angle, and f_{ij} is line flow between buses i and j.

In (6.2), the decision variable x and operation variable bus angle θ are nonlinearly related. However, if the x is given, (6.2) becomes linear.

6.2.2 Adequacy Expansion

For this problem, the target is to minimize the investment under the condition the full load is served.

$$\begin{aligned} Min \quad & C \cdot x \\ s.t. \quad & UE \quad = 0 \end{aligned} \tag{6.3}$$

where C is the cost to build the new line, x is the decision variable for the candidate line, and UE is the summation of unserved energy.

The subproblem to formulate UE is as follows.

$$\begin{aligned} Min \quad & e \cdot r & \\ s.t. \quad & sf + g + r & = l \\ & f_{ij} - (\gamma_{ij} + \acute{\gamma}_{ij}) \cdot (\theta_i - \theta_j) & = 0 \\ & |f_{ij}| & \leq (f_{max} + \acute{f}_{max} \cdot x) \\ & |g| & \leq g_{max} \end{aligned} \tag{6.4}$$

where r is the bus load shedding vector, e is the bus load shedding penalty vector, f is the line flow vector, s is the node-branch incidence matrix, g is the bus generation vector, l is the bus load vector, γ is the existing line susceptance, $\acute{\gamma}$ is the candidate line susceptance, f_{max} is the existing line limitation, $\acute{f}_{max}$ is candidate line limitation, and g_{max} the is the generation limit.

This subproblem is also called the minimum load shedding problem (MLS) [20]. However planning for adequacy only is not enough for bulk transmission systems, since industry planning criteria also imposes performance standards for unexpected component loss. We refer to the associated step in the process outlined in this dissertation as security expansion.

6.2.3 Security Expansion

After the adequacy expansion, the system obtains a feasible operating point. In order to ensure this operating point remains feasible under contingencies, the security expansion needs to be done. For this problem, the goal is to minimize the investment under the condition that all line overloads are eliminated. The corresponding problem statement is:

$$\begin{aligned} Min \quad & C \cdot x & \\ s.t. \quad & MO & = 0 \end{aligned} \tag{6.5}$$

where C is the cost to build the new line, x is the decision variable for the candidate line, and MO is the summation of overload under all contingencies.

The subproblem to formulate MO is as follows.

$$\begin{aligned} Min \quad & e \cdot \eta & \\ s.t. \quad & sf & = l - g^0 \\ & f_{ij} - (\gamma_{ij} + \acute{\gamma}_{ij}) \cdot (\theta_i - \theta_j) & = 0 \\ & |f_{ij}| - \eta & \leq (f_{max} + \acute{f}_{max} \cdot x) \end{aligned} \tag{6.6}$$

where g^0 is the generation output (fixed/from adequacy planning problem) and η is the overload vector.

This subproblem is also called the minimum overload problem (MO). Reference [20] has proved it will always be feasible for a connected network.

6.2.4 Risk expansion

Risk-based expansion and security expansion are overlapping problems. For simplicity, we will not describe the complete problem with constraints here; instead we will write only the decomposed stage I problem and stage II problem step by step. The whole objective function is formulated as follows:

$$Min \quad C \cdot x + \beta \sum_{k=1}^{N} P_k \cdot Sev_k \tag{6.7}$$

where N is the number of contingencies, k is the index of contingencies, P_k is the probability of contingency k, β is the weight, and Sev_k is severity function of contingency k.

The stage I problem is:

$$\begin{aligned} Min \quad & C \cdot x & \\ s.t. \quad & MO & = 0 \end{aligned} \tag{6.8}$$

The stage II problem is

$$
\begin{aligned}
Min \qquad & \textstyle\sum_{k=1}^{N} P_k \cdot Sev_k && && (6.9)\\
s.t. \qquad & sf && = l - g^0 \\
& f_{ij} - (\gamma_{ij} + \acute{\gamma}_{ij}) \cdot (\theta_i - \theta_j) && = 0 \\
& |f_{ij}| - \epsilon && \leq 0.9 \cdot (f_{max} + \acute{f}_{max} \cdot x) \\
& Sev_k && = sum(\epsilon)
\end{aligned}
$$

The risk expansion problem ensure that the operating point is not only feasible after contingency but also that post-contingency line flows for high probability contingencies are well-below their limits.

6.2.5 Solution Procedure

A flow chart of the solution procedure is given in Fig. 6.2 and described as follows:

Step 1 Check to see if the system is adequate; if yes go to step 3.

Step 2 Perform the adequacy expansion to find a feasible operating point.

Step 3 Check to see if the system is secure, i.e., check if the operating point found in step 2 is still feasible under contingency conditions. If yes go to step 5.

Step 4 Perform the security expansion.

Step 5 Evaluate the risk using (6.9).

Step 6 Check if the cost plus risk is a minimum. If not go back to step 4.

Step 7 Finish and output results.

These three problems can either work together or separately. For example, an adequate system may not need the adequacy expansion step and the risk evaluation can be directly performed on a secured system.

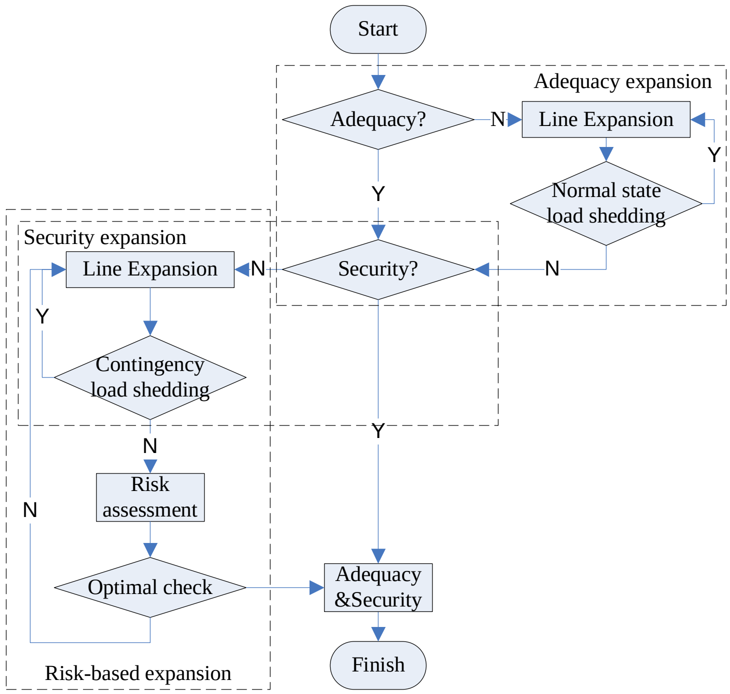


Figure 6.2: Flowchart of the approach for line expansion

6.3 Illustration

We will use a small 6-bus test system from [70] shown in Fig. 6.3. The generation and load information are shown in Table 6.1, and all the line information is in Table 6.2. Some data are modified from the original to show the strength of our approach. The generation bus 6 is not initially connected to the system. There exists enough generation capacity to meet all loads only if bus 6 is connected to the system and some existing lines are reinforced.

The adequacy and security expansion are using the no optimality problem special form of Benders decomposition. Their solving process gradually eliminates the load shedding or overload through increasing the investment. The risk-based expansion is the standard form of Benders decomposition, which avoids the load shedding and overload first then to locate the balance point between investment and risk.

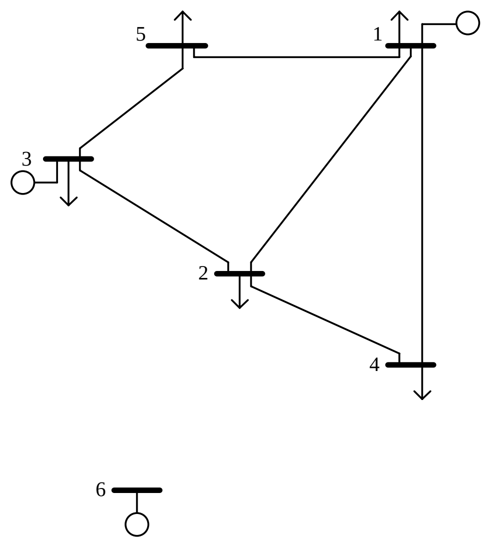


Figure 6.3: The 6-bus test system for line expansion

Table 6.1: Generation capacity and loads

Bus	Generation Capacity	Load
1	150	80
2	0	240
3	360	40
4	0	160
5	0	240
6	600	0
Total	1110	760

6.3.1 Adequacy Expansion

The minimum investment needed to make the system adequate is pu$130. Two additional duplicated lines between buses 3 and 5, one new line between buses 2 and 6, and two lines between buses 4 and 6 are installed. The updated system is shown in Fig. 6.4a.

The adequacy expansion procedure gives us an adequate system, that is, one with an operating point that can meet the full load. We still need to see if the system is secure or not; in the following subsection the security expansion will be performed.

Table 6.2: Candidate transmission line information

Line	Cost	Susceptance	Capacity
(1,2)	40	2.50	55
(1,3)	38	2.63	100
(1,4)	60	1.67	30
(1,5)	20	5.00	65
(1,6)	68	1.47	70
(2,3)	20	5.00	110
(2,4)	40	2.50	75
(2,5)	31	3.22	100
(2,6)	30	3.33	100
(3,4)	59	1.69	82
(3,5)	20	5.00	95
(3,6)	48	2.08	100
(4,5)	63	1.59	75
(4,6)	30	3.33	100
(5,6)	61	1.64	78

6.3.2 Security Expansion

The N-1 reliability criteria is used here, so only one line outage contingency is considered. From Fig. 6.4b, we can see that in order to obtain a secure system, an additional investment, pu$50 is needed. Two additional lines, one between buses 2 and 3 and one between buses 4 and 6 are added. In the following subsection, we will use the risk-based expansion to see which decision we should take according to the contingency probabilities.

6.3.3 Risk-based Expansion

The idea of risk-based expansion is to reduce (or eliminate) the need to operate lines at their thermal limits (relieving congestion) from an expected value perspective, so the probability of the contingency should be provided. Suppose that after performing the failure probability estimation process, the contingency probabilities are those given as in Table 6.3.

After the risk based-expansion is performed, one line between buses 1 and 5 is added in addition to the two lines (2-3, 4-6) added by security expansion.

As shown in Fig. 6.5, the risk faced by the system of the security expansion is much higher

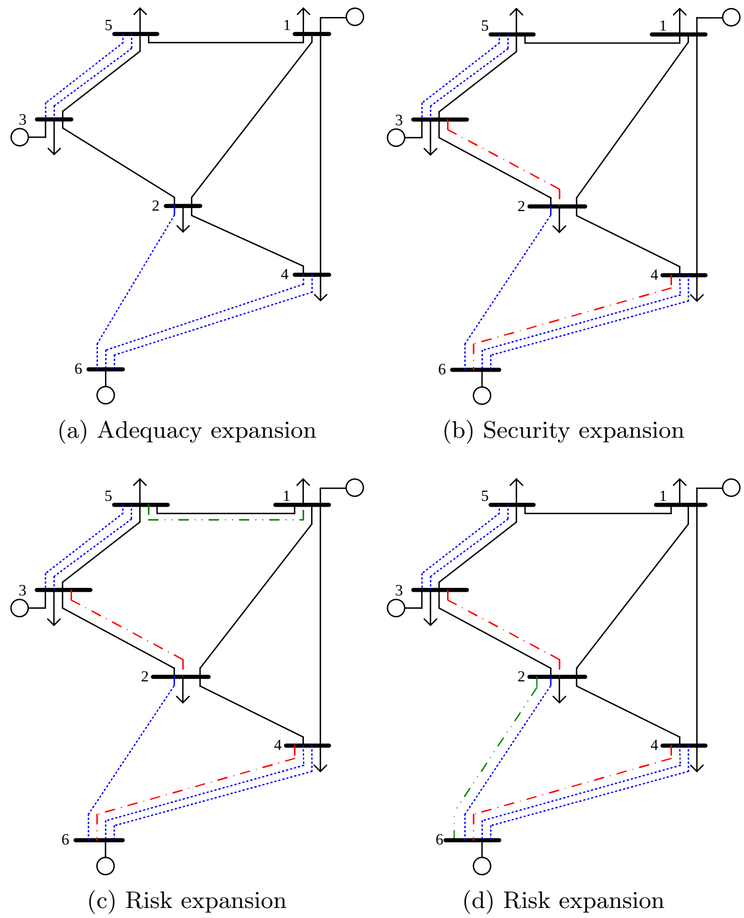


Figure 6.4: The effect of different line expansion strategy

than the risk-based expansion. But more investment, pu$20, is required.

6.3.4 Sensitivity Analysis

In the above analysis, we can assign different weights to risk. Fig. 6.5 shows the sensitivity results. We see that if we assign more weight to the risk, the risk will decrease. A small weight on risk will lead to security expansion while a huge weight will produce a redundant system. This makes sense, i.e., the more spent wisely, the less the risk.

The probability of the contingency also plays a role. In Fig. 6.5, the cone shows the result of increasing the contingency probability of line between bus 2 and bus 3 by 10 times, which has the same effect as a higher weight. Fig. 6.4d shows the expanded system under the

Table 6.3: Line failure probability

Line	Probability
(1,2)	0.011
(1,4)	0.020
(1,5)	0.014
(2,3)	0.005
(2,4)	0.005
(2,6)	0.022
(3,5)	0.015
(4,6)	0.012

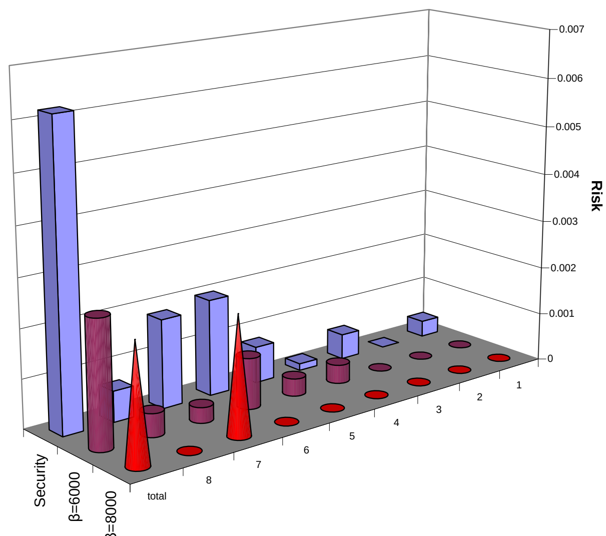


Figure 6.5: Risk sensitivity comparison

higher weight or probability. Instead of adding a line between bus 1 and 5, a line between bus 2 and 6 is added, at an additional cost of pu$30 instead of pu$20 in order to achieve a lower risk level.

6.4 Approach Extensions

Several extensions to the above approach will be briefly introduced in this section. Also, due to the flexibility of the Benders decomposition, the extensions are not limited and can be tailored to satisfy practical needs.

6.4.1 Multiple Load Scenarios

An important and useful refinement for planning is to consider different load scenarios. Using Benders decomposition, it is very easy to incorporate multiple load scenarios into the approach.

The adequacy expansion considering multiple load scenarios is as follows:

$$\begin{aligned} Min \quad & C \cdot x \\ s.t. \quad & UE_1 \leq \epsilon_1 \\ & \vdots \\ & UE_m \leq \epsilon_1 \end{aligned} \tag{6.10}$$

where UE_m is the summation of unserved energy for load scenario m, and ϵ_1 is the tolerance for the unserved load. Here, compared with the original formulation (6.3) the ϵ_m, which can be zero or slightly bigger than zero, is introduced because it is not economic to eliminate all the infeasibility in multiple load scenarios.

The security expansion considering multiple load scenarios is as follows:

$$\begin{aligned} Min \quad & C \cdot x \\ s.t. \quad & MO_1 \leq \epsilon_2 \\ & \vdots \\ & MO_m \leq \epsilon_2 \end{aligned} \tag{6.11}$$

where MO_m is the summation of overload under all contingencies for load scenario m, and ϵ_2 is the tolerance for the overload.

The risk will be evaluated as following:

$$\sum_{j=1}^{M} P_j \sum_{k=1}^{N} P_k \cdot Sev_{jk} \tag{6.12}$$

where P_j is the probability for load scenario j, and M is the total number of load scenarios.

The procedures will be the same as in the single scenario case with only necessary changes to the Benders cuts are needed as introduced in section 3.2.

6.4.2 Integration of Operating Cost and Candidate Generator Capacity

Sometimes a pure line expansion may not provide the most economic plan. For example, the operating point may not be the most economic one and from a long term point of view this could be very costly; in the illustration earlier the new unit capacity is limited by the line capacity. So the consideration of the operation cost and integrating the line and generator expansion is necessary.

Here we provide an approach to integrate the operating cost and generation capacity into adequacy expansion. Integrating operating cost and generation capacity into security and risk expansion is similarly done.

For this problem, the target is to minimize investment and future operating cost under the condition that full load is served.

$$\begin{aligned} Min \quad & C \cdot x + O \cdot y & \\ s.t. \quad & y & \leq G_{max} \\ & UE & = 0 \end{aligned} \tag{6.13}$$

where O is the generation cost of the existing and candidate generation units, y is the generation unit output, and G_{max} is the maximum generation output for existing units and maximum available output for candidate units.

The subproblem to formulate UE is as follows.

$$\begin{aligned} Min \quad & e \cdot r + e \cdot z & \\ s.t. \quad & s \cdot f + g + r - z & = l \\ & f_{ij} - (\gamma_{ij} + \acute{\gamma}_{ij}) \cdot (\theta_i - \theta_j) & = 0 \\ & |f_{ij}| & \leq (f_{max} + \acute{f}_{max} \cdot x) \\ & g & = y^* \end{aligned} \tag{6.14}$$

where z is the generator output decrease, and y^* is the generation output from problem (6.13).

6.4.2.1 Illustration

In Table 6.4, the results for different generation cost cases are provided. Opt cost is the generator operating cost. Candidate line results represent how many new lines need to be built for 15 candidate lines shown in Table 6.2. Cap means the lowest capacity for the generator in bus 6.

Table 6.4: Expansion Considering Operation Cost and New Unit Capacity

#	Op Cost			Candidate Line Results															Cap.
	1	3	6	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	6
1	-	-	-	0	0	0	0	0	0	0	0	1	0	2	0	0	2	0	2.64
2	0	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	2	0	2.64
3	6	3	1	0	0	0	0	0	0	0	0	1	0	2	0	0	2	0	2.65
4	1	3	6	0	0	0	0	0	0	0	0	1	0	2	0	0	2	0	2.50
5	60	30	10	0	0	0	0	0	0	0	0	2	0	2	0	0	2	0	3.86
6	100	300	200	0	0	0	1	0	0	0	1	4	0	0	0	0	2	0	5.87

Case 1 does not consider operating cost. In case 2, generation costs are zeros and the same results are obtained as for case 1. In cases 3 and 4, the generation cost is considered but is much smaller than transmission line investment. It can be observed that the transmission line expansion decisions are unaffected and unit 6 capacity is affected slightly. In cases 5 and 6, we can see that the long run generation cost, equal or even greater than the transmission line expansion investment is considered. It is easy to see that both the line expansion decisions and the unit 6 capacity are affected.

6.4.3 Transmission and Generation Expansion

When considering transmission line expansion in terms of operating cost and candidate unit capacity, the problem formulation is similar to the integrated expansion of transmission line and generation. In formulation (6.13), the y can be thought as the capacity of candidate generation unit and O can be thought as generator unit building per pu cost. Additional, a risk minimization part can be added to form the risk-based transmission line and generation integrated expansion. This approach can easily degenerate to pure (risk-based) generation expansion.

6.4.4 Computation Speed Analysis

There are two key attributes affecting the computation speed analysis. One is the number of the integer decision variables and the other is the number of scenarios.

The upper bound of the number of the integer decision variables is decided by the combination C_2^N, where N is the total bus number. This could be a huge number for a large system. For 6 buses, the number is 15 and for 100 buses the number grows to 4950. But practically the number of candidate lines is much smaller than this combination number. The reason can be geographical and so on. A modern integer programming problem solver, like CPLEX, can handle thousands of variables in a reasonable time [60].

Although the number of the scenarios could be a huge, almost all of them are independent from one another and the parallel computation can easily be applied. Therefore the proposed approach can be used for large systems.

6.5 Conclusion

This work introduces a risk-based transmission line expansion approach. This approach can provide answers to the following three questions, 1) how to expand a transmission system from inadequacy to adequacy; 2) how to expand the system from unsecured to secure; 3) how to manage the post-contingency risk. The Generalized Benders Decomposition based stochastic programming approach is proposed to solve the problem. The result is illustrated on a 6-bus test system. This approach can easily be extended to multiple scenario situation, to consider the operating cost, and to be integrate with the generation expansion planning.

CHAPTER 7 RISK-BASED VAR RESOURCE ALLOCATION AND VAR GAP

Reactive power planning may be considered to have at least three purposes, which we characterize as follows: adequacy: to meet the future load under normal condition without operational violation; security: to meet the future load under both normal and contingency conditions without steady-state operational violation; risk: to further improve the voltage profile and obtain additional loading margin. In this dissertation, a systematic approach, which we refer to as risk-based Var expansion planning, is developed to address all three of these issues.

7.1 Risk Index for the Var Resource Allocation

Severity provides a quantitative evaluation of what could happen to a power system in a particular condition. Traditionally, the objective of the Var planning problem is to determine a minimum cost expansion plan that ensures feasible system operation both in the normal situation and contingency situations [23]. Although this approach is easy to apply, it provides only a feasible operating point. In contrast, more recent efforts have included consideration of voltage instability constraints [24]. This approach has the added advantage that it ensures an explicit loading margin; however, it requires significantly more computation to do so.

Fig. 7.1 qualitatively illustrates the relationship between bus voltage and loadability at a lagging power factor, showing that if a feasible operating point is found and, subsequently, more reactive power is supplied, then bus voltage [71] and loadability [72] both will increase. Therefore, the available voltage level can be treated as a sensitivity index with respect to the loadability.

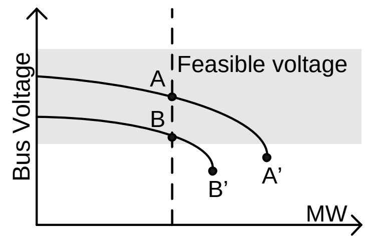


Figure 7.1: Relation of bus voltage with loadability

The limitation on loadability may be considered to be a reactive power adequacy issue that results because, given desired MW loading and generator set point voltages, the necessary reactive power cannot be obtained, i.e., the reactive power balance equation (7.1) in power flow fails to hold:

$$Q_D - Q_S + Q_L = 0 \tag{7.1}$$

where Q_D is reactive demand, Q_S is reactive supply (generation/compensation), and Q_L is reactive loss, including effects of line charging.

In (7.1), Q_S is the total of the computed reactive supply and not simply the sum of the reactive capabilities over the resources, a point which recognizes the typically localized nature of voltage instability problems within a network. Voltage instability problems may therefore be effectively addressed by increasing the range of Q_S, at certain locations.

Following traditional Var deployment as in [23], one or more contingencies will result in voltages at some buses just at the minimum level. If additional reactive power is supplied at or close to these buses, then their post-contingency voltage will be higher. In addition, it will necessarily be the case that post-contingency loading margin will increase as well. In defining the severity function, we directly account for the first effect (on voltage magnitude) and indirectly for the second (on loading margin), according to (7.1).

$$Sev = M \times \epsilon \tag{7.2}$$

where ϵ is the vector measuring how much dummy reactive power needed to support a higher voltage, and M is the cost vector for the additional reactive power.

This severity function is illustrated in Fig. 7.2. Following execution of the traditional Var planning method [23] under certain post-contingency constraints on voltage magnitude (e.g. [0.95, 1.1]), there will be one or more buses having post-contingency voltage at or close to the minimum threshold (e.g., 0.95). The voltage severity function reflects how much (dummy) reactive power injection is required to move the voltage of these buses to a target voltage level. We assume this target voltage level is 1.0 in this dissertation.

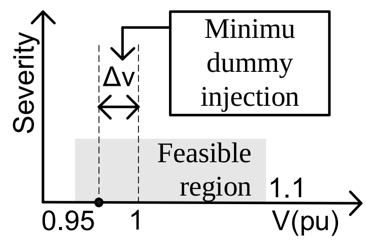


Figure 7.2: The illustration of the voltage collapse severity function

The fact that conditions closer to the maximum loadability point require more reactive power to achieve the same voltage level than conditions further from the maximum loadability point is what provides the indirect capture of loading margin in this severity function. Shown in Fig. 7.3, operating point $O2$ needs more reactive power support (Q_c) than $O1$ (0) to reach the same voltage level.

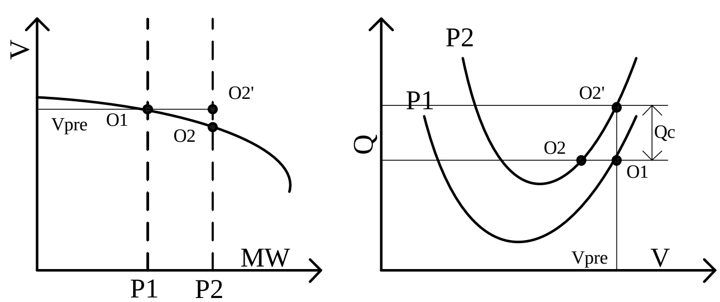


Figure 7.3: The relationship of voltage, loadability and Var injection

7.2 Problem Formulation and Solution Procedure

The risk-based Var expansion planning has three stages: 1) reactive adequacy expansion (investment decision and adequacy check); 2) security expansion (investment decision and security check); 3) risk evaluation (investment on additional voltage and loadability improvement).

Four attributes of this problem drive our choice of solution approach. First, these three problems are sequential, where solution to a latter problem depends on solution to the earlier-stage problems. For example, we need to know the location of the new Var resource before we can evaluate the effect of an allocation. Second, these two problems are related, but they can be decoupled. Third, the risk evaluation part will involve different contingencies, each one effectively a different “scenario ”of quantifiable probability. This motivates a stochastic programming approach. Fourth, we observe that the investment problem (first and second stages) is integer: invest, or not, at each bus. In contrast, the operation subproblem is continuous, and because the AC power flow model must be used, it is also nonlinear.

7.2.1 Problem Formulation: Adequacy and Security Expansion

For this problem, the target is to minimize the investment under the condition that the load is fully served.

$$Min \quad \sum_{k=1}^{N} d_k r_k + c_{rk} q_{rk} + c_{ck} q_{ck} \tag{7.3}$$

$$s.t. \quad MDR = 0 \tag{7.4}$$

$$q_{rk} \leq \bar{q}_r \cdot r_k \quad k = 1, \ldots N \tag{7.5}$$

$$q_{ck} \leq \bar{q}_c \cdot r_k \quad k = 1, \ldots N \tag{7.6}$$

where N is the number of candidate buses, r_k is the decision variable for Var location k, d_k is the fixed cost of installing reactive capacities on bus k, q_{ck} is the additional capacitive compensation at bus k, q_{rk} is the additional bus inductive compensation at bus k, c_{rk} is the variable cost of installing one unit of inductive Var on bus k, c_{ck} is the variable cost of installing one unit of capacitive Var on bus k, $\bar{q}_r$ is the maximum amount of inductive capacity that can be installed on bus k, $\bar{q}_c$ is the maximum amount of capacitive capacity that can be installed on bus k, and MDR is the minimum dummy reactive power injection.

Equation (7.4) indicates whether additional reactive power is needed after the Var expansion. For a feasible Var allocation, this amount should be zero. Equations (7.5) and (7.6) constrain the amount of inductive and capacitive compensation, respectively; the decision variable r_k in these equations is equal to 1 if a Var resource is installed.

As described in Chapter 3, the Benders method seeks to decompose an optimization problem into a single master problem and one or more subproblems. Here, the master problem is exactly the same as that posed earlier except without the constraint (7.4), so it will not be repeated here. The subproblem for each contingency, which identifies MDR, is as follows [20].

$$MDR = Min \quad \sum_{k=1}^{N}(y_{1k} + y_{2k}) \tag{7.7}$$

$$s.t. \quad P_k = 0 \tag{7.8}$$

$$Q_k - y_{1k} + y_{2k} = 0 \tag{7.9}$$

$$-q_{rk} + \underline{Q}_{Gk} \leq Q_{Gk} \leq \bar{Q}_{Gk} + q_{ck} \tag{7.10}$$

$$\underline{V}_k \leq V_k \leq \bar{V}_k \tag{7.11}$$

where y_{1k} is the dummy capacitive reactive power injection vector, y_{2k} is the dummy inductive reactive power injection vector, and Q_{Gk} is reactive power generation/compensation Constraints (7.8) and (7.9) are active and reactive power balance equations, respectively. In constraint (7.10), the q_{rk} and q_{ck} are from the master problem. Both y_{1k} and y_{2k} are positive.

For Var expansion planning concerned only with adequacy, the MDR problem considers only the normal condition. For Var expansion planning concerned with security, both the normal condition and each contingency condition are considered.

7.2.2 Problem Formulation: Risk Expansion

For simplicity, we will not list the complete problem with constraints here; instead we will list the decomposed stage I problem and stage II problem step by step. The whole objective function is formulated in (7.12).

$$Min \quad \sum_{k=1}^{N}(d_k r_k + c_{rk} q_{rk} + c_{ck} q_{ck}) + \beta \sum_{m=1}^{M}(P_m \cdot Sev_m) \tag{7.12}$$

where M is the number of contingencies, m is the index of contingencies, P_m is the probability of contingency m, β is the weight, and Sev_m is the severity function of contingency m.

The stage I problem of the risk-based Var expansion planning problem is the security expansion problem as introduced in subsection 7.2.1. The stage II problem is as follows.

$$\begin{aligned} Min \quad & \textstyle\sum_{k=1}^{M} P_k \cdot Sev_k \\ s.t. \quad & 1.0 \leq V_k \leq \bar{V}_k \\ & Sev_k = M \cdot MDR \end{aligned} \tag{7.13}$$

where ΔV_k is the specified voltage improvement at bus k.

The first stage of the risk-based Var expansion approach will determine a feasible operating point within the voltage constraints (e.g. [0.95, 1.1]), and the second stage will identify how far this point is to the enhanced voltage constraint limits (e.g. [1.0 1.1]). At the same time the loadability is increased.

7.2.3 Solution procedure

A flow chart of the solution procedure is given in Fig. 7.4 and described as follows, which is similiar to Fig.6.2.

Step 1 Check to see if the system is adequate; if yes go to step 3.

Step 2 Perform the adequacy expansion to find a feasible operating point.

Step 3 Check to see if the system is secure, i.e., check if the operating point found in step 2 is still feasible under contingency conditions. If yes go to step 5.

Step 4 Perform the security expansion.

Step 5 Perform the risk evaluation.

Step 6 Check if the cost plus risk is a minimum. If not return to step 4.

Step 7 Finish and output results.

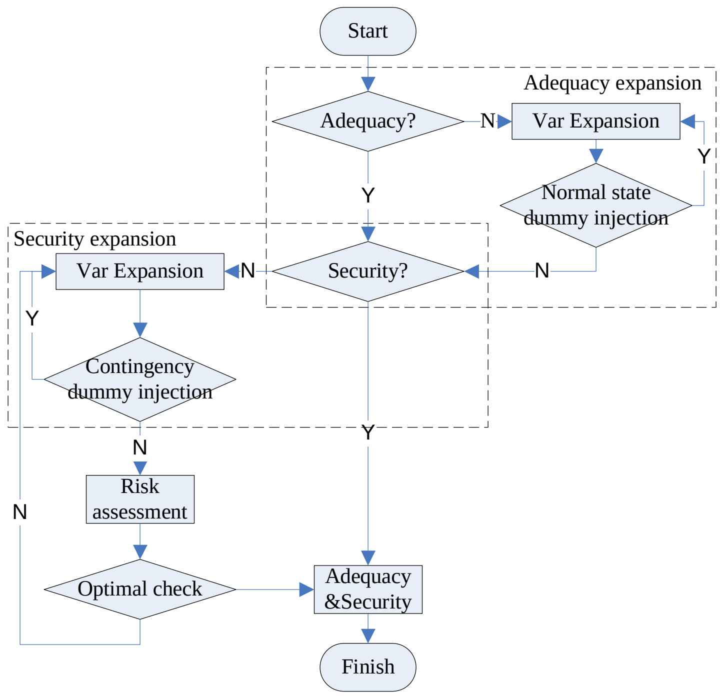


Figure 7.4: The flowchart of the risk-based Var resource allocation

These three problems can be solved together, but they may also be solved separately. For example, an adequate system may not need the adequacy expansion step, and a secured system can directly perform the risk evaluation.

7.3 Illustration

The AEP 14-bus test system is used here. The original system has abundant Var support. To illustrate the method, these Var sources are removed which results in insufficient VAR support and a low voltage profile. The cost information for capacitive and inductive reactive power is shown in Table 7.1. Circuit outage contingency probabilities are listed in Table 7.2.

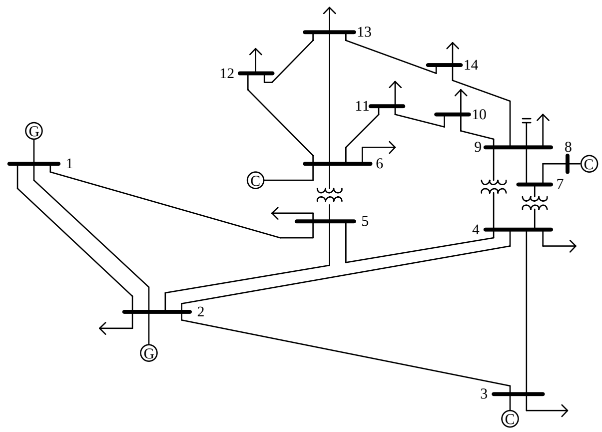


Figure 7.5: The AEP 14-bus test system

7.3.1 Adequacy Expansion

The minimum investment needed to make the system adequate is \$16.72M. The adequacy expansion procedure gives us an adequate system, i.e., an operating point that can meet the entire load. Still we need to see if the system is secure or not. Security expansion is described in the following subsection.

7.3.2 Security Expansion

The N-1 reliability criteria is used here, so only one line outage contingency is considered. The minimum investment needed to make the system secure is \$21.37M. We can see that in order to obtain a secure system, \$4.65M additional investments are needed.

7.3.3 Risk-based expansion

In this subsection, we use the risk-based expansion to see how contingency probabilities affect decision making. The objective function value is obtained at a cost of \$23.10M. Figure 7.6a shows that the risk exposure with and without the effects of the risk-based expansion; although the latter is less exposed, it is also more expensive in that an additional \$1.73M has to be spent.

Table 7.1: Candidate Var cost information ($M)

Bus	Fixed cost	Variable cost		Maximum	
		Cap	Ind	Cap	Ind
3	4	9	6	0.5	0.4
4	6	8	5	0.45	0.4
5	3	6	7	0.55	0.4
6	7	5	8	0.4	0.3
7	3	9	4	0.46	0.2
8	8	7	9	0.38	0.1
9	6	4	6	0.56	0.3
10	7	7	7	0.35	0.5
11	9	6	5	0.47	0.4
12	6	8	8	0.55	0.24
13	8	7	6	0.48	0.22
14	9	5	7	0.30	0.31

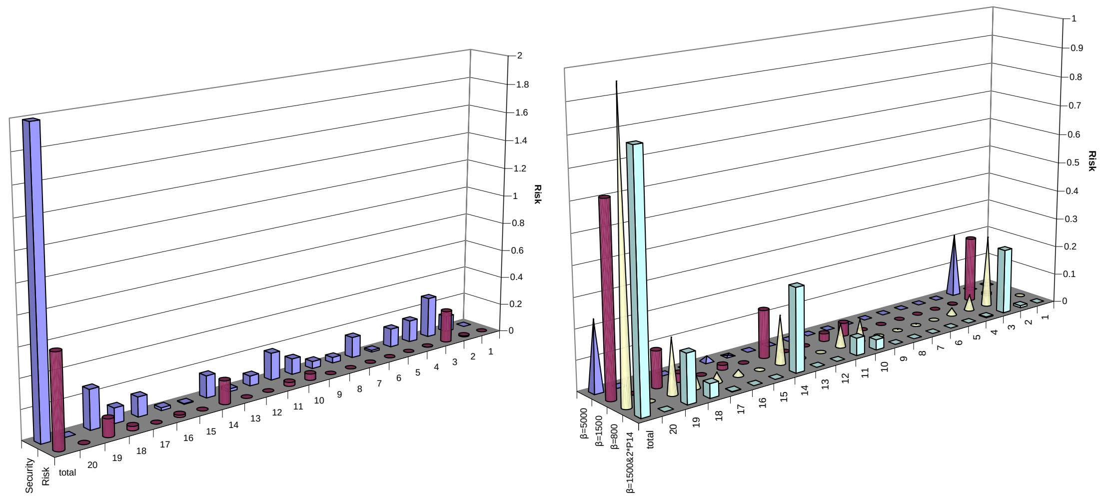
Table 7.2: Line outage probability (1E-3)

Line	Prob	Line	Prob	Line	Prob
$(1,2)$	1.0	$(4,5)$	2.5	$(7,8)$	1.2
$(1,2)$	1.0	$(4,7)$	0.5	$(7,9)$	1.2
$(1,5)$	1.5	$(4,9)$	1.2	$(9,10)$	2.0
$(2,3)$	1.1	$(5,6)$	1.4	$(9,14)$	1.8
$(2,4)$	2.0	$(6,11)$	2.0	$(10,11)$	2.0
$(2,5)$	3.0	$(6,12)$	2.5	$(12,13)$	1.0
$(3,4)$	1.1	$(6,13)$	0.8	$(13,14)$	2.6

7.3.4 Sensitivity analysis of the risk-based approach

In this analysis, we vary the weights on risk. Fig. 7.6b shows the sensitivity results. We can see that if we put more weight on risk, risk will decrease and if we put less weight on risk the risk will increase. An extremely small weight on risk will lead to security expansion and a large weight will lead to a redundant system.

We can also study the influence of the contingency probabilities. In Fig. 7.6b, the contingency probability of line 15 (from bus 7 to 8) is doubled, which results in smaller risk compared to the base case under outage of line 15.



(a) Voltage risk (b) Sensitivity of risk

Figure 7.6: Voltage risk sensitivity analysis

7.3.5 Comparison

Results of the above Var expansions are given in Table 7.3. All the selected Var resources are capacitive.

Table 7.3: Cost comparison for different strategies

Adequacy		Security		Risk	
Bus	Size	Bus	Size	Bus	Size
3	0.498	3	0.454	3	0.406
-	-	7	0.056	7	0.246
9	0.56	12	0.473	12	0.410
\$16.72M		\$21.37M		\$23.10M	

7.4 Var Gap

Figure 7.7 shows the effects of Var resources; it also illustrates the philosophy of the Var allocation approach. Operating point A is the operating point without Var planning. After the allocation process considering only voltage support, the system will operate at point B. If a minimum security margin μ_{min} min is enforced, the allocation process considering the voltage stability constraint will allocate more resources to obtain the collapse point C'.

7.4.1 The Concept of Var Gap

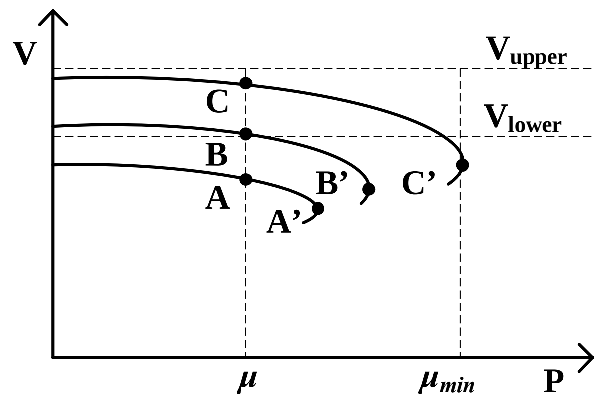


Figure 7.7: The effect of reactive power shown by PV curve

The concept of Var gap (VG) will be proposed here. We will consider two kinds of Var gap: voltage Var gap (VVG) and security margin Var gap (SVG). Both Var gaps represent system level rather than bus level quantities. The voltage Var gap is defined as the minimum amount of Var resource needed to support the entire power system buses within a predefined voltage feasible region for a future load scenario. Similarly, the security Var gap represents the minimum amount of Var resource needed to obtain a required security margin. The voltage Var gap in Fig.7.7 is the minimum amount of reactive power needed to move the operating point from A to B. The security margin Var gap in Fig.7.7 is the minimum amount of reactive power needed to move the point of collapse from A' to C'.

When we perform the Var resource allocation, the requirement is to allocate enough Var to eliminate one or both of these two Var gaps. Typically it is hard to say which Var gap is larger, and both must be checked to make sure the planning is reliable under a minimum investment request.

When the risk index is used to cover the uncertainty, the Var gap can serve as the severity function.

7.4.2 Calculation of VVG

The calculation of VVG is introduced in section 7.2 as problem (7.7), which will repeated here for convenience.

$$
\begin{aligned}
VVG \;=\; Min \quad & \textstyle\sum_{k=1}^{N}(y_{1k}+y_{2k}) && (7.14)\\
s.t. \quad & P_k = 0 && (7.15)\\
& Q_k - y_{1k} + y_{2k} = 0 && (7.16)\\
& -q_{rk} + \underline{Q}_{Gk} \le Q_{Gk} \le \bar{Q}_{Gk} + q_{ck} && (7.17)\\
& \underline{V}_k \le V_k \le \bar{V}_k && (7.18)
\end{aligned}
$$

7.4.3 Calculation of SVG

In order to calculate the security margin, generally two methods can be used in addition to simple repeated power flow. The first method is the continuation power flow [73] and the second is the optimization approach [71]. Typically the continuation method can not only produce the security margin but can also provide the trajectory from the operating point to the margin point.

When we calculate the SVG, the optimization technique will be used because the trajectory is not required in this situation. But, instead of maximizing the load increase, the additional Var needed to obtain a specified security margin is minimized. The SVG calculation is given as follows:

$$
\begin{aligned}
SVG \;=\; Min \quad & \textstyle\sum_{k=1}^{N}(y_{1k}+y_{2k}) && (7.19)\\
s.t. \quad & P_k(\mu) = 0 && (7.20)\\
& Q_k(\mu) - y_{1k} + y_{2k} = 0 && (7.21)\\
& -q_{rk} + \underline{Q}_{Gk} \le Q_{Gk} \le \bar{Q}_{Gk} + q_{ck} && (7.22)\\
& \underline{V}_k \le V_k \le \bar{V}_k && (7.23)
\end{aligned}
$$

where μ is related to the requirement for the security margin. For example, if 25% is needed μ will be 1.25 and both the real power load and reactive power load will be multiplied by 1.25.

Voltage limit is very meaningful in the calculation of the SVG because the collapse point at each different voltage scope will need a different Var resource, as shown in Fig.7.8.

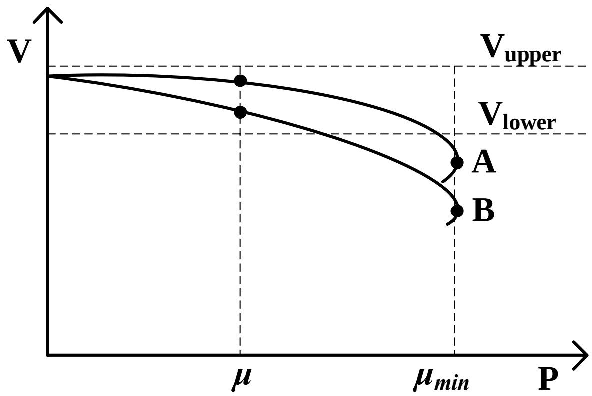


Figure 7.8: The collapse point at different voltage level

Comparing (7.14) and (7.19), it is easy to see that they are similar and that the method used in the risk-based Var resource allocation considering only VVG can easily be adapted to consider SVG without major modification.

7.4.4 Different Types of Var Allocation Formulation Using VGs

After the concept of VG is proposed, the Var resource allocation can be formulated and solved in the manners as shown in Table 7.4.

Table 7.4: Summary of Var resource formulation

Type	Deterministic		Uncertainty	
	Feasibility		Optimality	
	VVG	SVG	VVG	SVG
I	V			
II	V	V		
III	V		V	
IV	V	V		V
	Tolerance		Severity	

Although there are other types that can also be formulated, the four types in Table 7.4 are more common. The purpose of type I is to eliminate the voltage Var gap and obtain a good voltage profile. The type II will make both the voltage Var gap and security margin Var gap to obtain a good voltage profile and required security margin. Type I and type II are both deterministic cases. The tolerance in the last row of Table 7.4 means sometimes some level of infeasibility is acceptable such as the multiple load scenario situation. The severity in the last row of Table 7.4 reflects the fact that the VVG and SVG work as the severity function for the risk index. The type III has been introduced in earlier part of this chapter, and the type IV approach will be illustrated later.

7.5 Illustration of Var Allocation and VGs

Several cases using the same AEP 14-bus test system can be used to illustrate the Var allocation and Var gaps.

7.5.1 Type II Illustration

Although generally the SVG should be a stricter constraint than the VVG, this is not always true. As shown in Table 7.5, the first two columns correspond to the two situations plotted in Fig. 7.8. The security margin requirement is 5%. At a lower voltage collapse point, the security margin constraint is not active at all, and the same results as those for the type I is obtained. If a higher voltage collapse point is required more investment is needed.

Table 7.5: Collapse point voltage effects

	VVG & SVG (1.05)		VVG
V lower bound	0.95	0.75	0.95
3	0.498	0.454	0.454
7	0.102	0.056	0.056
12	0.507	0.473	0.473
cost	\$22.45M	\$21.37M	\$21.37M

7.5.2 Type IV Illustration

The planning requirement is that, under normal condition the security margin is 30%. In a contingency situation the minimum security margin may be as low as 5%, but a value of 30% is preferred. The upper bound of the candidate capacitors are increased by a factor of 1.2. The cost information for different strategies for type IV Var allocation is shown in Table.7.6.

Table 7.6: Cost comparison for different strategies for type IV Var allocation

Adequacy		Security		Risk	
Bus	Size	Bus	Size	Bus	Size
3	0.091	3	0.497	3	0.427
7	0.114	7	0.103	6	0.48
9	0.672	12	0.507	7	0.312
\$17.54M		\$22.455M		\$23.056M	

A sensitivity analysis is performed with the results shown in Fig.7.9. The pyramid is the base case. The cylinder represents the situation that the probability of the contingency 16 is increased by a factor of 2, and it is easy to observe that the risk of contingency 16 decreases greatly. The other two results represent the situations of bigger weight and the risk decreases in both situations.

7.6 Conclusion

Var resource allocation is one of the oldest topics in the power system area. In this chapter, a systematic approach to Var resource allocation, covering both deterministic and uncertainty and considering both voltage issues and security margin, is well developed and illustrated. Benders decomposition is used to solve this problem. As a planning problem, this approach is likely to be very useful when applied to practical large systems.

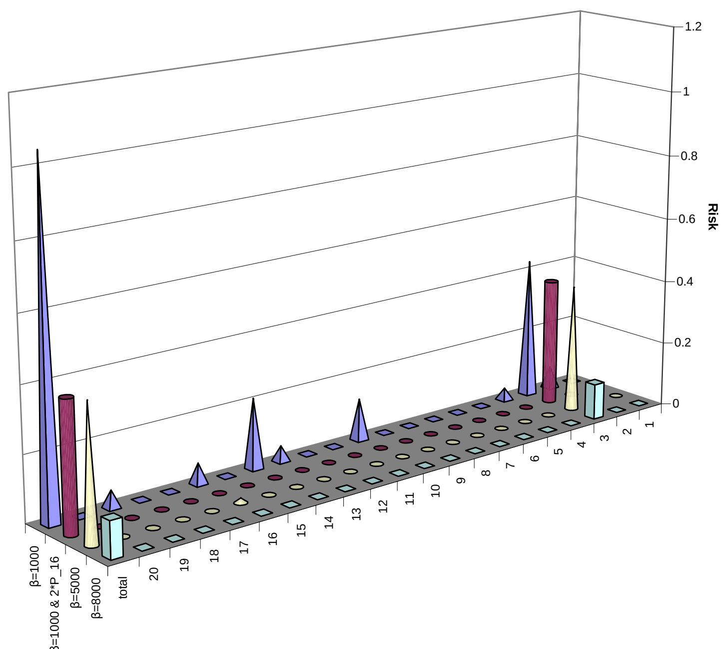


Figure 7.9: Type IV sensitivity analysis

CHAPTER 8 GENERAL BENDERS DECOMPOSITION STRUCTURE AND SOA BASED PLATFORM

A series of decision making problems are formulated and solved using a similar structure and same algorithm in this dissertation. Most of these problems are formulated through either integration of other more basic problems, or as sections of more advanced problems, and organized by Benders decomposition. A general structure should cover all these problems naturally, which will be introduced in this chapter. When applying this structure to the practical problems, a computation platform is needed, and this platform needs to be compatible with the structure of the problems. The design of this computation platform will be described in this chapter.

8.1 General Benders Decomposition Structure

8.1.1 Introduction

Power system decision problems typically require optimization of three conflicting objectives: economy (minimizing cost or maximizing social welfare), reliability (minimizing load curtailment and operational violations) and risk (minimizing expected impact). These three objectives are weakly coupled, which means the partition of this triplet is doable. In most situations this coupling is even linear. Benders decomposition is a natural method to decompose weakly coupled problems.

We will describe here a generalized Benders decomposition structure (GBDS) that has the following characteristics:

- *Efficiency*: Solution of a large problem via solution of multiple small problems reaps significant computational benefits because typically the computation complexity of such a large scale problem is not linear; in addition, Benders decomposition facilitates use of parallel computing. This is further explained in [74].

- *Generalization*: This framework represents a basis for multiple applications, including security-constrained optimal power flow, security-constrained unit commitment, etc., so that each application need only be cast in the described form to take advantages of the method's benefits.

- *Flexibility*: Different decision-making applications can use their own solution algorithm/tool within the Benders framework. For example, one can use either Lagrangian relaxation or branch and bound to solve a mixed integer problem. The new application should be easy to add in without affecting existing applications.

- *Integration*: Some decision-making applications will achieve better solution if considered together, for example the generation and transmission integrated planning or transmission and Var resource integrated planning. This framework facilitates such treatment.

8.1.2 GBDS Elements

We have observed that the following:

1. power system decision problems typically involve economy, reliability, and risk;

2. applications of Benders decomposition involve master problem, feasibility problem, and optimality problem.

The GBDS is based on the observation that there is a convenient mapping between these two sets of elements, as described in the following sections.

8.1.2.1 Economy

Economy plays the role of master problem in the GBDS framework. For the market operator, the objective is to maximize social welfare, and for the market player the objective is to maximize profit or minimize cost. A pure economic dispatch, unit commitment, generation allocation, or Var resource allocation, can function as the master problem. At this stage, it is a pure economic problem and can be modeled and solved without too much power system knowledge.

8.1.2.2 Reliability

We use the term “reliability ”here very narrowly, in that it refers only to load curtailment and operational violations. Reliability typically is the feasibility check subproblem within the GBDS framework. Generally OPF [3], SCOPF [59], or CSCOPF [19], will be used. Typical forms are minimum load curtailment, minimum overload, minimum dummy real power injection, or minimum reactive power injection.

8.1.2.3 Risk

Risk is the expected impact to the system, including both probability and consequence of contingencies. The purpose of the risk is to function as *an indicator which biases decisions conservatively when risk is too high and optimistically when risk is comparatively low, according to the information given.* The impact could be economic loss, load curtailment or operational violation. Once risk is considered, the problem becomes a stochastic programming problem, and Benders decomposition can be extended to solve stochastic programming problems. Risk is the optimality check subproblem in the GBDS framework. Because Benders decomposition is very flexible, the risk part can be deleted without affecting the other parts of the GBDS and if more than two stages are introduced the risk will always be the last subproblem, maintaining its status as the optimality check subproblem.

The triplet (economy, reliability, risk) for power system decision problems are mapped to the three elements (master problem, feasibility check subproblem, optimality check subproblem) in the Benders decomposition, as shown in Fig.8.1, and this forms the basis of the GBDS.

The better economy benefit can be achieved by lower the level of the reliability. From preventive level to the corrective level, cost can be lower [19]. Furthermore, increase the

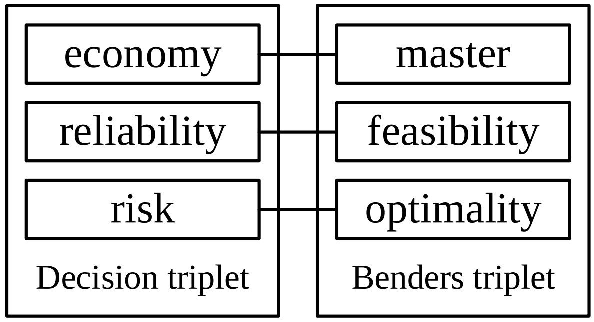


Figure 8.1: Mapping between decision triplet and Benders triplet

tolerance of the reliability more economy benefit can be achieved. This can be achieved by manipulating the feasibility check subproblem of Benders decomposition. Risk always grows as economy benefit increase. A balance need to be found between risk and economy, that is also the reason the risk is put in the optimality check subproblem. At the same time, the problem (3.2a) can be formulated symbolically as follows:

The following high-level problem statement is used to clarify the relationship among the triplet.

$$\begin{aligned} Min \quad & Economy + Risk \\ s/to \quad & Reliability \leq tolerance \end{aligned} \tag{8.1}$$

where "tolerance "represents the relaxation of the reliability requirement.

Here we can see that improved economy can be achieved by lowering the reliability level through increasing the tolerance This is achievable by manipulating the feasibility check subproblem of Benders decomposition. Similarly, risk typically decreases as economy degrades. A balance needs to be found between risk and economy, an achievable objective that is achievable through use of the optimality check subproblem.

After using this structure, the flowchart of Benders decomposition algorithm in Fig.3.1 can be illustrated as shown in Fig.8.2.

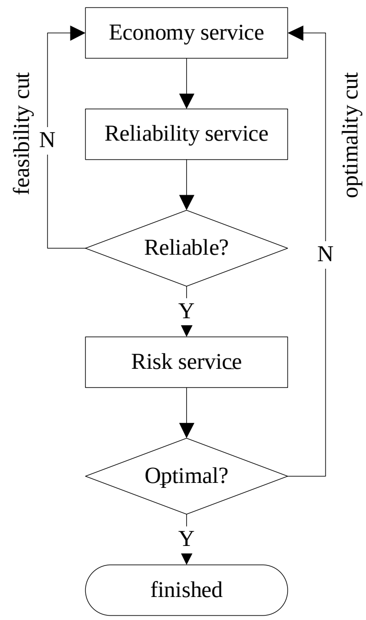


Figure 8.2: Decision making using GBDS

8.1.3 GBDS Information Communication

An intriguing attribute of GBDS is that it facilitates information exchange through the coupled constraints and cuts introduced in Section 3.2, as will be described in the following two subsections.

8.1.3.1 Coupled constraints

Physically, the coupled constraints represent the limitation of available resources or given controls for subproblems and optimal decisions from the master problems. For example, the location and maximum amount of the Var is determined by the economy problem. After this information is posted, the subproblems can retrieve it and knows just what Var resources are available to them. These available resources will be put in the coupled constraints and used to evaluate the reliability and risk. The coupled constraints represent the information passed from the master problem to the subproblems.

8.1.3.2 Cuts

There are two kinds of cuts: feasibility cut (3.5) and optimality cut (3.7). The physical meaning of these two kinds of cuts is very interesting. The feasibility cut will tell the master problem the direction to eliminate the infeasibility (load curtailment or operation violation). The optimality cut will tell the master problem how to adjust the estimation of the second stage problem. Cuts represent information passed from the subproblems to the master problem.

8.1.4 Structured Programming using GBDS

One direct application of GBDS is structured programming. The triplet of the Benders decomposition can be placed into three different functions. The Benders process will work as the main function. Parameters passing between these functions are very uniform. The standard form will be used as an example. The master problem passes the x to the subproblems. The feasibility subproblem will return v, E, and λ. The optimality subproblem will return w, E, and π. Once these programming codes are generated, they can be easily used in other applications with little or no modification.

8.1.5 GBDS Unbundled Services

In the power industry, computational services could be unbundled in a manner similar to the unbundling of the generation, transmission and distribution. Computation services could be economic modeling and optimization, reliability analysis, or risk evaluation. Thus all the subproblems within the GBDS can be evaluated by different entities at different locations under the communication protocol introduced in section 8.1.3.

8.1.6 Conclusion

In this section, a general Benders decomposition structure for power system decision problems has been proposed. In this structure, the three elements of the decision problems are mapped into the three types of Benders subproblems. An information communication strategy is introduced, the application to the structured programming, and the idea of service unbundling is proposed. The structure is efficient, generalizable, flexible, and promotes integratability. It could be very helpful for decision problems in power systems.

8.2 BenSOA–A Decision Making Paradigm

8.2.1 Introduction

Decision-making in large, modern organizations has become very complex. People have discovered that the complexity and effort in decision making is a hockey stick function of the problem scale (Fig.8.3), which means that after the size of the organization or the system increases beyond a certain point the complexity and effort needed to make decisions increases dramatically. In order to deal with this kind of situation, distributed computation and decomposition techniques have been developed and utilized. The power industry is, of course, no exception to this trend. At the beginning, power systems were just small isolated systems. Then interconnected power systems emerged. In the past, the power systems were operated by the vertical utilities that embraced function of generation, transmission, and distribution, each within its own isolated territory. With a deregulated power industry, it was possible to combine a number of utility territories to form a power market, covering a much larger territory than that of a traditional utility. Furthermore, these power markets are constantly expanding and merging. As power systems have become ever larger, associated decision making activities in the power industry have become extremely complex. To deal with this complexity, a need for decomposed techniques and distributed computation is more critical than ever before.

Decomposition techniques such as Benders decomposition have been widely used in the power industry for the past 30 years and have become more and more attractive for application in the deregulated power markets environment. One reason for this trend is that such techniques break a big problem into smaller problems to enhance the solvability and speed. Another reason for this trend is that, in the power market environment, the entities are self-interested and the functions are separated, resulting in the self-centered optimization and distributed decision making.

When applying decomposition techniques to large scale real-world problems, how the paral-

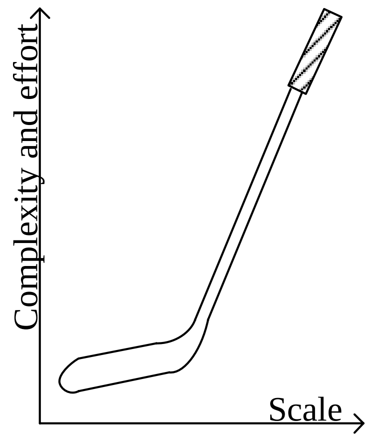


Figure 8.3: The hockey stick function

lel computation is performed, how smaller problems interact with each other, how information security is insured, and how the user can interface with these problems become essential questions. A structure and a protocol are critically needed.

Information technology is also evolving as reflected in such methodologies as structured programming, object oriented programming and service oriented architecture (SOA). SOA in particular can powerfully address many of the issues stated above in a manner quite different than that of other standard approaches such as object oriented programming. SOA is in some ways an art form, with no standard template in which a problem can be inserted. It requires knowledge of both the specific problem and the general SOA methodology.

A Benders decomposition and SOA based decision making diagram for power systems will be described in following sections.

8.2.2 Service Oriented Architecture

Service Oriented architecture (SOA) has been widely used in the business world [75]. A brief introduction of SOA will be provided here.

8.2.2.1 Concepts and Explanations

Service oriented architecture (SOA) is a paradigm for the realization and maintenance of business processes that span large distributed systems with flexibility. The word "Paradigm "means that, rather than comprising a concrete architecture, it is something that leads to a concrete architecture but not a specific technology [76]. The two key parts of the realization of a SOA are service and infrastructure. Services exist as physically independent software programs with distinct design characteristics that support the attainment of certain strategic goal. Each service is assigned its own distinct functional context and is comprised of a set of capabilities related to this context. Those capabilities suitable for invocation by external consumer programs are commonly expressed via a published service contract which establishes the terms of engagement, providing technical constraints and requirements as well as any semantic information the service owner wishes to make public [77]. The service and service design principles [76, 77, 78] are shown in Fig.8.4.

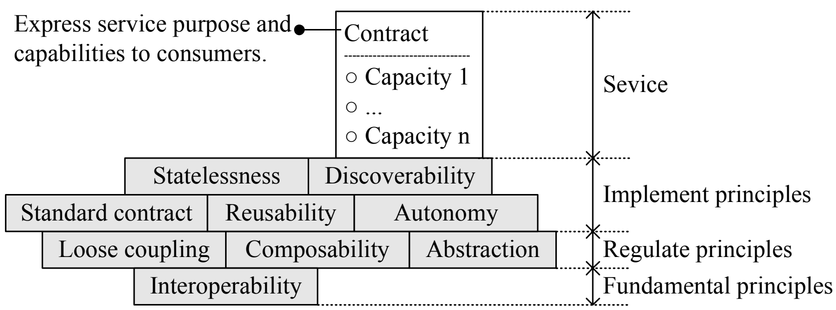


Figure 8.4: Service and service design principles

Infrastructure is the technical part of SOA that enables high interoperability. The infrastructure of an SOA landscape is called an enterprise service bus (ESB). The key feature of the ESB is that it facilitates calling of services between heterogeneous systems. Its responsibilities include data transformation, (intelligent) routing, dealing with security and reliability, service management, monitoring, and logging [76].

8.2.2.2 Service Classification

Although there are many kinds of classification, one introduced in [76] fits our needs and context best and will therefore be chosen. There are three types of services: basic services, composed services, and process services.

Basic services provide basic functionalities at a level where it does not make sense to split into multiple services. Examples include data retrieval and data update. These services are typically stateless and can be invoked synchronously. Composed services will utilize the existing services and add their own functionality to finish specific tasks. Composed services are also called orchestrated services. Process services are used to complete certain decision-making process. It will utilize composed services and is stateful.

8.2.2.3 Web Services, XML, WSDL and BPEL

Although SOA is not a specific technology, web services are widely regarded as the way SOA should be realized in practice. Once choosing the web services as a technical platform, the service contract will be described by XML schema, WSDL and BPEL.

The Extensible Markup Language (XML) is a general-purpose specification for creating custom markup languages. It is classified as an extensible language because it allows its users to define their own elements. Its primary purpose is to facilitate the sharing of structured data across different information systems, particularly via the Internet, and it is used both to encode documents and to serialize data.

The Web Services Description Language (WSDL) is an XML-based language that provides a model for describing Web services.

Web Services Business Process Execution Language (WS-BPEL or BPEL for short) is a language for specifying business process behavior based on Web Services. Processes in WS-BPEL export and import functionality by using Web Service interfaces exclusively. WS-BPEL defines an interoperable integration model that should facilitate the expansion of automated process integration in both the intra-corporate and the business-to-business spaces.

8.2.3 Benders Decomposition and SOA: BenSOA

The spirit of Benders decomposition is to decompose the large and complex problem into loosely coupled small and easy problems. All the decomposed problems are autonomic problems and typically independent of each other. At the same time, these subproblems are stateless and composable. These characteristics are similar to the principles of SOA shown in Fig.8.4. These similarities and the need for an SOA in power systems have stimulated the design of BenSOA: A Benders decomposition and SOA based diagram for power system decision making.

8.2.3.1 Mapping between Benders and SOA

The triplet of Benders decomposition: master problem, feasibility problem, and optimality problem are mapped to the composed services. The Benders process will be the process services.

8.2.4 Service Inventory

Before designing the SOA structure, we need to provide a blueprint for the services we could use and put the services having similar functions in one inventory as shown in Fig.8.5.

In Fig.8.5, the process services, composed services and basic services are introduced. Furthermore these services are categorized according their functionality.

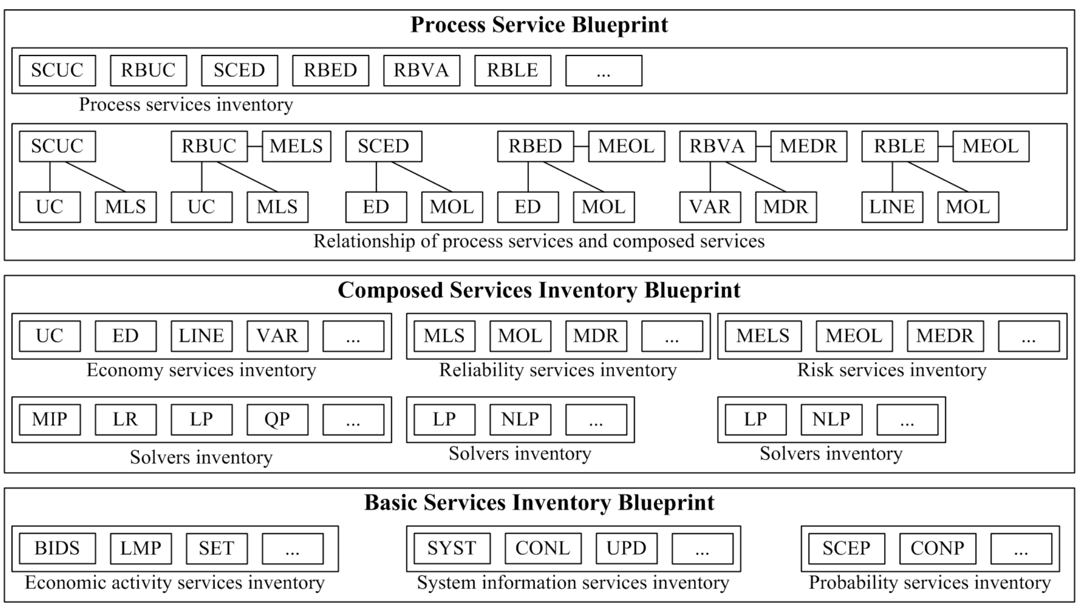


Figure 8.5: BenSOA services inventory

In basic services inventory, three categories are provided:

- Economic activity: BIDS is responsible for storage, retrieval and update of the bidding information. LMP service is used to obtain and update locational marginal price. SET is used to publish market clear results.

- System information: SYST provides the system topology information such as node-incidence matrix and admittance matrix. CONL will retrieve and update the contingency list. UPD is used to set the control information to the system.

- Probability services: CONP will provide the estimated probabilities for specific contingencies. SCEP will provide the probabilities for different load scenarios.

In the composed services inventory, three categories are included:

- Economic: UC provides unit commitment service. ED provides economic dispatch service. LINE provides transmission line expansion service. VAR provides reactive power allocation service.

- Reliability: MLS provides minimum load shedding service. MOL provides minimum overload service. MDR provides minimum dummy reactive power injection service.

- Risk: MELS calculates expected minimum load shedding. MEOL calculates expected minimum overload service. MEDR calculates expected minimum dummy reactive power injection.

In the process services inventory, the following information is given:

- Process services: SCUC provides the security-constrained unit commitment service. SCED provides the security-constrained economic dispatch service. RBUC provides the risk-based unit commitment service. RBED provides the risk-based economic dispatch service. RBVA provides the risk-based Var resource allocation function. RBLE provides the risk-based transmission line expansion function.

- Relationship between process services and the composed services: the process services will utilize the services provided by composed services.

The services listed in Fig.8.5 are not exhaustive. Because of easy expandability of the SOA structure, new services can be easily added in and existing services can be easily updated, for example, UC solver can be switched from LR to MIP without affecting other services.

8.2.5 Structure Design of BenSOA

Based on the blueprint of services inventory, a structural design of the BenSOA is provided in Fig.8.6. Benders decomposition is the spirit of BenSOA and the structure is the backbone of BenSOA. Although the final version of the BenSOA diagram should ideally be fully automated, this will be a gradually evolving process and during this process, human expertise will still continue to play an important role in this diagram.

The services are basically taken from the service inventory. The basic services are responsible for data exchange with the energy management system, market management system, and other distributed data providers. The composed services realize the master problems and subproblems in the Benders decomposition scheme. Their computational ability require the support of several existing solvers including mixed integer programming, linear programming, and nonlinear programming. Each process service is supposed to completing a specific decision making task. All these services are connected to the ESB, which fulfills all the functions introduced in section 8.2.2.1.

Security is very important in the design of the BenSOA. In the BenSOA design, the access of the service is controlled under "AAA "(authentication, authorization and accounting) [76]. Authentication is used to verify an identity and finds out who is calling the service. Authorization has to do with determining what an identity is allowed to do. Accounting is to keep track of the consumption of resources. The exchanged information can also be encrypted. Users are categorized into internal user and public user.

8.2.6 BenSOA and Decision Making System

There are already two existing very large management systems in power system. The first one is the energy management system (EMS). With the help of the SCADA system, the EMS can monitor the status of the entire power system in a real-time manner. Control can also be applied through the EMS system. The EMS system, however, does not support decision making. EMS has been well developed. After the restructure of the power industry, another system, the market management system (MMS), came into wide use. The typical function

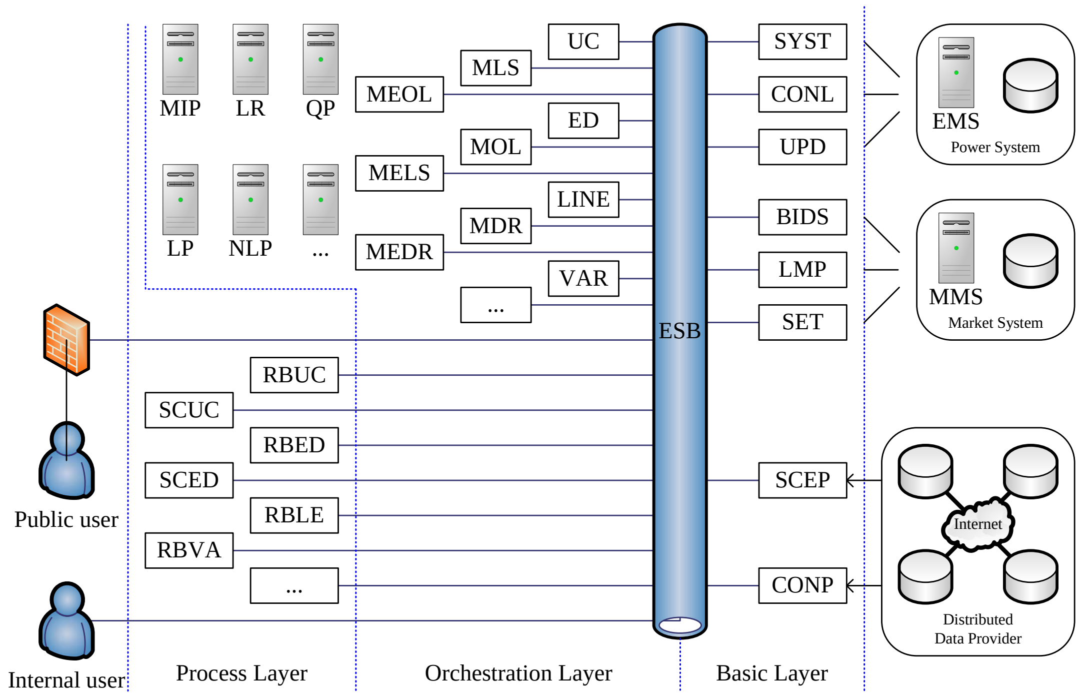


Figure 8.6: Structure design of BenSOA

of MMS is to clear the market, which involves optimization. The MMS has limited decision making ability. The power system is in great need of a strong decision making system (DMS).

BenSOA is a good candidate for developing such a DMS. BenSOA is designed for large and complex decision problems, which is the characteristics of the power system decision making problem. The design of BenSOA provides a smooth connection to the EMS and MMS systems, which can provide DMS necessary information and makes the decisions easily applied to power system.

8.2.7 Conclusion

In this chapter, the general benders decomposition structure is introduced first. Then a decision making diagram, BenSOA, based on GBDS and SOA is introduced in detail. This structure can support decision making under uncertainty and can be used as a decision making system.

CHAPTER 9 CONCLUSION

9.1 Contributions

The dissertation proposes decomposed computational and optimization techniques that can be applied to facilitate the decision making problems in power system under uncertainty conditions. The research work is integrated into a general framework for the power system decision making. The proposed methods cover most of the decision making problems, and a fast simulation algorithm and software structure is provided to realize the proposed framework.

The main contributions of the dissertation can be summarized as:

- The risk index is further developed by proposing the enhanced risk index considering both the severity controllability and tolerance. The enhanced risk index is used to cover the uncertainty in the decision making of power systems.
- A general Benders decomposition structure is proposed which covers the three elements of the decision making problem in power system under uncertainty.
- DSCOPF, Risk-based optimal power flow, risk-based unit commitment, risk-based transmission expansion, and risk-based Var allocation approaches are systematically developed and illustrated, which have the similar structure and can be easily expanded to other decision making problem.
- A Benders decomposition and service oriented architecture integrated computation platform is designed to realize the decision making algorithm.

9.2 Further Research Direction

Based on the research work described in this dissertation, further research could take a variety of directions. Potential research focus could be in the following areas:

- The convergence study of Benders decomposition for the non convex problems in power system area.
- Apply Benders decomposition to optimal control problems.
- Study Benders decomposition with possible application to game theory.
- Short-term and long-term maintenance.
- Generation planning.

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