Optimal Upfc Control And Operations For Power Systems

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by

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ABSTRACT

The content of this dissertation consists of three parts. In the first part, optimal control strategies are developed for Unified Power Flow Controller (UPFC) following the clearance of fault conditions. UPFC is one of the most versatile Flexible AC Transmission devices (FACTs) that have been implemented thus far. The optimal control scheme is composed of two parts. The first is an optimal stabilization control, which is an open-loop 'Bang' type of control. The second is an suboptimal damping control, which consists of segments of 'Bang' type control with switching functions the same as those of a corresponding approximate linear system. Simulation results show that the proposed control strategy is very effective in maintaining stability and damping out transient oscillations following the clearance of the fault. In the second part, a new power market structure is proposed. The new structure is based on a two-level optimization formulation of the market. It is shown that the proposed market structure can easily find the optimal solutions for the market while takeing factors such as demand elasticity into account. In the last part, a mathematical programming problem is formulated to obtain the maximum value of the loadibility factor, while the power system is constrained by steady-state dynamic security constraints. An iterative solution procedure is proposed for the problem, and the solution gives a slightly conservative estimate of the loadibility limit for the generation and transmission system.

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CHAPTER 1

INTRODUCTION

1.1 Structure of a Generic Electric Power System

No matter how different two electric power systems might be, they are all composed of two parts: the generating stations and the transmission network [1][2]. Generating stations, which generate electric power, usually have synchronous machines that are driven by turbines (steam, hydraulic, diesel, or internal combustion). Electric power is transmitted to consumers through an intricate network of apparatus including transmission lines, transformers, and switching devices. An industrial transmission network could be classified as transmission system (typically, 230 kV and above), sub-transmission system (typically, 69 kV to 138 kV), and distribution system (typically 4.0 and 34.5 kV in the primary feeders for small industrial customers, and 120/240 V in the secondary distribution feeders for residential and commercial customers).

In a modern power systems, generating stations are usually interconnected, and generated power is transmitted from the generating sites over long distances to load centers that are spread over wide areas. Voltage and frequency levels within the system are required to remain within tight tolerance levels to ensure a high quality product [3][4].

1.2 Modern Power System and Deregulation

After several decade's of development, the modern power system has evolved into one of the most complex man-made systems. Its planning and operation depend not only on technical concerns, but also economical, geographical, and even political ones [5]. Due to environmental and capital concerns, the construction of transmission and generation facilities usually lags behind the growth of demand for electric power. As a result, the stability margin of the whole system has been severely compromised. On the other hand, principles derived from economics demand the power industry be deregulated [6], that is, to separate the transmission sector out and form a new business. In the mean time, customers requirements for electricity quality are getting more and more diverse and sophisticated [7][8][9]. All the above demands and requirements give the industry strong incentives to make use of new technologies to remain competitive in the business. Among the technologies used, Flexible AC Transmission Systems is receiving most of the attention at present.

1.3 Flexible AC Transmission Systems

Flexible AC Transmission Systems (FACTS) identifies alternating current transmission systems incorporating power electronics-based controllers to enhance the controllability and increase power transfer capability [10][11]. The implementation of FACTS devices requires technology for high power (multi-hundred MVA) electronics with its real-time operating control. The objectives of FACTS devices are three fold:

- To increase the power transfer capability of transmission systems.

- To keep power flow over designated routes.

- To realize overall system optimization control.

After more than a decade's development, the FACTS family has quite a few members. Among them, those ahead of the list are Static Var Compensator (SVC), Thyristor-Controlled Series Capacitor (TCSC), Static Synchronous Compensator (Statcom), Static Synchronous Series Compensator (SSSC), the Unified Power Flow Controller (UPFC) and the Interline Power Flow Controller (IPFC).

1.4 Optimal Transient UPFC Control

Power system dynamics and transients have been a subject of interest and concern for researchers and system operators ever since the widespread used of electric power [12][13][14][15][16][17]. The rapid development of FACTs technology gives engineers a powerful tool to influence the dynamic and transient responses of a given power system. UPFC is one of the most versatile devices in the FACTS family. Depending on the mode of operation, it can be used as a series/parallel compensator, phase shifter, and voltage regulator. Due to its quick response, UPFC also possesses the potential to drastically improve the transient characteristics of a power system. In [22][23][24], transient UPFC control strategies are proposed for a power system working under stressed conditions. In this dissertation, we go one step further along this track by proposing an optimal control strategy following the clearance of faulted conditions. The purpose of the optimal UPFC control strategy is to maximize the chance the system will remain stable following the clearance of fault on the one hand, and on the other hand, minimize the time needed to damp down the transient oscillation.

1.5 Optimal Operations of Power System

Optimization concepts and algorithms were first introduced to power system dispatching, resource allocation, and planning in the mid-sixties in order to mathematically formalize decision-making with regard to the myriad of objectives subject to technical and nontechnical constraints [25]. In recent years, the topic of how to apply optimization in electric power engineering has attracted a lot of attention from researchers. In this dissertation, based on our previous research results [26][27], two practical applications are presented. In the first one, a new power market model is proposed. The model is based on a two-level optimization formulation and solved with the help of the Optimal Dispatch Rule (ODP). Then, an optimal non-iterative power market structure is obtained for pool-type electricity market. In the second application, a new formulation using mathematical programming theory is presented. This formulation, after being solved by an iterative solution procedure, can be used to estimate the loadability of a generation and transmission system.

CHAPTER 2

MATHEMATICAL BACKGROUND AND ITS APPLICATION TO POWER SYSTEM

Calculus of variation is the mathematical discipline that deals with finding the optimum value of a functional. It is the mathematical foundation for modern optimal control. Good coverage on this topic can be found in [18][19]. In this chapter, a brief review of the basic concepts and principles is provided. We first give the definitions for some important concepts in the calculus of variation. Then, necessary and sufficient conditions are stated for the optimum of a function and a functional. Finally, the variational approach to the optimal control problem is presented. A comprehensive treatment of this approach can be found in [20]. At the end of this chapter, the applications of these optimization tools to power system problems are outlined.

2.1 Basic Concepts of Calculus of Variation

2.1.1 Function and Functional

Function

A variable f is a *function* of a variable x, if to every value of x over a certain range of x, there exist a unique f that is corresponding to the choice of value x. A typical example is

$$f(x) = 3x^2 + 2. \tag{2.1.1}$$

Functional

A variable quantity J is a *functional* dependent on a function $f(x)$, if to each function $f(x)$, there corresponds a unique value J. An example is

$$J(f(x)) = \int_{x_0}^{x_f} f(x)dx. \tag{2.1.2}$$

In (2.1.2), the value of functional J depends on the choice of function $f(x)$. That is, a functional is a function of a function.

2.1.2 Increment

Increment of a Function

The increment of a function f, denoted by $\triangle f$, is defined as

$$\triangle f \triangleq f(t + \triangle t) - f(t), \tag{2.1.3}$$

where $\triangle t$ is the increment of the independent variable t.

Increment of a Functional

The increment of a functional J, denoted by $\triangle J$ is defined as

$$\triangle J \triangleq J(x(t) + \delta x(t)) - J(x(t)), \tag{2.1.4}$$

where $\delta x(t)$ is called *variation* of the function $x(t)$.

2.1.3 Differential and Variation

Differential of a Function

The differential of a function f at point t^* is defined as

$$df = \left(\frac{df}{dt}\right)_{t^*} \triangle t. \tag{2.1.5}$$

It is clear that differential is the first order approximation to the increment $\triangle f$.

Variation of a Functional

The variation of a functional J, is defined as

$$\delta J = \frac{\partial J}{\partial x}\delta x(t). \tag{2.1.6}$$

Variation is also called the *first variation*. It is the first order approximation of the increment $\triangle J$.

The *second variation* is defined as

$$\delta^2 J = \frac{1}{2}\frac{\partial^2 J}{\partial x^2}\left(\partial x(t)\right)^2. \tag{2.1.7}$$

.

2.2 Optimum of a Function and a Functional

2.2.1 Definition

Optimum of a Function

A function $f(t)$ is said to have a relative optimum at point t^* if there is a positive parameter ϵ such that for all points t in a domain D that satisfy $|t - t^*| < \epsilon$, the increment of $f(t)$ has the same sign (positive or negative).

Optimum of a Functional

A functional J is said to have a relative optimum at x^* if there is a positive ϵ such that for all functions x in a domain Ω which satisfy $|x - x^*| < \epsilon$, the increment of J has the same sign.

2.2.2 Necessary and Sufficient Conditions for Optimum of a Functional

Theorem

The necessary condition for $x^*(t)$ to be a candidate for an optimum is that the variation of J must be zero on $x^*(t)$ for all admissible values of $\delta x(t)$. The sufficient condition for minimum is second variation $\delta^2 J > 0$, and for maximum $\delta^2 < 0$.

Euler-Lagrange Equation

Let $x(t)$ be a scalar function with continuous first derivatives. The problem is to find the *optimal* function $x^*(t)$ for which the functional

$$J(x(t)) = \int_{t_0}^{t_f} V(x(t), \dot{x}(t), t)dt \tag{2.2.1}$$

has a relative *optimum*. It is assumed that the integrand V has continuous first and second partial derivatives w.r.t. all its arguments; t_0 and t_f are known and the end points are fixed.

For (2.2.1), derive its increment, and use the necessary condition theorem (for an optimum the variation of a functional vanishes), we find the necessary condition for $x^*(t)$ to be an optimal of the functional J is given by

$$\left(\frac{\partial V}{\partial x}\right)_* - \frac{d}{dt}\left(\frac{\partial V}{\partial \dot{x}}\right)_* = 0. \tag{2.2.2}$$

which is called Euler-Lagrange Equation.

2.2.3 Extrema with Conditions

Extrema of Functions with Conditions

Consider the extrema of a continuous, real-valued function $f(\mathbf{x}) = f(x_1, x_2, \cdots, x_n)$ subject to the conditions

$$\begin{array}{rcll} g_1(\mathbf{x}) & = & g_1(x_1, x_2, \cdots, x_n) & = & 0 \\ g_2(\mathbf{x}) & = & g_2(x_1, x_2, \cdots, x_n) & = & 0 \\ & \cdots & & & \\ g_m(\mathbf{x}) & = & g_m(x_1, x_2, \cdots, x_n) & = & 0 \end{array} \tag{2.2.3}$$

where f and g have continuous partial derivatives, and $m < n$. Let $\lambda_1, \lambda_2, \cdots, \lambda_m$ be the Lagrange multipliers corresponding to m conditions, such that the augmented Lagrangian function is formed as

$$L(\mathbf{x}, \lambda) = f(\mathbf{x}) + \lambda' \mathbf{g}(\mathbf{x}), \tag{2.2.4}$$

where λ' is the transpose of λ. Then, the optimal values $\mathbf{x}^*$ and λ^* are the solutions of the following $n + m$ equations

$$\frac{\partial L}{\partial \mathbf{x}} = \frac{\partial f}{\partial \mathbf{x}} + \lambda' \frac{\partial \mathbf{g}}{\partial \mathbf{x}} = 0, \tag{2.2.5}$$

$$\frac{\partial L}{\partial \lambda} = \mathbf{g}(\mathbf{x}) = 0. \tag{2.2.6}$$

Extrema of Functionals with Conditions

Consider the extremization of a functional

$$J = \int_{t_0}^{t_f} V(\mathbf{x}(t), \dot{\mathbf{x}}(t), t) dt, \tag{2.2.7}$$

where $\mathbf{x}(t)$ is an nth order state vectro, subject to the following plant equation

$$g_i(\mathbf{x}(t), \dot{\mathbf{x}}(t), t) = 0; \qquad i = 1, 2, ..., m \tag{2.2.8}$$

and boundary conditions $\mathbf{x}(0)$ and $\mathbf{x}(t_f)$ (which are given). The Lagrangian L is given by

$$L(\mathbf{x}(t), \dot{\mathbf{x}}(t), \lambda(t), t) = V(\mathbf{x}(t), \dot{\mathbf{x}}(t), \lambda(t), t) + \lambda'(t) g_i(\mathbf{x}(t), \dot{\mathbf{x}}(t), \lambda(t), t) \qquad (2.2.9)$$

and the Lagrange multiplier $\lambda(t) = [\lambda_1(t), \lambda_2(t), ..., \lambda_m(t)]'$. The augmented functional is

$$J_a = \int_{t_0}^{t_f} L(\mathbf{x}(t), \dot{\mathbf{x}}(t), \lambda(t), t) dt. \qquad (2.2.10)$$

Apply Euler-Lagrange equation on J_a, we have

$$\left(\frac{\partial L}{\partial \mathbf{x}}\right)_* - \frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\mathbf{x}}}\right)_* = 0, \qquad (2.2.11)$$

$$\left(\frac{\partial L}{\partial \lambda}\right)_* - \frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\lambda}}\right)_* = 0, \qquad (2.2.12)$$

Since (2.2.9) is independent of $\dot{\lambda}_i$, $i = 1, 2, ..., m$, therefore, (2.2.12) is equivalent to (2.2.8).

2.3 Variational Approach to Optimal Control

The knowledge obtained by studying the calculus of variations can be used to solve optimal control problem. In this section, we briefly review the variational approach to the *Bolza* problem.

Consider the performance index as

$$J(\mathbf{u}(t)) = S(\mathbf{x}(t_f), t_f) + \int_{t_0}^{t_f} L(\mathbf{x}(t), \mathbf{u}(t), t) dt, \qquad (2.3.1)$$

and given boundary conditions as

$$\mathbf{x}(t_0) = \mathbf{x}_0; \quad \mathbf{x}(t_f) \text{ is free and } t_f \text{ is free} \qquad (2.3.2)$$

The plant is described as

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), t). \tag{2.3.3}$$

2.3.1 Necessary Conditions for Optimum

Assume $\mathbf{u}^*(t)$ is the optimal value for control, and $\mathbf{x}^*(t)$ is the optimal value for state. We define Hamiltonian H as

$$H = L(\mathbf{x}(t), \mathbf{u}(t), t) + \lambda'(t)\mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), t) \tag{2.3.4}$$

where $\lambda'(t)$ is the Lagrange multiplier vector.

Treat time t as a variable, and make use of the Euler-Lagrange equation, we can get the necessary conditions for the optimum.

$$\begin{aligned} \dot{\lambda}^*(t) &= -\left(\frac{\partial H}{\partial \mathbf{x}}\right)_* && (2.3.5) \\ \dot{\mathbf{x}}^*(t) &= \left(\frac{\partial H}{\partial \lambda}\right)_* && (2.3.6) \\ \left(\frac{\partial H}{\partial \mathbf{u}}\right)_* &= 0. && (2.3.7) \\ & && (2.3.8) \end{aligned}$$

and two other conditions at the terminal time

$$\begin{aligned} \left[H^* + \frac{\partial S}{\partial t}\right]_{t_f} &= 0, && (2.3.9) \\ \left[\left(\frac{\partial S}{\partial \mathbf{x}}\right)_* - \lambda^*(t)\right]_{t_f} &= 0. && (2.3.10) \end{aligned}$$

Expression (2.3.6) is equivalent to (2.3.3). (2.3.5) is also called the *costate* equation. (2.3.7) contains information about the form of the optimal control. (2.3.9) is also called the *transversality* condition, and it is useful in calculating the optimal process time. (2.3.10) guarantees that the terminal state constraints are satisfied by using the optimal control.

The problem formulated in (2.3.5)-(2.3.10) is a typical *two-point boundary-value problem.*

2.3.2 Minimum-time Problems

If the objective is to find a control so that the system could be moved from its initial state $\mathbf{x}_0$ to a final state $\mathbf{x}_f$ in a minimum amount of time. Then, for the performance index stated in (2.3.1), we have

$$\begin{aligned} S(\mathbf{x}(t_f), t_f) &= 0, && (2.3.11) \\ L(\mathbf{x}(t), \mathbf{u}(t), t) &= 1. && (2.3.12) \end{aligned}$$

And, the Hamiltonian becomes

$$H = \lambda'(t)\mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), t). \qquad (2.3.13)$$

It is easy to show that if H is not an explicit function of time, we have

$$\dot{H} = 0. \qquad (2.3.14)$$

Therefore,

$$H = C. \qquad (2.3.15)$$

where C is a constant.

On the other hand, at the optimum, the transversality condition (2.3.9) must be satisfied. This leads to

$$H_{t_f} = 0. \tag{2.3.16}$$

Combined with (2.3.15), we can conclude that for minimum-time problem, if H is not an explicit function of time,

$$H(\mathbf{x}(t), \mathbf{u}(t), t) = 0 \tag{2.3.17}$$

holds true for all the time t.

2.4 Pontryagin Minimum Principle

In this section, a summary for the famous Pontrygin Principle is provided. This principle is used in late chapters for the derivation of optimal control strategies. A thorough treatment of this principle can be found in reference [38].

Given the plant as

$$\dot{x}(t) = f(x(t), u(t), t), \tag{2.4.1}$$

the performance index as

$$J = S(x(t_f), t_f) + \int_{t_0}^{t_f} V(x(t), u(t), t)dt, \tag{2.4.2}$$

and the boundary conditions as

$$x(t_0) = x_0 \quad \text{and} \quad t_f, \;\; x(t_f) = x_f \quad \text{are free.} \tag{2.4.3}$$

The Hamiltonnian function is give by

$$H(x(t), u(t), \lambda(t), t) = V(x(t), u(t), t) + \lambda^T(t) f(x(t), u(t), t). \tag{2.4.4}$$

The Pontryagin Minimum Principle says that the necessary condition for the constrained optimal control system is that the optimal control should minimize the Hamiltonian, that is,

$$H(x^*(t), u^*(t), \lambda^*(t), t) \leq H(x^*(t), u(t), \lambda^*(t), t), \tag{2.4.5}$$

where "*" denotes the corresponding variables at optimality.

2.5 Application of Optimization Approaches in Solving Power System Problems

Like many other physical systems, the dynamics of a power system can be describe by a set of differential equations. Combined with all the relevant algebraic equations, the energy flow, current and voltage relations, *etc.*, of an inter-connected power system can be satisfactorily described by the resulting Differential-Algebraic Equations (DAEs). The inclusion of inequalities to the DAEs will also incorporate concerns such as stability into the mathematical formulation. Once the mathematical formulation is obtained, optimization approaches described in the previous sections can be readily used to solve any optimization or optimal control problems that may be formulated.

Except for very simple problems, analytical solutions are usually difficult to find. For power systems, analytical solutions are often limited to very simple systems, such as a single-machine-infinite-bus system with extremely simplified machine and transmission line model. Therefore, for most practical applications, numerical approaches have to be explored to find the solution. Numerical approaches are usually based on iteration-based methods starting from an initial guess of the solution. Then, according to the nature of the problem, an algorithm that uses iteration methods such as Steepest Decent, Newton-like Method and Quasi-Newton Method could be used to find the solution. A good coverage on numerical approaches is provided in [21].

CHAPTER 3

OPTIMAL TRANSIENT UPFC CONTROL

3.1 Introduction

In today's power system worldwide, the transient and dynamic stability margin is reduced due to increased power transfer. With proper control strategies, fast responding Flexible AC Transmission Systems (FACTS) could be used to improve the transient and dynamic performance of the system so that the system transmission could be safely expanded by increasing the level of utilization of the existing facilities towards their thermal limits. On the other hand, by fully taping their ability to shape the transient and dynamic response of the system, the higher cost (compared with the traditional mechanically controlled power flow controller, *e.g.* adjustable transformers and capacitor banks) of FACTS devices can be better justified.

In the FACTS family, UPFC is one of the most powerful and versatile FACTS devices available so far. Being able to almost instantaneously insert a synchronous voltage of arbitrary magnitude (within a pre-specified range) and phase angle (with respect to the sending-end voltage) into the transmission line, UPFC can be used to adjust the real electrical power output of a electric power system in real time. Thus, UPFC is regarded by many researchers as an ideal candidate for improving the transient and dynamic performance of an electric power system. In [28][29], UPFC is incorporated into the Phillips-Heffron model of a linearized power system. Then, the well-established linear control techniques are used to design a UPFC damping control. Dramatic improvement in dynamic stability performance is reported in their study. Nevertheless, due to the nature of linearization, the technique developed there can not be extended to study the transient response of the system. In [30] and [31], the effects of UPFC on system transient stability improvement is studied more or less qualitatively, and improved transient response is reported in each study. In [32] and [33], nonlinear PID and coordinated control design techniques are employed, respectively, to design UPFC controller to improve transient stability of a power system. Even though improved transient responses were reported in both cases, neither gave any indication as to whether the performance could be improved further, and if it could, what the limit would be. To the best of our knowledge, there are no results in the literature yet that address the issue of optimal UPFC control design which is aimed at pushing the transient and dynamic performance improvement of the system to its up-limit.

The purpose of this chapter is to develop an optimal UPFC control strategy to improve the transient and dynamic performance of a power system following the clearance of a major fault. It is optimal in the sense that it brings the transient and dynamic performance improvement to its up-limit. The proposed optimal control strategy consists of two objectives which are fulfilled one after another:

1. Develop an optimal UPFC control that will maximize the system's chance to

remain stable following the clearance of a major fault.

2. Develop an optimal UPFC control that will damp the transient and dynamic oscillation most effectively.

3.2 UPFC Principle and Control Structure

3.2.1 UPFC concept and structure

A UPFC consists of two voltage-sourced converters, converter 1 and converter 2, as shown in Figure 3.1. Converter 1 is parallel connected with the transmission line through a parallel transformer, and converter 2 is connected in series with the transmission line through a series transformer. The two converters are linked together by a common dc link, which is a dc storage capacitor labelled "C" in Figure 3.1. This arrangement enables real power to be transferred freely from the ac side of converter 1 to the ac side of converter 2, and vice versa. Meanwhile, converter 1 and converter 2 are both capable of independently generating (or absorbing) reactive power at their own ac output terminals. It is important to note that only real power can be transferred across the capacitor "C".

The function of converter 1 is two-fold: first, it is responsible to supply or absorb the real power demanded by converter 2 at the common dc link; second, it can generate or absorb a controllable amount of reactive power independently, and thereby provide independent shunt reactive compensation for the line - voltage support.

The function of converter 2 is to inject a controllable synchronous voltage V_{pq} into the system. Ideally, the magnitude of V_{pq} is capable of varying from 0 to a

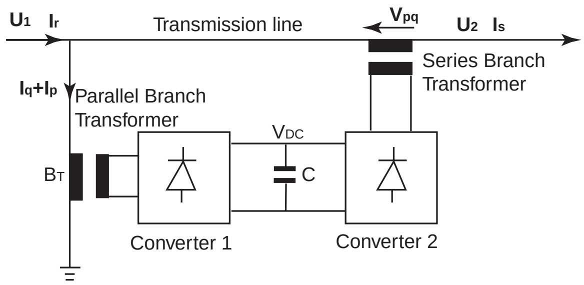

Figure 3.1: UPFC conceptual structure

maximum value V_{pqmax}, which is determined by physical limits, and its phase angle varies from 0 to 2π.

The transformer that injects voltage V_{pq} into the line can be considered as a voltage source. Line current flows through this voltage source resulting in real and reactive power exchanges between converter 2 and the ac system. The real power exchanged at the ac terminal of converter 2 is converted into dc power which appears at the dc link as positive or negative real power demand.

Altogether a UPFC has 3 controllable parameters: susceptance B_T, representing the UPFC parallel branch reactive compensation effect; magnitude of V_{pq}; and angle of V_{pq}. By properly adjusting these 3 parameters, UPFC can be used as voltage regulator, phase shifter, series compensator and the combination of the three. Therefore, UPFC can be ideally used to meet multiple control objectives. In this chapter, it is assumed that B_T will be adjusted to maintain the UPFC parallel branch ac side voltage.

3.2.2 UPFC Control Structure

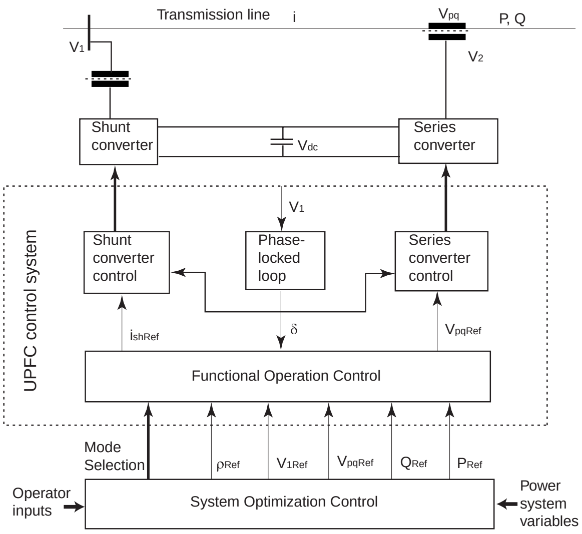

Figure 3.2: Overall UPFC control structure.

The overall UPFC control structure is shown in Figure 3.2. At the "System Optimization Control" level, one of the tasks of the control algorithm is to determine the reference value of electrical real power output P_{Ref} for the UPFC control system. The proposed optimal UPFC control strategy should work at this level by giving out a sequence of P_{Ref} instructions so as to achieve the desired control objectives. The "UPFC control system" block is responsible for detailed shunt converter and series converter control so that the bus voltage is at right level, and there is proper amount of reactive power injection into the system.

3.3 Model of the System

Before we proceed any further, the following assumptions have to be laid out:

- The delay between UPFC receiving an instruction and the implementation result is in place is negligible. Since the time constants of UPFC are much smaller than those of the rest of the system, this assumption is valid in most cases.
- Generator mechanical friction is the only source of real power loss. This assumption will allow us to focus on the major problems of the control design.
- The mechanical power input to the system, P_m, remains unchanged in the duration of study.
- During the fault, the system real power output is 0.
- During the first swing, the generator mechanical damping effect is negligible.

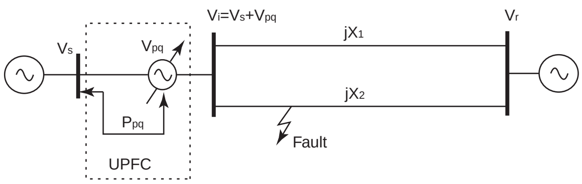

Figure 3.3: Conceptual representation of UPFC in a SMIB system

A conceptual representation of UPFC, in a Single Machine Infinite Bus (SMIB) system with double conductors, is given in Figure 3.3, in which UPFC is represented by a synchronous voltage source that can insert a synchronous voltage with angle ρ ($\rho \in [0, \pi]$) and magnitude V_{pq} ($V_{pq} \in [0, V_{pqmax}]$, where V_{pqmax} is the maximum insertion voltage magnitude possible.)

Assume that the sending end voltage and the receiving end voltage are of the same magnitude, that is $V_s = V_r = V$; then, the steady state electrical power output is given by [34]

$$P_e(\delta, \rho) = P_0(\delta) + P_{pq}(\delta, \rho), \tag{3.3.1}$$

with

$$\begin{aligned} P_0(\delta) &= \frac{V^2}{X} \sin \delta, && (3.3.2) \\ P_{pq}(\delta, \rho) &= \frac{V V_{pq}}{X} \sin \rho, && (3.3.3) \end{aligned}$$

where δ is the voltage angle difference between the sending end and the receiving end, ρ is the insertion voltage angle with respect to the sending end voltage, and $X = X_1 \| X_2$, is the combined impedance of the transmission line.

P_{pq} is the amount of real power that could be influenced by UPFC operations, and it satisfies the following relationship:

$$-\frac{V V_{maxpq}}{X} \leq \frac{V V_{pq}}{X} \sin \rho \leq \frac{V V_{maxpq}}{X}. \tag{3.3.4}$$

The dynamic relation of the system is given by

$$M\ddot{\delta} = P_m - D\dot{\delta} - P_e, \tag{3.3.5}$$

where M is inertia constant of the machine on the left in Figure 3.3, and D is the damping ratio. If we let

$$\begin{aligned} x_1 &= \delta - \delta_r, \\ x_2 &= \dot{x}_1, \end{aligned}$$

where δ_r is the reference power angle. It can be the initial power angle following the clearance of a fault, or the power angle at certain equilibrium. Then, (3.3.5) can be written as

$$\dot{x}_1 = f_1 = x_2, \tag{3.3.6}$$

$$\dot{x}_2 = f_2 = \frac{1}{M}(P_m - Dx_2 - P_e). \tag{3.3.7}$$

The power-angle relation of the system (with $D = 0$) before and after a fault condition at one of the transmission line is shown in Figure 3.4. The area between the dashed lines is the UPFC action envelop.

Assume that the system originally works at point “A” as shown in Figure 3.4, with real power output P_m and power angle δ_0, then, a bolted three-phase to ground fault happens at time t_0, and is cleared at time t_i with the faulted transmission line removed from service. The power angle at t_i is increased to δ_i due to the energy stored in the system during the fault, and the working point jumps back to point “B”. The power angle thereafter will inevitably increase because 1) there usually is a big difference between the mechanical power input P_m (which is assumed to be a constant during the transient period) and the electrical power output at point “B”; 2) there are potential and kinetic energy stored in the system during the fault. If the fault is

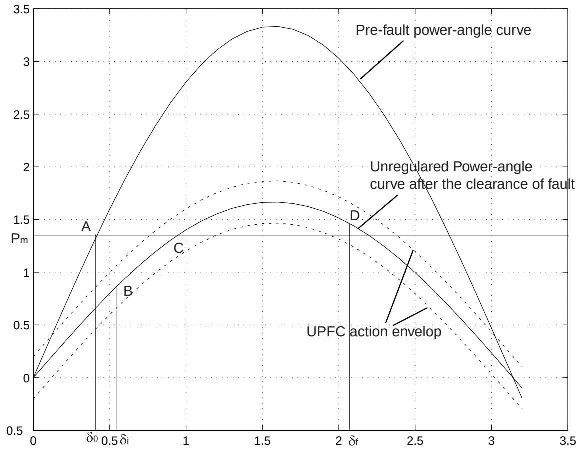

Figure 3.4: Power-angle curves of the system with UPFC action envelop

cleared within the CCT, and if no actions are taken, the system will first move up along the "Unregualted power-angle curve" shown in Figure 3.4 to the point "D" with zero speed where the system potential energy equals the energy stored in the system right at the time when the fault is cleared. Then, a period of diminishing oscillation follows with the system moving along the "Unregulated power-angle curve," till the system settles down at point "C" as a result of a total dissipation of the stored energy due to friction. If a UPFC is installed, the power-angle curve along which the system oscillates could be manipulated within the UPFC action envelop as shown in Figure 3.4.

3.4 Problem Formulation and Solution

The real power P_{pq} given in (3.3.3) is the control variable in the system. Without loss of generality, we assume it is a function of power angle x_1, the first derivative of power angle x_2 and time t, and denote it as $u(x_1, x_2, t)$. Thus, the electrical power output given in (3.3.1) becomes

$$P_e = \frac{V^2}{X} \sin(x_1 + \delta_r) + u(x_1, x_2, t). \tag{3.4.1}$$

Two control objectives are studied. The first one is designed to maximize the system's chance to remain stable following the clearance of a major fault. The second is designed to damp the oscillation in shortest time.

It should be noted that following the clearance of the fault with one of the transmission lines removed from service, the value of the combined impedance X in (3.3.2)(3.3.3) becomes the value of impedance X_1, that is

$$X = X_1. \tag{3.4.2}$$

3.4.1 Optimal First-swing Stabilization Control

The control is the solution to the following optimization problem,

$$\min_{u(x_1, x_2, t)} J_1 = x_{1f}, \tag{3.4.3}$$

subject to

$$
\begin{aligned}
\dot{x}_1 = x_2 &= f_1, && (3.4.4)\\
\dot{x}_2 = \frac{1}{M}[P_m - Dx_2 - \frac{V^2}{X}\sin(x_1+\delta_0) - u] &= f_2, && (3.4.5)\\
\int_{x_{10}}^{x_{1f}} (P_m - P_e)dx_1 &= A, && (3.4.6)\\
|u(x_1, x_2, t)| &\leq u_{max}, && (3.4.7)
\end{aligned}
$$

with boundary condition

$$
\begin{aligned}
x_1(t_0) &= 0, && (3.4.8)\\
x_2(t_0) &= \dot{\delta}_0, && (3.4.9)\\
x_2(t_f) &= 0, && (3.4.10)
\end{aligned}
$$

where J_1 is the performance index; x_{1f} is the power angle at the end of the first swing; x_{10} is the initial power angle; A is the initial potential and kinetic power; u_{max} is the upper limit of real power output that can be regulated by UPFC, and it is given by

$$u_{max} = \frac{VV_{maxpq}}{X}; \tag{3.4.11}$$

t_0 is the initial time, and t_f is the final time.

During the first swing, the effect of damping is negligible. Therefore, for the first swing stabilization problem, we have

$$D = 0. \tag{3.4.12}$$

3.4.2 Solution to the Optimal First-swing Stabilization Problem

Solution to the problem posted in (3.4.3) (3.4.7) is found out to be

$$u(x_1, x_2, t) = u_{max}. \tag{3.4.13}$$

Proof:

First, we transform the integral constraint (3.4.6) by adding a new state to the system, that is

$$x_3 = \int_{x_{10}}^{x_{1f}} (P_m - P_e)dx_1 = \int_{t_0}^{t_f} (P_m - P_e)x_2 dt. \tag{3.4.14}$$

Therefore, the dynamics of x_3 is

$$\dot{x}_3 = f_3 = (P_m - \frac{V^2}{X}\sin x_1 - u)x_2, \tag{3.4.15}$$

with boundary condition $x_3(t_0) = 0$, $x_3(t_f) = A$.

By employing the above transformation, problem posed in (3.4.3)-(3.4.10) is transformed into a classical functional optimization problem with dynamic and boundary constraints. By employing the Lagrange approach, the system dynamics are incorporated in the performance index. Taking into account the boundary conditions, the extended performance index is given as

$$J_1 = [\phi + \mu_2 x_2 + \mu_2(x_3 - A)]_{t=t_f} + \int_{t_0}^{t_f} \sum_{i=1}^{3} \lambda_i (f_i - \dot{x}_i)dt, \tag{3.4.16}$$

where $\phi = x_1$; μ_2 and μ_3 are constants to be determined to satisfy the boundary conditions; λ_1, λ_2 and λ_3 are co-state functions, and they are functions of time.

The Hamiltonian for this problem is

$$H = \lambda_1 f_1 + \lambda_2 f_2 + \lambda_3 f_3. \tag{3.4.17}$$

The functions for the co-state functions are

$$\dot{\lambda}_1 = -\frac{\partial H}{\partial x_1} = (\frac{\lambda_2}{M} + \lambda_3 x_2)\frac{V^2}{X}\cos x_1, \tag{3.4.18}$$

$$\dot{\lambda}_2 = -\frac{\partial H}{\partial x_2} = -\lambda_1 - \lambda_3(P_m - \frac{V^2}{X}\sin x_1 - u), \tag{3.4.19}$$

$$\dot{\lambda}_3 = -\frac{\partial H}{\partial x_3} = 0. \tag{3.4.20}$$

with boundary conditions

$$\lambda_1(t_f) = \frac{\partial \phi}{\partial x_1}(t_f) = 1, \tag{3.4.21}$$

$$\lambda_2(t_f) = \mu_2, \tag{3.4.22}$$

$$\lambda_3(t_f) = \mu_3. \tag{3.4.23}$$

The necessary condition for optimal control $u(x_1, x_2, t)$, without considering the constraints on u, is

$$\frac{\partial H}{\partial u} = -(\frac{\lambda_2}{M} + \lambda_3 x_2) = 0. \tag{3.4.24}$$

Under the optimal control given by (3.4.24), (3.4.18) becomes

$$\dot{\lambda}_1 = 0. \tag{3.4.25}$$

Combined with (3.4.21), we can conclude that

$$\lambda_1 = 1. \tag{3.4.26}$$

Take the first derivative of (3.4.24), arrange terms, and also take (3.4.20) into account we have

$$\frac{\dot{\lambda}_2}{M} + \lambda_3 \dot{x}_2 = 0. \tag{3.4.27}$$

Use (3.4.19) and (3.3.7) to replace $\dot{\lambda}_2$ and $\dot{x}_2$ in (3.4.27), and collect terms we have

$$\frac{1}{M} = 0. \tag{3.4.28}$$

Since $M \neq 0$, we can conclude that the following must be true

$$\frac{\partial H}{\partial u} \neq 0. \tag{3.4.29}$$

Based on Pontryagin Minimum Principle[36], for the case where $u \in [-u_{max}, u_{max}]$, the optimal control can only be

$$u(x_1, x_2, t) = \pm u_{max}. \tag{3.4.30}$$

Compared with $u = u_{max}$, $u = -u_{max}$ will store more potential energy when $P_e < P_m$, and absorb less when $P_e > P_m$, thus will result in a bigger x_{1f}. Therefore, the optimal control for the first-swing stability problem is

$$u(x_1, x_2, t) = u_{max}. \tag{3.4.31}$$

3.4.3 Optimal Damping Control During The Transient

Since a remarkable amount of energy is often stored in the system during the fault, major transient swings usually follow after the clearance of the fault. The control objective in this section is to damp down the transient swings to dynamic level, and then to a new steady state in minimum time. Without loss of generality, we assume that the optimal stabilization control developed in the previous section is employed during the first swing, and the system is stable following the first swing before the optimal damping control take over. The whole process can be best explained with the help of Figure 3.5.

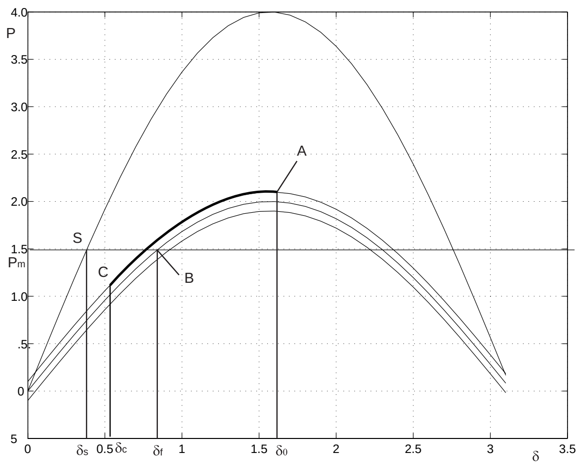

Figure 3.5: Conceptual Illustration of the Damping Control Objective

Initially, the system works at the steady state "S" with real power output P_m and power angle δ_S. Then, a three-phase bolted fault occured, and is cleared with power angle increased to δ_C. Then, optimal UPFC stabilization control is committed to maximize the system's chance to stay stable by setting $u = u_{max}$. The system moves to the right along the thick curve "CA" as shown in Figure 3.5 till it reaches point "A" at time t_0 with $\dot{\delta} = 0$. The task of the optimal damping control is to find a control u such that the system settles down at point "B" in a minimum amount of time.

The problem can then be formulated as

$$\min J_2 = t_f - t_0, \tag{3.4.32}$$

subject to

$$\begin{aligned} \dot{x}_1 &= x_2 = f_1, && (3.4.33) \\ \dot{x}_2 &= \frac{1}{M}[P_m - \frac{V^2}{X}\sin(x_1 + \delta_e) - u] = f_2 && (3.4.34) \\ |u| &\leq u_{max}. && (3.4.35) \end{aligned}$$

with boundary conditions

$$x_1(t_0) = \delta_0 - \delta_e, \quad x_1(t_f) = 0; \tag{3.4.36}$$

$$x_2(t_0) = \dot{\delta}_0, \quad x_2(t_f) = 0; \tag{3.4.37}$$

where δ_0, $\dot{\delta}_0$ and $\delta_e$are the initial power angle, the initial derivative of power angle and the power angle at the equilibrium, respectively. They are all known quantities.

Since mechanical friction is usually considered to be small, and also in the hope of not obscuring the major aspect of the problem, we assume that the damping ratio D is zero.

3.4.4 Properties of the Optimal Transient Damping Problem

The time optimal control problem posed in (3.4.32)-(3.4.37) contains nonlinear terms. As a result, no solution has been found yet in the literature that could provide an analytical solution to this problem. In this study, we developed a suboptimal control law that achieves good control result. In this section, properties of the system is studied first, then, in the following sections, analytical solution is provided for a linear equivalent system. A method, which makes use of the results obtained for the linear system, is proposed to obtain a suboptimal solution for the nonlinear time optimal control problem.

The Hamiltonian of the system is

$$H = 1 + \lambda_1 f_1 + \lambda_2 f_2 = 1 + \lambda_1 x_2 + \frac{\lambda_2}{M}[P_m - \frac{V^2}{X}\sin(x_1 + \delta_e) - u]. \tag{3.4.38}$$

The control which absolutely minimizes H is given by

$$u(t) = u_{max} sgn(\lambda_2). \tag{3.4.39}$$

The Euler-Lagrange equations are

$$\dot{\lambda}_1 = -\frac{\partial H}{\partial x_1} = \frac{\lambda_2 V^2}{MX}\cos x_1, \tag{3.4.40}$$

$$\dot{\lambda}_2 = -\frac{\partial H}{\partial x_2} = -\lambda_1 + \frac{\lambda_2 D}{M}, \tag{3.4.41}$$

Since we are minimizing time, and H is not an explicit function of time, we have

$$H = 0. \tag{3.4.42}$$

The following properties for the time-optimal control system are in order:

- There is no possibility of singular control. This is because the function $\lambda_2(t)$ can not be zero over a finite interval of time, as this would require $\lambda_1(t) = \lambda_2(t) = 0$. As a result, during this period of time (3.4.42) can not be satisfied.

- The time-optimal control must be piecewise constant and must switch between $-u_{max}$ and u_{max}.

- It is very difficult to find the analytical solution for $\lambda_2(t)$.

3.4.5 Solution to the Equivalent Linear System

The nonlinear term in the time-optimal control problem (3.4.32)-(3.4.37) makes it very difficult to find an analytical solution. However, if the nonlinear term is replaced by a linear term, analytical solution can be found precisely [37]. In this section, solution to the linear time-optimal control problem is presented.

Suppose that a system is described by the differential equation

$$\frac{d^2y(t)}{dt^2} + \omega^2 y(t) = Kv(t). \tag{3.4.43}$$

where $K > 0$ and the control $v(t)$ satisfies $|v(t)| \leq 1$.

If the state variables are defined as

$$y_1(t) = y(t), \tag{3.4.44}$$

$$y_2(t) = \dot{y}(t). \tag{3.4.45}$$

Then, the state space form of the system (3.4.43) is

$$\dot{y}_1(t) = y_2(t), \tag{3.4.46}$$

$$\dot{y}_2(t) = -\omega^2 y_1(t) + Kv(t). \tag{3.4.47}$$

Define

$$\begin{aligned} x_1(t) &= \frac{\omega}{K} y_1(t), \\ x_2(t) &= \frac{1}{K} y_2(t). \end{aligned}$$

Then, the state space form can be transformed into a more convenient form

$$\dot{x}_1(t) = \omega x_2(t), \tag{3.4.48}$$

$$\dot{x}_2(t) = \omega x_1(t) + v(t). \tag{3.4.49}$$

The time-optimal control law that forces the system (3.4.48)(3.4.49) from any initial state (ξ_1, ξ_2) to the origin (0,0) in minimum time, with $|u(t)| \leq 1$ is given by:

$$v^* = \begin{cases} +1 & \text{for all } (\omega x_1, \omega x_2) \in R_+ \cup \gamma_+, \\ -1 & \text{for all } (\omega x_1, \omega x_2) \in R_- \cup \gamma_-. \end{cases}$$

where γ_+ and γ_- are defined as

$$\gamma_+ = \cup_{j=0}^{\infty} \gamma_+^j, \tag{3.4.50}$$

$$\gamma_- = \cup_{j=0}^{\infty} \gamma_-^j. \tag{3.4.51}$$

γ_+^j and γ_-^j are given by

$$\gamma_+^j = \{(\omega x_1, \omega x_2) : [\omega x_1 - (2j+1)]^2 + (\omega x_2)^2 = 1; \omega x_2 < 0\}, \tag{3.4.52}$$

$$\gamma_-^j = \{(\omega x_1, \omega x_2) : [\omega x_1 + (2j+1)]^2 + (\omega x_2)^2 = 1; \omega x_2 > 0\} \tag{3.4.53}$$

with $j = 0, 1, 2, \ldots$.

R_- and R_+ are given by

$$R_- = \cup_{j=1}^{\infty} R_-^j \tag{3.4.54}$$

$$R_+ = \cup_{j=1}^{\infty} R_+^j \tag{3.4.55}$$

where R_-^j denotes the set of states which can be forced to the γ_+^{j-1} curve in no more than π/ω seconds by the control $u = -1$; R_+^j denotes the set of states which can be forced to the γ_-^{j-1} curve in no more than π/ω seconds by the control $u = +1$.

The semicircles of γ_+^j and γ_-^j, $j = 0, 1, 2, \ldots$, and the R_+^j and R_-^j, $j = 1, 2, \ldots$ regions are shown in the following Figure.

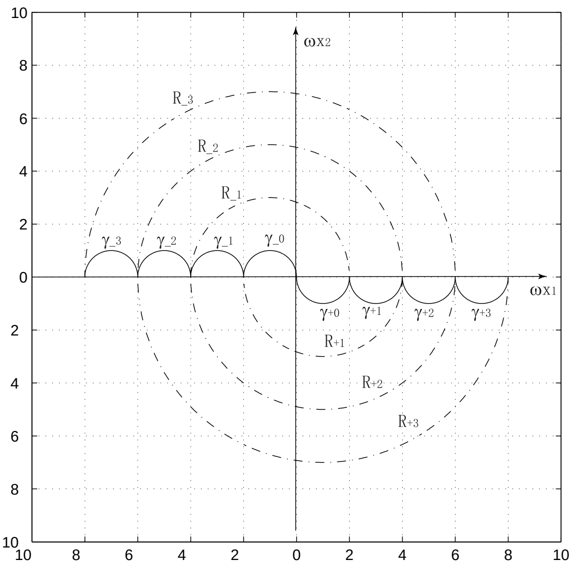

Figure 3.6: The γ_{+-} Semicircles and the R_{+-} Regions

Important properties of the time-optimal solution to the second order linear problem with system dynamics given in (3.4.43) as listed below.

- The time-optimal control is unique.

- The time-optimal control is piecewise constant and switches between $+1$ and -1.

- The time-optimal control can remain constant for no more than π/ω seconds.

- There is no singular control exists for the time-optimal problem.

3.4.6 Suboptimal Control for the Nonlinear System

In this section, a method is developed that utilizes the result shown in the previous section to obtain a suboptimal solution to the nonlinear time-optimal control problem.

If we replace the nonlinear dynamics (3.4.34) by the following linear dynamics, we have

$$\dot{x}_2 = -kx_1 + \frac{1}{M}u, \tag{3.4.56}$$

where k is given by

$$k = \frac{V^2[sin(\delta_e + \frac{\delta_0 - \delta_e}{2}) - sin(\delta_e)]}{MX(\frac{\delta_0 - \delta_e}{2})}. \tag{3.4.57}$$

In (3.4.57), k is chosen in such a way so as to keep the overall difference between the nonlinear dynamics (3.4.34) and the linear dynamics (3.4.56) over power angle from δ_0 to δ_e is small. This is shown graphically in Figure 3.7.

The control objective is to damp transient oscillation in minimum time, and restore the system to the equilibrium point as shown in Figure 3.7. The dynamics of the harmonic oscillator that passes the equilibrium point problem can be written as

$$\dot{x}_1 = x_2, \tag{3.4.58}$$

$$\dot{x}_2 = -kx_1 + \frac{1}{M}u \tag{3.4.59}$$

$$|u| \leq u_{max}. \tag{3.4.60}$$

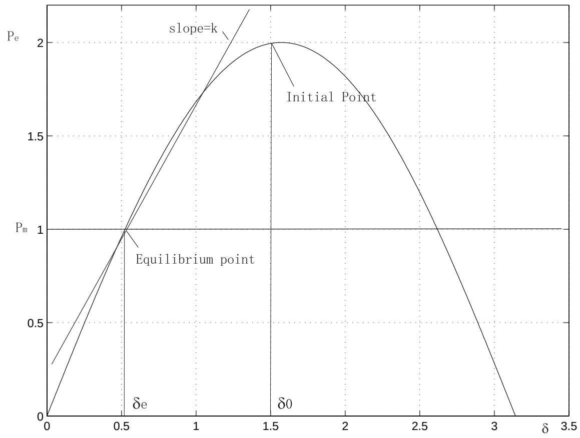

Figure 3.7: Graphic View of Suboptimal Control Approximation Principle.

where k is given in (3.4.57).

The analytical solution for linear system (3.4.58)-(3.4.60) can be obtained precisely. A suboptimal control is obtained by the nonlinear system by following the procedures listed below:

1. Obtain the switching curve for time-optimal control problem (3.4.58)-(3.4.60).

2. Replace the linear dynamics (3.4.59) by the nonlinear dynamics (3.4.34).

3. Solve the nonlinear approximation system using the switching curve obtained in 1. and following the optimal control law developed for the linear system as shown in the previous section.

The solution obtained by following the above-mentioned procedures is not strictly optimal. However, since dynamics of the nonlinear system and that of the

Table 3.1: System Data of the SMIB System with UPFC Installed

M	V	X_1	X_2	D	P_m
1.0	1.0	0.5	0.5	0	1.5

equivalent linear system are not too different, it is reasonable to conclude that the optimal control obtained for the nonlinear system is fairly close to the real optimal one.

3.5 Simulation Results

For the power system shown in Figure 3.3, simulation studies are carried out to demonstrate the effectiveness of the proposed optimal UPFC control strategy. The system data are given in Table 2.1 (all the data use *per unit* system):

For a single-machine-infinite-bus system as shown in Figure 3.3, its power angle curves before and after the fault are shown in Figure 3.8, where P_m is the constant mechanical power input. The pre-fault power angle is given by $\delta_0 = 0.3844$. The UPFC action region is $[P_0 - 0.2, P_0 + 0.2]$ *per unit*.

3.5.1 Optimal UPFC Stabilization Control Simulation

In this study, the CCTs of the power system are compared with UPFC employing the proposed optimal stabilization control, no control, in-phase voltage control and quadratic voltage control, respectively.

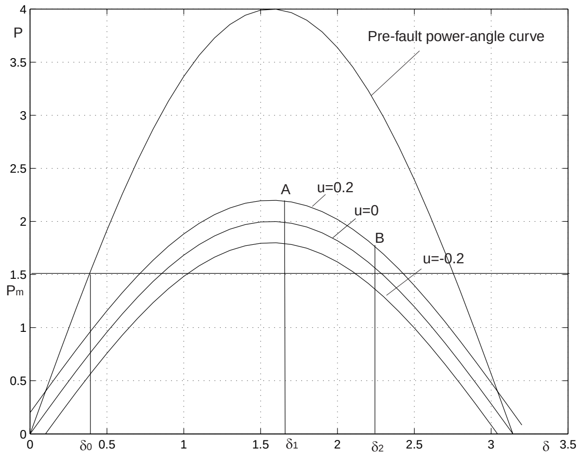

Figure 3.8: Pre and after fault power-angle curve ($u_{max} = 0.2$).

For in-phase voltage control, at full-thrust, the electrical real power output is given by

$$P_e = \frac{V^2}{X}\sin\delta + \frac{VV_{pqmax}}{X}\cos\delta. \tag{3.5.1}$$

For quadratic voltage control, at full-power, the electrical real power output is given by

$$P_e = \frac{V^2}{X}\sin\delta + \frac{VV_{pqmax}}{X}\sin\delta. \tag{3.5.2}$$

When $u_{max} = 0.2\ p.u.$, it can be shown that

$$V_{pqmax} = 0.1 \tag{3.5.3}$$

The CCT of different UPFC control strategy is given in Table 3.2

Table 3.2: Critical-clearance-time for Different UPFC Control Strategies.

Type of UPFC control	CCT (s)
no control	0.5967
In-phase voltage	0.6240
Qudratic voltage	0.7891
Optimal stabilization control	0.8042

3.5.2 Optimal UPFC Transient Damping Control Simulation

For the transient damping control, initial data is given as

$$\begin{aligned} P_m &= 1, \\ \delta_0 &= 1.5, \\ \delta_e &= 0.523. \end{aligned}$$

The comparison of the system with and without the sub-optimal UPFC damping control are give in Figure 3.9, Figure 3.10 and Figure 3.11, respectively.

3.6 Conclusions and Future Research Extensions

In this chapter, it is demonstrated that UPFC can be used to effectively damp system oscillation and extend the system stability margin following the clearance of a fault. Optimal control strategies are developed to maximize the system first swing stability margin, and to minimize the time required for the system to damp down the transient and dynamic oscillations after the system is stabilized. It is noteworthy to point

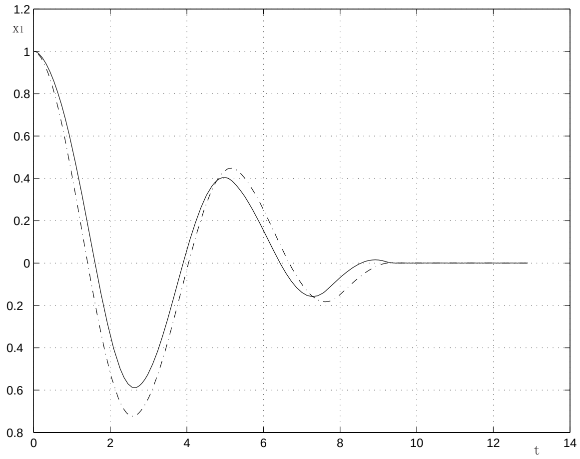

Figure 3.9: Nonlinear (Solid line) and Linear (Dashed line) Trajectories of x_1

out that the optimal damping control works even better than the intuitively best control in bringing the system quickly away from dangerously high power angle values. Simulation results show that the proposed optimal control strategies are effective in doing what they are designed to do.

The proposed control strategies work as well for other mechanical/electrical systems as long as their dynamic relations could be described as a *pendulum equation* (Just as the electrical power system is).

Even though the results presented in this chapter are developed for a SMIB system, it is possible to use the same method to study a multi-machine-multi-bus (MMMB) system. After all, the static model of a MMMB system can eventually be reduced to an equivalent static SMIB system. However, for a MMMB system, what makes the problem complicated is the interaction between the transients caused by

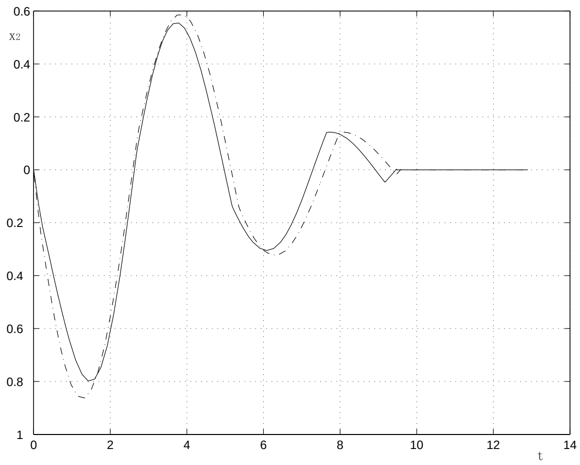

Figure 3.10: Nonlinear (Solid line) and Linear (Dashed line) Trajectories of x_2

UPFC control actions and the transients resulting from system interconnection. Only after this interaction of transients, which are from two different sources, is studied carefully, can meaningful UPFC controls be designed for MMMB systems. In brief, extending the optimal transient UPFC control laws for SMIB system to MMMB system is a challenging and practical further research topic to pursue. The result out of the research will bring UPFC one step closer to real-world transient control application in the power industry.

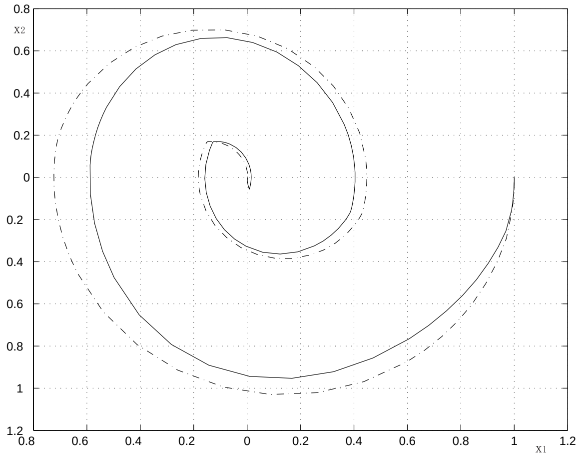

Figure 3.11: Nonlinear (Solid line) and Linear (Dashed line) Phase Portrait of x_1 and x_2

CHAPTER 4

A OPTIMAL ALGORITHM-BASED POWER MARKET STRUCTURE

In a successful competitive electricity market both social welfare and the producers' benefit should be maximized, and the cost for reaching a settling price should be kept low. In this chapter, a market structure that fulfills the above-mentioned requirements is proposed. In the proposed electricity market, the trading framework is modelled as a two-level optimization problem. At the higher level, the objective is to maximize the social welfare. At the lower level, based on current market situation, bidders submit their bids iteratively to maximize their own profit. The higher level objective is achieved by following the Optimal Dispatch Rule (ODR). At the lower level, instead of letting the iterative bidding process actually happen, an algorithm is developed to replace the bidding process. The bidders provide the market operator with cost curves, upper and lower limits that reflect their production conditions. Using these information, the market operator runs the algorithm to find a solution. The solution found by the proposed is the best solution possible had the actual bidding process have happened. Social welfare is assured because only producers with lowest cost are selected to supply the demand. On the other hand, producers' benefit is guaranteed by the fact that the winning bidder's price is not lower than its cost and the product of price times allocated generation quantity is optimal under the market situation of concern. Since the iterative bidding process is eliminated, the cost of operation is low.

4.1 Introduction

The power industry has been undergoing massive restructuring worldwide since the 1980's with the objectives of eliminating monopolies, encouraging development of new technologies, and improving efficiency in mind. It's believed that by introducing a well-designed market structure and enacting sound rules of play, suppliers will behave in such a way so as to maximize social welfare through fair and ferocious competition. However, the emergent power market does not turn out to be a perfect one. But rather, it helplessly evolves into an oligopoly, in which sellers are so few that the actions of any one of them will materially affect price and have a measurable impact on other competitors. The reason behind this outcome is the existence of special characteristics of the power industry. Transmission constrains and losses discourage customers from buying power from far away places; high entry barriers prevent new suppliers from entering the scene. All these end up with the reality that only a few electricity generation companies serve a given geographic region.

Since the power market is an oligopoly, players in it are apt to bid strategically to obtain maximum profit. As a result, the study on bidding strategies has been receiving attention from power suppliers, system operators and big customers for some time. A considerable number of results have been published in the literature on this subject. It is obvious that the development of bidding strategies should be based on market model and rules of activity.

Most bidding methods developed so far require knowledge about a rival bidders' bidding behavior. To this end, techniques such as probability analysis and fuzzy set are often used. In [40], by modelling the competitor's cost function as a probability density function, a bidding strategy was proposed for two participants competing for a single block of energy. The problem with the use of probability analysis and fuzzy theory is that some of the crucial probabilities could not be calculated satisfactorily due to a lack of data. Obviously, this is because the electricity market does not have a very long history. In [41] and [42], by assuming that complete information about rival bidders' bid is given, a two-level optimization problem is formulated to describe the bidding problem. One level represents social welfare, and the other the individual generator's profit. In the real world however, it is unlikely that such information will be available. On the other hand, in order to reach an equilibrium, market participants might be required to submit their bids iteratively until certain stop criteria are met. Furthermore, all bidders are required to use the optimal bidding strategies proposed by the authors to come up with new bids.

Game theory is also found its use in the study of bidding strategies[44]-[50]. However, bidding strategies have to be discretized as "bidding high", "bidding medium" or "bidding low" before methods and results in game theory can be used. Nevertheless, in the real world, bids offered by bidders can be continuous. Thus, a theoretical equilibrium obtained from game theory analysis is not guaranteed to exist in realistic situations.

In this chapter, a scheme is proposed in which generators provide a cost curve and its production limits, instead of just a quantity and price. Therefore, much more information is available to the market operator. Thus, the task of searching for an optimal solution becomes more reachable. The proposed market model has the following features:

- A best solution could be reached without the bidders having to actually bid iteratively.
- Both social welfare and the profit of producers are maximized.
- Stability is assured.
- Demand side elasticity can be easily accommodated.
- Fairness is guaranteed. Generators with higher incremental production cost are bidden out the market first.
- Instead of gaming, producers could focus on coming up with accurate cost curves and production limits in the short term; thus reducing production cost in the long run.

This chapter is arranged as follows: a simple example with two generators competing for a single block of energy is given to show that an iterative bidding process by bidders could be replaced by an optimization algorithm. Then, a realistic model is established for a system composed of multiple generators. A two level optimization problem is formulated, and solution provided. A simple pool-type market with five generators is used as an example to demonstrate the effectiveness of the proposed model.

4.2 Non-Iterative Implementation of Iterative Biding Process

Almost all operating electricity markets worldwide employ sealed bid auction[39]. This means bidders submit their bid only once in the bidding process, and the bid submitted is final. In a market operated this way, it is rare that the whole system can reach an optimal solution, in which the benefits of all parties of interest are maximized and any change from this equilibrium point will reduce benefits at least to the party who changed its bid. As shown in [41][42][43], iterative bidding is generally needed to reach optimal results. On the other hand, it happens often that bidders may want to change their bid once the bidding result is public. Therefore, it seems that it is beneficial to bid iteratively until an equilibrium is reached or a maximum number of allowable iteration is exceeded. However, iterative bidding is not without its own problem. A few drawbacks related to iterative bidding are listed below:

- Optimality is not guaranteed.
- Efficiency is low.
- Gaming is encouraged.
- Increased costs. Communication and personnel costs will certainly go up.

Actually, the bidding process could be replaced by algorithms. To show this, a simple example is given below.

Suppose there are two suppliers ‘A’ and ‘B’ competing for the right to supply a single block of energy demand. Assume both ‘A’ and ‘B’ alone can provide the demand, and the market rules are:

1. The market operator will choose the bidder who offers the lowest price to supply the energy demand;

2. If ‘out-bidden’, the bidder is willing to lower its bid to the point where it could just win the bid;

3. Bidders will not bid below their cost.

The actual bidding process is shown in Figure 4.1.

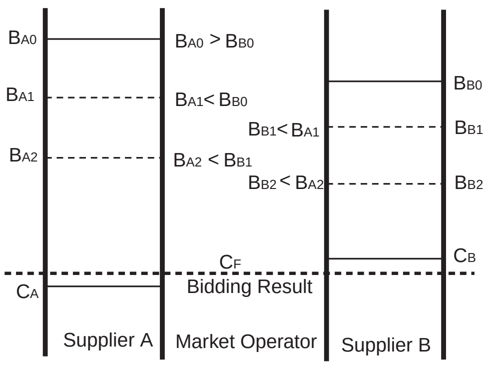

Figure 4.1: Illustration of actual bidding process

At the beginning of the bidding process, supplier A and supplier B submit their initial bid, B_{A0} and B_{B0}, respectively. Since $B_{A0} > B_{B0}$, supplier A decides to lower its bid until $B_{A1} < B_{B0}$. To avoid losing the bid, supplier B submits new bids until $B_{B1} < B_{A1}$. The process goes on iteratively until one of the bidders cannot lower its bid any more due to cost constraint, at which point, the rival bidder wins the bid with a bid just below the losing bidder's cost. In this case, supplier A wins the bid, and the final result for the bid is C_F, the price for providing the block of energy demand.

In fact, the iterative bidding process can be replaced by well-designed market operation mechanism. For example, instead of submitting their bid several times, suppliers could submit their cost and initial bid to the market operator, the market operator then uses the agreed-upon and publicized algorithm and bid-decrease interval to imitate the actual would-be bidding process as shown in Figure 4.1 until the settling price C_F is reached.

In a market as described above, suppliers could focus on accurately calculating their production cost, while using their initial bid to express their expectation for profit. In the end, suppliers with lower cost will win the bid, and the energy price is just below the losing bidder's production cost. This result will give producers strong incentives to reduce their cost of production compared with that of their competitors.

4.3 Problem Formulation

The formulation and solution presented are obtained under the following assumptions.

Assumption 1: Only a given set of committed generators are considered. This set of generators is always on-line. No generators will be shut down even if a particular generator is operating at its lower limit.

Assumption 2: Market participants are only concerned with incremental costs.

Assumption 3: All suppliers are reasonable bidders. This means they all intend to maximize their profit given a certain demand for electricity.

In this section, we study the case in which a market is composed of multiple generators with quadratic cost function as shown in equation (4.3.1).

$$C_0(g) = \alpha + \beta g + \gamma g^2. \tag{4.3.1}$$

where C_0 is the generator generation cost in dollar, and α, β, γ are generator cost parameters.

The incremental cost of a generator is given by

$$IC_0 = \frac{dC_0}{dg} = \beta + 2\gamma g. \tag{4.3.2}$$

In a competitive electricity market, we propose to add an positive quantity m to the linear term β to represent the supplier's expectation for return above its cost of production. We then define 'Composite Incremental Cost' as

$$IC = \beta + m + 2\gamma g. \tag{4.3.3}$$

where m is a supplier's price bid.

In words, composite incremental cost is defined as the sum of the incremental cost of a generator and the supplier's expectation for a price above its production cost. Composite cost is then given by:

$$C(g) = \alpha + (\beta + m)g + \gamma g^2. \tag{4.3.4}$$

where C is the composite generation cost in dollar.

For ease of presentation, from this point on, the terms 'cost' and 'incremental cost' shall be interpreted as composite cost and composite incremental cost, respectively.

The problem of optimal market operation and optimal bidding for a market with multiple generators can then be formulated as the following:

$$\min_{g_1, g_2, \dots g_n} C = \sum_{i=1}^{n} \alpha_i + (\beta_i + m_i)g_i + \gamma_i g_i^2, \tag{4.3.5}$$

Subject to:

$$\sum_{i=1}^{n} g_i = D, \tag{4.3.6}$$

$$Ll_i \leq g_i \leq Lu_i, \quad (i = 1, ..., n.) \tag{4.3.7}$$

$$\begin{cases} \max_{m_i} & f_i = m_i g_i \\ \text{Subject to:} & 0 \leq m_i < T \end{cases} \tag{4.3.8}$$

$$(i = 1, \dots, n.)$$

where g_i is the ith generator's output in MW; n is the number of generators; D is the demand for electricity; T is the ceiling for price add-up.

In the formulation above, the top level of the optimization problem, expression (4.3.5), corresponds to actions taken by the market operator to properly allocate quantities of generation g_1 ,..., g_n to generators so as to minimize buyers' payment; while expression (4.3.8), lower levels of the optimization problem, corresponds to the behavior of individual supplier to adjust m_i so as to maximize its profit.

From (4.3.8), it seems that by increasing m_i, the ith supplier could increase its profit. At the system level, however, the market operator is expected to minimize the customer's or society's payment for electricity. Therefore, the system operator must reduce generation allocation g_i, thus adversely affecting generator i's profit. It is obvious that it is beneficial to both customer and generators to find an optimal m_i^* and g_i^* so as to maximize supplier i's profit, while at the same time keeping customer's payment low. As stated in the previous section, instead of iterative bidding, algorithms could be developed to obtain an optimal solution, which the traditional iterative process is trying to achieve. By solving the problem presented in (4.3.5)-(4.3.8), the optimal point can be found.

4.4 Problem Solution

4.4.1 Application of Optimal Dispatch Rule

It is observed that the top level of the optimization problem, expression (4.3.5), together with equality constraint (4.3.7), is a typical classical economic dispatch problem if m_1, m_2,...,m_N are given. An classical economic dispatch problem can be solved by following the well known Optimal Dispatch Rule(ODR)[51]. When generator limits are not considered, ODR is stated as:

Operate every generator at the same incremental cost.

When generator limits are considered, the rule is:

Operate all generators, not at their limits, at equal incremental cost.

Based on these rules, the solution to the multilevel optimization problem can be developed.

4.4.2 Exclusion of Inequality Constraints

Before we start, we assume that the n generators of interest are organized in such a way so that $\beta_i \geq \beta_j$ if the index $i < j$.

According to ODR, the market should be operated in such a way so that

$$IC_1 = IC_2 = \ldots = IC_n = IC. \tag{4.4.1}$$

It should be noted that IC is a quantity that can not be determined by the choice of m_i, since a change in the value of m_i will make the value of g_i change in the opposite direction. For the i's supplier, we have

$$\beta_i + m_i + 2\gamma_i g_i = IC, \tag{4.4.2}$$

and

$$g_i = \frac{IC - \beta_i - m_i}{2\gamma_i}. \tag{4.4.3}$$

Substituting (4.4.3) into (4.3.8), we have

$$f_i = \frac{(IC - \beta_i)m_i - m_i^2}{2\gamma_i}. \tag{4.4.4}$$

f_i is a concave quadratic function, it reaches maximum at

$$m_i^* = \frac{IC - \beta_i}{2}. \tag{4.4.5}$$

When m_i takes the value m_i^*, IC can be written as

$$IC = \beta_i + m_i^* + 2\gamma_i g_i^*. \tag{4.4.6}$$

Substituting (4.4.6) into (4.4.5), we have

$$m_i^* = 2\gamma_i g_i^*. \tag{4.4.7}$$

Substituting (4.4.7) into (4.4.6), we have

$$IC = \beta_i + 4\gamma_i g_i^*. \tag{4.4.8}$$

Therefore, (4.4.1) becomes

$$\beta_1 + 4\gamma_1 g_1^* = \ldots = \beta_n + 4\gamma_n g_n^* = IC. \tag{4.4.9}$$

Combined with the following equality constraint

$$g_1^* + g_2^* + \ldots + g_n^* = D, \tag{4.4.10}$$

the multilevel optimization problem can be solved. The solution is given below:

$$g_1^* = \frac{D - \sum_{i=2}^{n} \frac{\beta_1 - \beta_i}{4\gamma_i}}{1 + \sum_{i=2}^{n} \frac{\gamma_1}{\gamma_i}}, \tag{4.4.11}$$

$$g_j^* = \frac{\beta_1 - \beta_j}{4\gamma_j} + \frac{\gamma_1}{\gamma_j} g_1^*, \tag{4.4.12}$$

$$(j = 2, \ldots, n.)$$

and

$$m_k^* = 2\gamma_k g_k^*. \tag{4.4.13}$$

$$(k = 1, \ldots, n.)$$

A few points of importance need to be laid out:

1. From (4.4.10) and (4.4.9), it is observed that for each specific demand level D, there is a unique incremental cost IC corresponding to it. The higher D is, the bigger IC is going to be.

2. Generators with higher β might turn out a negative g^* for certain demand level. This means that that particular supplier already lost in the competition, and its generation should be reduced to zero. From (4.4.11), it is clear that the critical demand level, D_c, below which the 1th supplier will be out of the market can be calculated by

$$D_c = \sum_{i=2}^{n} \frac{\beta_1 - \beta_i}{4\gamma_i}. \tag{4.4.14}$$

3. The solution obtained in (4.4.11)-(4.4.13) is the optimal solution. The optimality of the top level is guaranteed by ODR, and the optimality of the lower levels is assured by choosing m_is using (4.4.7).

4.4.3 Inclusion of Inequality Constraints

When inequality constraints are included, solving the problem presented in (4.3.5)-(4.3.8) analytically is not a trivial task. Of course, an exhaustive search can always be used as the last resort. However, drawbacks such as low efficiency keep this straight-forward method from being of much practical usefulness in the real world, especially when the number of generators involved is big. A better algorithm needs to be developed to deal with this problem. Due to the nature of the problem, we categorize the problem into two groups.

1. Lower Generation Limits All Zero

An algorithm, with the method developed in the previous section as its core, can be developed to accommodate all zero lower and higher generation limits. The algorithm used is shown in Figure 4.2, and we name it *Algorithm A*.

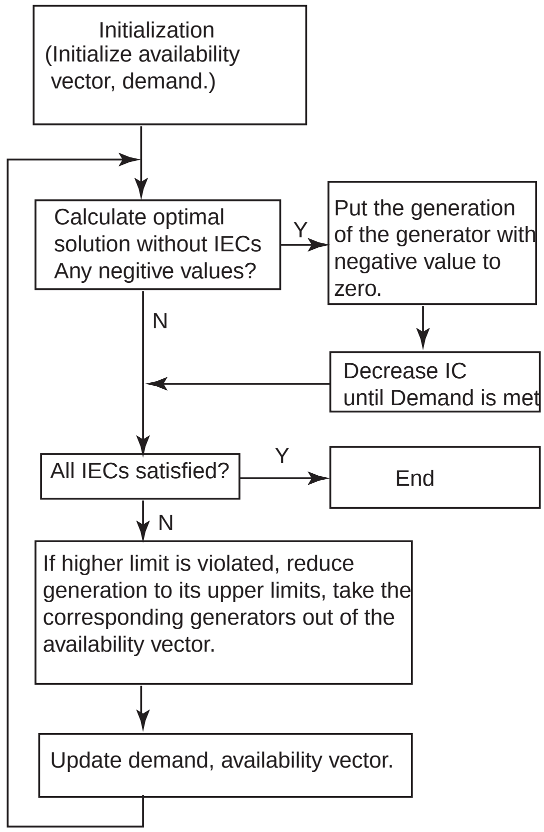

Figure 4.2: (Algorithm A) Algorithm for the case in which all lower limits are zero.

In Figure 4.2, IEC stands for inequality constraints.

2. Lower Generation Limits Not All Zero

Close inspection of the ODR rule with inequality generation constraints active reveals that the essence of this rule is to operate the market with a lowest incremental cost (IC) possible while at the same time satisfy the demand and observe all the inequality constraints. This principle is shown graphically in Figure 4.3.

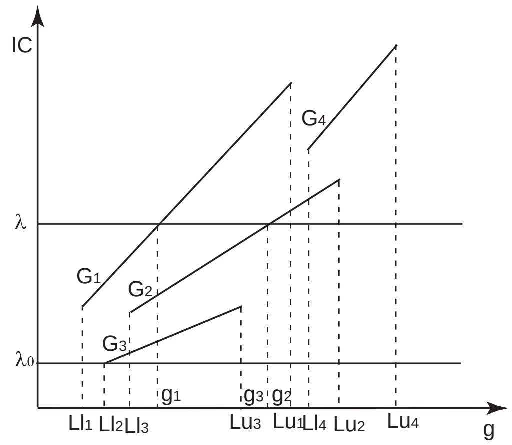

Figure 4.3: Principle of ODR with inequality constraints active

In Figure 4.3, a market with four generators on duty is used as an example, where L_l and L_u denote the lower and upper limits of a generator, respectively. The four generators are G_1, G_2, G_3 and G_4. Four line segments, obtained using (4.4.9), correspond to the optimal incremental cost curves of the four generators with their lower and upper generation limits, respectively. λ is the settled smallest possible incremental cost for the current market situation. When $IC = \lambda$, we have

$$g_1 + g_2 + g_3 = D. \tag{4.4.15}$$

It is also noted that due to the effect of ODR we have

$$g_3 = Lu_3, \tag{4.4.16}$$

and

$$g_4 = 0. \tag{4.4.17}$$

The reason behind this result is that G_3's IC is lower than λ at its upper limit, while G_4's IC is higher than λ at its lower limit.

An algorithm can be developed that works according to ODR with inequality generation constraints active. The algorithm is shown in Figure 4.4, and we call it *Algorithm B*.

In Figure 4.4, after initialization, the algorithm first finds the lowest incremental cost λ_0, which corresponds to the lowest incremental cost of all the suppliers at their lower generation limit, as the starting point, and let $\lambda = \lambda_0$. It then allocates generation to generators using (4.4.8) with $IC = \lambda$. The generation allocation obtained at this stage corresponding to the case where generation limits are not considered. Next, the algorithm checks to see whether the generation allocations obtained above violates any of the limits on the generations. If, for any generator, the lower limit is violated, the allocation to that generator is set to 0; if upper limit is violated, the allocation is set to its upper limit. After all generation allocations are validated, it then sum them all up to see whether the demand has been met; if not, λ is increased by a small amount $\Delta\lambda$, and redo generation allocation and validation till the demand is met.

3. Algorithms Comparison

It is worthwhile to point out that when all the lower generation limits are zero, algorithms A and algorithm B generate the same result. The only difference is that the efficiency of algorithms A is much higher. Nevertheless, algorithm B can deal with situations in which lower generation limits are not zero. Therefore, it could be more useful in the real world.

To study the nature of and to gain insight into the proposed market model, it is usually necessary to set all lower generation limits to zero. In this case, algorithms A should be used due to its high efficiency.

Algorithm B is an iterative search method in nature. However, the search dimension has been reduced from $2n$ (exhaustive search) to 1 (just search a proper IC). This makes it possible to solve the multilevel optimization problem in a real world setting with an acceptable speed.

4.5 Bidding Model for Pool-Type Market

The proposed bidding market model works like this:

1. All bidders submit their cost curve plus upper and lower output limits to the pool manager or market operator.

2. Organizations such as ISO, which are in charge of system stability, evaluate the generation limits submitted by suppliers and make changes if necessary.

3. With bidders' bids imbedded in the model, the market operator performs optimal demand allocation based on ODR.

4. The bidding can be hold for each hour of the next 24 hours. The bidding result is known before bidders bid for the next hour.

5. The task of individual generator is to come up with a cost curve and generation limits that takes into account the generator's previous loading condition, and internalize all involved costs and physical constaints.

6. Each and every generator is paid the same final incremental cost λ.

7. Optimality is guaranteed by the mathematical model based on which the market operates.

4.6 Demand Elasticity

The proposed model can easily incorporate demand elasticity. It is clear from the solution procedure that if demand drops due to high price, suppliers will be forced to work at a lower incremental cost; furthermore, the more expensive generators might even be forced out of the market automatically; this in return will cause a drop in the price of electricity, and a new balance point will be found. An example is given below to demonstrate this point.

4.7 Example System and Simulation Results

A simple example is given below. Assume a power pool consists of five generators, and their information is shown below.

n	α	β	γ	Ll(MW)	Lu(MW)
1	224.5	53.1	0.018	0	50
2	900	45	0.01	0	700
3	2500	43	0.003	0	800
4	1800	41.5	0.015	0	600
5	2600	40	0.02	0	650

Using the algorithm presented in Figure 4.2, an optimal supply *vs* incremental cost curve can be obtained as shown in Figure 4.5.

In Figure 4.5, the 'Supply-price curve' is obtained using the algorithm presented in this chapter, while the 'Demand-price curve' is a typical example of this kind of curves. It is observed that the intersection of these two curves is the point where the market strikes a deal.

Next, the market situation at different demand level is shown in the table below.

D(WM)	g_1^*	g_2^*	g_3^*	g_4^*	g_5^*
2201.3	50.0	567.9	800	436.9	346.5
1800	50.0	382.7	800	313.5	253.8
1400	0	221.2	800.0	205.8	173.1
1000	0	129.5	598.5	144.7	127.3
600	0	56.8	356.1	96.2	90.9
400	0	20.5	234.8	72.0	72.8
200	0	0	101.9	45.4	52.8
100	0	0	27.8	30.6	41.7
60	0	0	0	23.6	36.4
16	0	0	0	0	16.0

Two observations could be made based the above table:

- Suppliers with higher β lose the bid first.
- The quadratic term γ plays an important role in determining the share of the total demand a particular supplier can get if it wins.

4.8 Conclusion and Future Research Extensions

It has been shown in this chapter that iterative bidding process could be replaced by an algorithm. The proposed market structure can reach an optimal solution without the suppliers bidding iteratively. The settled-upon price (incremental cost) obtained reflects the actual market value of electricity, not just its cost of production. The focus of an individual supplier is on production and reducing cost, and gaming is discouraged. The proposed market structure can easily accommodate demand elasticity. In brief, the proposed market structure is fair, optimal and efficient.

Stability is always a very important concern for the power industry. It is usually the Independent System Operator (ISO)'s job to make sure that there is enough stability margin system wide. Right now, the common practice is that ISO perform security assessments before give the green light to a market transaction. How to incorporate these assessment process into the market environment is a question of practical importance. If this can be done, the efficiency can be improved further, and the solution reached will guarantee system stability. In summary, to include the stability assessment process in the proposed market structure can be a practical and important extension to the proposed structure.

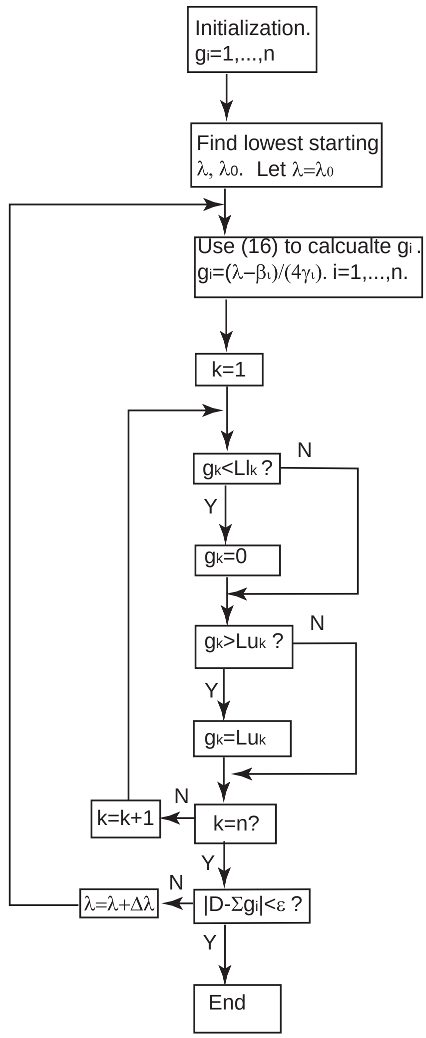

Figure 4.4: (Algorithm B) Algorithm based on ODR with inequality contraints active

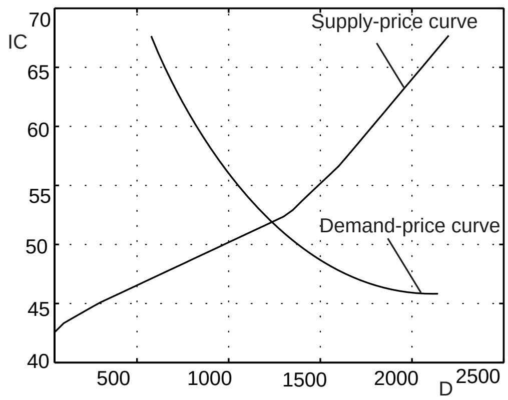

Figure 4.5: Supply-price curve & demand-price curve

CHAPTER 5

LOADABILITY DETERMINATION USING MATHEMATICAL PROGRAMMING THEORY

Estimating loadability of a generation and transmission system is of practical importance in power system operations and planning. This study presents a new formulation for the estimation problem using mathematical programming theory. Both steady-state and dynamic security are taken into accounts in the proposed formulation. The difference between the proposed formulation and existing ones is that dynamic security is handled by an integration method. Using the new formulation, an iterative solution procedure is developed to solve the corresponding mathematical programming problem numerically. The method normally yields a slightly conservative estimate on the loadability of a generation/transmission system. Simulation results of a test power system are provided.

5.1 Introduction

Construction and enhancement of generation/transmission systems generally requires huge amounts of capital investment. Regardless of whether or not capital investment is available for constructing systems and enhancing their capacities, efficient utilization of existing power facilities is always desired for both economical and environmental concerns. In fact, efficient utilization, which can be divided into such issues as optimal system scheduling and optimal facility maintenance, becomes increasingly important for the utilities as they face deregulation. On the other hand, optimal facility allocation known as optimal power system planning, is the method of addressing how to optimize capital investment while meeting demand and security requirements [66]. To address these two problems, one has to estimate loadability of the transmission system under consideration.

Garver, et al., proposed in [60] a method to compute loadability of generation/transmission networks based on linear programming. The method presented in [64] takes stability limit into account through the use of energy function method. Recently, the relationship between voltage stability and loadability has been explored in [52, 65, 61]. Conceptually, estimating loadability of a generation/transmission system is a generalized mathematical programming problem. It is not a standard mathematical programming problem because some of the constraints (specifically, dynamic security constraints) have to be expressed not in algebraic forms but in the form of differential equations [55, 56].

Analytically, estimating the loadability of power systems is somewhat similar to the so-called generation rescheduling problem. However, there are a few important distinctions. First, computational effort of estimating loadability is several times more than that of generation rescheduling. Second, loadability of power systems is dependent upon the pattern of load increasing. In our previous results [56, 57], a general framework for generation rescheduling problems is proposed based on mathematical programming theory. In this paper, the iterative procedure proposed in [56, 57] is modified to estimate the loadability of power systems so that loadability of power systems is solved using the mathematical programming method. To reduce the computational effort, we propose to use the approach of pseudo-inverse based security analysis to deal with steady-state security, while dynamic security is checked by fast integration combined with automatic contingency selection. The method takes into account the effects of both steady-state and dynamic security. Simulation results of a 6-machine 22-node test power system are reported.

5.2 Mathematical Formulation

In this section, the problem of estimating loadability of transmission systems is formulated using the terminology of mathematical programming theory. We begin with two remarks pertaining to the new formulation. The first one is about an assumption on changes of active and reactive power. It is assumed that the changes of active and reactive power at each power station are proportional to each other in the proposed formulation. While this assumption is not necessarily required (as one may simply impose any other rule on changes of power generation), such an assumption is made for the ease of presentation. The second one is about numerical algorithm. Although the proposed formulation is given in the form of mathematical programming, typical algorithms such as simplex algorithm and steepest descent algorithm etc cannot be used to solve the problem. This is because the formulation, as will be discussed later, is much more complicated than conventional mathematical programming models. Consequently, heuristics-based algorithms will have to be developed to solve the formulation. Now we are in a position to present the formulation.

Objective:

$$\text{Max} \quad \alpha \tag{5.2.1}$$

subject to the following constraints:

$$P_i(V,\theta) + P_{mi} - \alpha P_{Li}^0 = 0, \quad i = 1, 2, ...NB, \tag{5.2.2}$$

$$Q_i(V,\theta) + \alpha Q_{mi}^0 - \alpha Q_{Li}^0 = 0, \quad i = 1, 2, ...NB, \tag{5.2.3}$$

$$\underline{P}_{mi} \leq P_{mi} \leq \bar{P}_{mi}, \quad i = 1, 2, \ldots, N_g, \tag{5.2.4}$$

$$-\bar{T}_i \leq T_i \leq \bar{T}_i, \quad i = 1, 2, \ldots, NL, \tag{5.2.5}$$

and

$$|\delta_i^l(t) - \delta_j^l(t)| \leq \delta^{lim}, \quad t = [0, t^{sp}], \quad i, j = 1, 2, \ldots, N_g, \quad l = 1, 2, \ldots, N_c. \tag{5.2.6}$$

In (5.2.1), α is the so-called loadability factor and is also the objective function of the programming problem. The controllable variables in the above formulation are α and P_{mi} (the latter denotes the mechanical power of ith generator). $P_i(\mathbf{V},\theta)$ and $Q_i(\mathbf{V},\theta)$ represent active and reactive power injections at the ith bus, respectively. These power injections, whose expressions are well-known, come from external network. Q_{mi}^o, P_{Li}^o and Q_{Li}^o refer to initial reactive power generation, initial active power load and reactive power load at the ith bus, respectively. $\underline{P}_{mi}$ and $\overline{P}_{mi}$ denote upper and lower limits of active power generation at the ith bus, respectively. T_i is the active power in the ith transmission line, and $\overline{T}_i$ denotes the thermal limit of active power of the ith transmission line. NB, NL and N_g represent the number of buses, the number of transmission lines and the number of generators, respectively.

Note that (5.2.2) up to (5.2.5) constitute *steady-state security constraints* which have been simplified to a certain extent. The effect of *dynamic security* is included as (5.2.6). Here, dynamic security refers to whether or not the power system under study is stable when it suffers from a major disturbance. In (5.2.6), $\delta_i^l(t)$ and $\delta_j^l(t)$ denote rotor angles of the ith and jth machines at time t under the lth contingency; respectively. δ^{lim} is the limit of maximum relative swing angle allowed (for instance, 180 degrees). N_C represents the number of specified contingencies under consideration. Machine angles δ_i and δ_j are the solutions to the following ordinary differential equations:

$$\begin{aligned} \frac{d\delta_i}{dt} &= \omega_i \\ M_i \frac{d\omega_i}{dt} &= P_{mi} - P_{gi} \quad i = 1, 2, \ldots, N_g, \end{aligned} \tag{5.2.7}$$

where ω_i represents rotor angular deviation, M_i is the inertial constant, and P_{gi} is the electrical power output of ith generator. Further explanation regarding (5.2.7) can be found in [63, 62].

It should be noted that, in the proposed formulation, dynamic security is explicitly considered through a robust procedure. Specifically, dynamic security is checked by the Rung-Kutta method which is most reliable at present. In addition, the programming problem given by (5.2.1) up to (5.2.7) is not solvable using any existing mathematical programming package because of the presence of constraints (5.2.6) and (5.2.7). To solve this programming problem, one has to rely on engineering judgment. In the following section, an algorithm based on such an approach is provided.

5.3 The Proposed Solution Procedure

An overview of the proposed solution procedure is given first, followed by its detailed descriptions.

5.3.1 Overview of the procedure

It is obvious that the mathematical programming formulation, given by (5.2.1) up to (5.2.6) formulation, has three major components: the loadability factor and P_{mi}, steady-state security constraints given by (5.2.2) up to (5.2.5), and dynamic security constraints given by (5.2.6). The proposed procedure explores the relationship among these three components.

The objective of maximizing loadability factor α and its corresponding active power generation distribution can be met by using an iterative algorithm. The proposed iteration scheme, illustrated by figure 5.1, consists of two layers. Numerically, it is a two-kernel procedure: The first is *security assessment procedure*, and the second is *generation adjustment procedure*. The first layer is the outer-loop iteration within which loadability factor α is increased each time by a small increment. This layer of iteration is always repeated unless the first kernel fails a number of times consecutively. The second layer is the inner-loop iteration within which distribution of active power generation is adjusted through the second kernel to meet the steady-state and dynamic security constraints specified by the first kernel. Overall, iteration is continued until no meaningful improvement on loadability factor can be achieved. By nature, computational effort of the problem is several times more than that of a generation rescheduling problem (for which *outer loop iteration* is not needed).

It is apparent that efficiency of the inner-loop iteration depends on the algorithm chosen for generation adjustment and that performance of the security assessment routine has major impacts on the overall computation time. Procedures used for security assessment and generation adjustment will be discussed in sections 5.3.2 and 5.3.3, respectively.

5.3.2 Security Assessment

In general, steady-state security assessment should include $(n-1)$ contingency analysis. In this paper, evaluation of steady-state security is simplified to be a standard load flow analysis which is familiar to power audience. Contingency analysis, if desired, can easily be incorporated into the proposed framework.

The algorithm used for dynamic security assessment is a step-by-step integration procedure. It fully exploits sparse matix/vector techniques and contains an automatic contingency selection approach developed previously by the authors. Details about the algorithm can be found in [58].

5.3.3 Adjustment of Generation

The algorithm used to adjust generation is a numerical implementation of the following steps:

Step 1 Classify and group the available generators in the system into three sets: those machines that are severely disturbed, machines that are slightly disturbed, and generators connected to a swing bus. Criteria for classification should be based on machine acceleration at the instant when a fault occurs and on machine kinetic energy at the instant that the fault is cleared.

Step 2 Re-dispatch active power generations of the machines according to the following guidelines. For severely disturbed generators, reduce their active power generations by a small percentage (say 5%). For slightly disturbed machines, do not change their generations. For swing machines, increase their active power generation to compensate for the total reduction of generation at disturbed generators. Let the active power generations of the ith machine before and after the adjustment be denoted by P_{mi} and P'_{mi} $(i = 1, 2, ..., N_g)$, respectively.

Step 3 Evaluate line flow using the linearized line flow equation

$$T'_l = T_l + \sum_{i=1}^{N_g} H_{li}(P'_{mi} - P_{mi}) \tag{5.3.1}$$

where T_l and T'_l are the line flows of the lth transmission line before and after re-dispatching active power generation, respectively. Weighting H_{li} is the so-called sensitivity factor [67], and it relates active power injection to the line flow.

Step 4 Check inequality (5.2.5) to see if thermal limit of transmission lines has been violated. If $|T'_l| < \overline{T}_l$ for all $l = 1, 2, ..., NL$, stop adjusting generation and go to step "Re-compute load flow" defined at the bottom of figure 5.1. Otherwise, proceed with Step 5.

Step 5 Rewrite the linearized load flow equation (5.3.1) as

$$\triangle T = H(P''_m - P'_m) \tag{5.3.2}$$

where vector $\triangle T$ consists of all the changes of transmission line active power flow as its components, elements of matrix H are H_{li}, $l = 1, 2, ..., NL, i = 1, 2, ..., N_g$, vector P'_m is of dimension N_g and its elements are P'_{mi}, and P''_m denotes the new active power generation vector to be decided.

Form vector $\triangle T$ of appropriate dimension by defining its elements as $\triangle T_k = T'_k - T_k$, where $k \in \psi$, and ψ is the set containing the number of transmission lines at which violations of thermal limit on line flow are observed in Steps 3 and 4. Note that $\triangle T$ is a "condensed" vector, and its dimension is denoted by N_T. In other words, the transmission lines without any line flow violation are excluded from $\triangle T$.

Step 6 Construct N_T—by—N_g matrix S whose elements on the lth row are H_{li}, $i = 1, 2, ..., N_g$. It follows from (5.3.2) that

$$P''_m = P'_m + S^T(S \cdot S^T)^{-1} \cdot \triangle T \tag{5.3.3}$$

where superscript ^{T} denotes transpose. Equation (5.3.3) is the so-called *pseudo-inverse based steady-state security control formulation* in [53, 54].

Step 7 Set $P_m = P''_m$ and go to the step "Re-compute load flow" defined at the bottom of figure 5.1.

The procedure of generation adjustment involves verification of both dynamic security and steady-state security. Specifically, the steady-state security control algorithm given in [53, 54] is extended so that, while steady-state security is studied in steps 3 up to 7 based on the extended version of pseudo-inverse method, dynamic security is verified in Steps 1 and 2 (based on heuristics). This extension makes it possible to handle steady-state and dynamic security in a unified way in the dispatch algorithm.

5.4 Simulation Results

The proposed formulation has been applied to the 6-machine, 22-node test power system defined by figure 5.2. Original data of this test system is available upon request. Note that machine 6 is not a generating unit but a var resource. Consequently, it is not considered in the process of generation adjustment.

In the simulation, the *specified limit* on iteration counter K in figure 5.1 is set to be 4. The initial active power generation and demand are listed in table 5.1. Note that the test system is secure both in the steady state and dynamically under this initial pattern of power injection. For briefness, detailed results of security assessment are not included here.

To test the proposed numerical procedure, loadability factor is increased in

Table 5.1: Initial Power Injection Mode of Test Power System

Location	Active Power Generation	Active Power Load
1	5.7000	
2	5.4990	
3	3.0000	
4	1.6000	
5	4.3000	
6	-0.0100	
8		2.8700
9		3.7600
16		5.0000
18		0.7190
19		2.2650
20		0.7000
21		0.8600
22		4.300

increments of 1%. Our simulation shows that the test system remains to be secure at values of $\alpha = 1.0$, 1.01, and 1.02. However, when loadability equals 1.03, the test system is only dynamically secure but not steady-state secure. Generation injections in this case are listed in table 5.2.

At this point, the proposed procedure invokes generation adjustment algorithm described in section 5.3.3. After three inner iterations, the test system is made to be both steady-state and dynamically secure. The active power generations after adjustment are listed in table 5.3, and some of the dynamic security assessment results are listed in table 5.4.

Table 5.2: Power Injection Mode of Test Power System when α Is Increased to 1.03

Location	Active Power Generation	Active Power Load
1	6.1454	
2	6.1766	
3	3.1929	
4	1.6475	
5	4.4271	
6	-0.0100	
8		2.9553
9		3.8709
16		5.1483
18		4.4275
19		0.8856
20		0.7406
21		0.7209
22		2.3316

Our simulation also shows that, if α is increased to 1.04, secure active power generation configuration cannot be found even after generation adjustment. Therefore, the numerical simulation suggests that the maximum loadability factor of the test system is between 1.03 and 1.04. Further study is needed to see if this result is conservative.

Table 5.3: Active Power Generation after Adjustment when α Equals to 1.03

Location	Active Power Generation
1	7.0600
2	5.5000
3	3.0000
4	2.0000
5	4.0000
6	-0.0100

Table 5.4: Dynamic Security Assessment Results of Test System when α Equals to 1.03

Contingency Location		Maximum Relative Swing Angle (degree)
8	22	64.2
9	22	64.6
11	12	163.8
12	11	172.0
13	12	72.0
18	16	60.8

5.5 Conclusions

The problem of calculating loadability of generation/transmission systems has gained renewed interests in recent years partly because deregulation of utility industry are being undertaken in many countries. Finding an exact solution to the problem is formidable due to the limitations of existing mathematical methodologies. In this paper, a new algorithm is proposed to estimate the maximum loadability factor of a power system, and it is evolved from those algorithms developed previously by the authors for generation rescheduling. A successful application would involve judicious engineering judgment. The unique features of the method are that both steady-state and dynamic security are taken into account and that dynamic security is analyzed using an integration algorithm (which makes the proposed method more robust). Despite of simplification is employed in computing load flow equations and dynamic security constraints, our simulation results suggest that the proposed algorithm is quite promising. Research is under way to loose the assumptions currently employed in the algorithm.

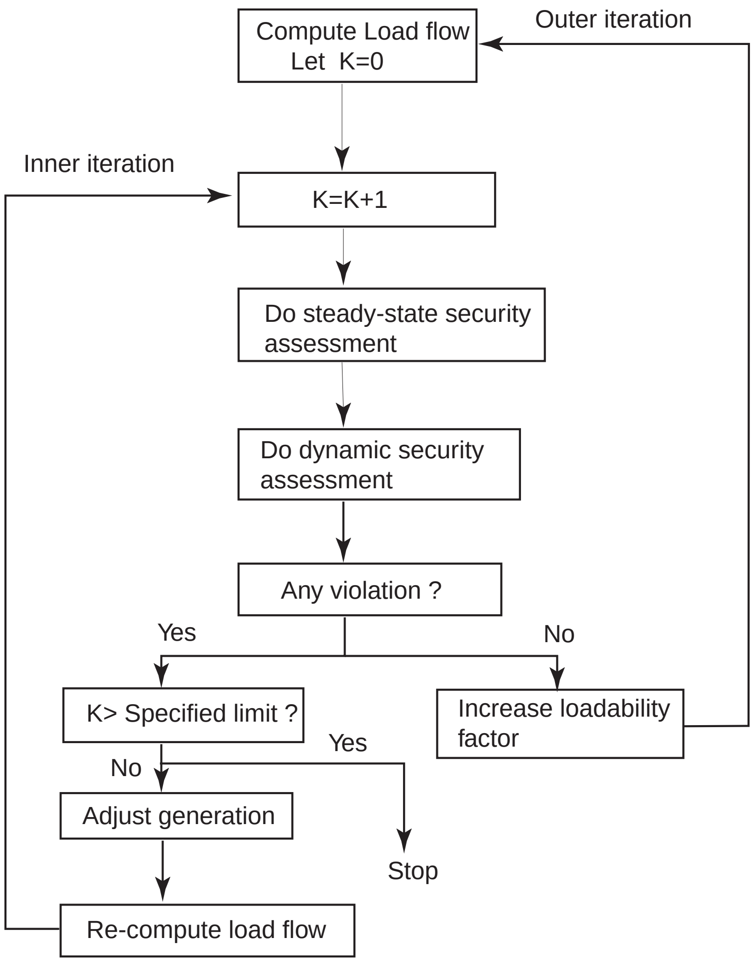

Figure 5.1: Flowchart of the solution procedure

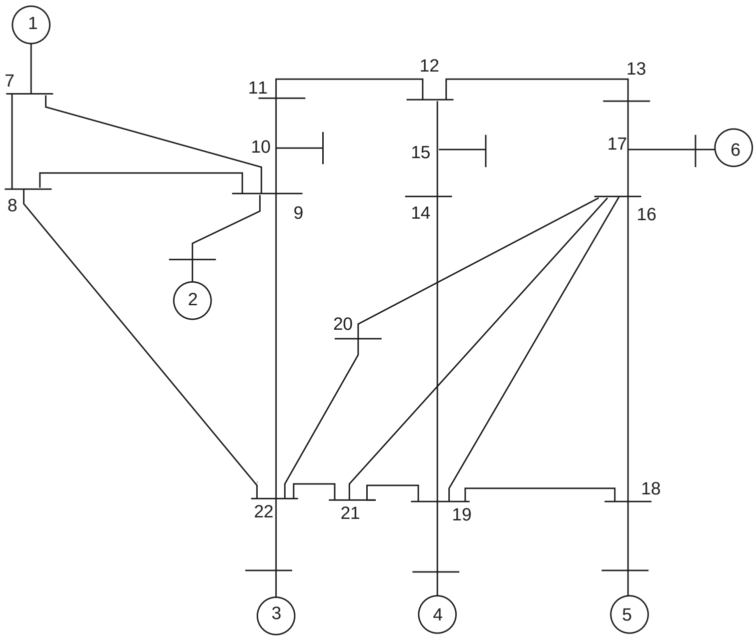

Figure 5.2: Single-line diagram of test power system

CHAPTER 6

CONCLUSIONS AND FUTURE RESEARCH EXTENSION

This dissertation presents research results in three areas in the power industry. All of them are of significant importance. First, optimal control strategies are developed for UPFC during the transient period following the clearance of a fault condition. The significance of this research is that the proposed control strategy drastically improved the transient response of the system. As a result, system stability margin is enlarged and system oscillation is minimized. Simulation results substantiated the above claims. Results also demonstrated the potential value of FACTs devices in influencing the system transient response, therefore, providing justification for the relative high cost of this kind of devices. Although, the analytical control law developed in this dissertation is obtained for a simplified version of the SMIB system, the insight obtained here is helpful in developing optimal control strategies for MMMB system. However, there are still many hurdles that must be overcome before any meaningful results can be obtained. Numerical approach might have to be used to get a solution. Since nearly all power systems in service today are MMMB system, the development of control strategy for MMMB system is of tremendous practical importance.

Second, a new power market structure is proposed. The significance of this research is that it provides a scheme that could dramatically reduce the power market operation cost, and improve the market efficiency, meanwhile the welfare of society is guaranteed. The proposed market structure eliminates the need for iterative bidding, and the settled solution is optimal in the sense that it is the best solution possible had the iterative bidding process really taken place. The solution in the research is obtained without considering system physical conditions, such as system stability margin, overheating of transmission lines, and so on. One step further along this line of research is to include all these concerns in the problem formulation. A solution to such a problem will eventually give a more comprehensive result to the market situation in question.

Third, a scheme is developed to solve the load flow problem such that loadability factor for the system can be maximized. Following the deregulation of the power industry, greater flexibility of the transmission system is demanded to satisfy the ever-changing market situation. A load flow solution that leaves the biggest room to accommodate market changes is very appealing to the market operators. Simulation results show that the proposed scheme works well for a realistic power system.

In summary, the research topics pursued in this dissertation are of practical importance to the operation of modern power system. The results obtained are satisfactory, and simulation results substantiated the validity of those results. Future extensions to the research topics are challenging tasks, and will eventually bring them closer to practical application in the industry.

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