Power Systems Engineering Research Center

Modeling Market Signals for Transmission Adequacy Issues: Valuation of Transmission Facilities and Load Participation Contracts in Restructured Electric Power Systems

Final Project Report

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Power Systems Engineering Research Center

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Executive Summary

Market-driven merchant transmission investments are contemplated as viable alternatives to regulatory-planning based investments. Two components are essential for inducing new transmission investments through market forces. First, price signals are needed to signify efficient investments, specifically, to help with the decisions on where and how much to invest. Second, proper (ownership and service) rights need to be introduced and awarded to investors as returns for recovering their capital and operating costs and creating the financial incentives. This project tackles several issues central to the two components: modeling market signals for inducing transmission-adequacy-driven investments and investigating market-based mechanisms for compensating such investments. Research findings are summarized in three areas.

I. Modeling market signals for valuing financial transmission rights and transmission facilities

First, the incentives and obstacles associated with existing mechanisms for allocating transmission costs and compensating transmission investments are documented. Then, the modeling of market signals through integrating fundamental power system simulation models with reduced-form stochastic electricity price models is carried out under a Locational Marginal Price (LMP)-based market structure. Specifically, to establish reduced-form stochastic models for electricity market price signals reflecting transmission adequacy requirements, a fundamental power system simulation framework is adopted which incorporates transmission network operational constraints, supply/demand fluctuations, power system contingencies, and system reliability requirements. Market prices obtained through the power system simulation models are used to calibrate a specific class of reduced-form stochastic electricity price models, which are termed as quantile-based GARCH models.

Under this framework, market price behaviors resulting from the DC and AC power flow based market dispatch models are studied through computational experiments with the IEEE Reliability Test Systems. Although the expected values of the simulated LMPs in the DC dispatch models approximate those in the AC models well during the off-peak hours, clear differences are documented during the on-peak hours. Such differences in the price behavior result in significant discrepancies in valuing market instruments (e.g., Financial Transmission Rights (FTRs) and FTR options) under extreme system conditions such as facility outages and load spikes. More importantly, it is found that the market risks faced by market participants (for instance, taking the risk measure to be the volatilities of LMP, FTR value, suppliers' revenue, and consumers' payment) can all be significantly underestimated in a case where the power market operations are subject to AC-flow based transmission and security constraints but modeled by a DC-flow based approximation. The sensitivity of model parameters to system conditions is investigated and qualitative relationships between model parameters and system reliability requirements are established.

II. Valuation of FTRs and interruptible loads as well as its implication on merchant transmission investments

Heuristic methods for identifying incremental FTRs resulting from typical network-deepening or network-expanding transmission investment projects are illustrated. Economic incentives for transmission investment based on financial transmission rights are evaluated through stochastic electricity price models calibrated to the proposed fundamental power system simulation model. Extensive numerical experiments on valuing financial transmission rights and interruptible load contracts subject to congestion and system reliability requirements are carried out in IEEE RTS networks. The computational analysis shows that the system reliability constraints can yield large price differentials among network nodes thus making those FTRs and interruptible load contracts located at certain nodes highly valuable. Thus the constraint-relieving transmission investments or interruptible loads may be properly compensated by market-based compensation mechanisms, such as the one rewarding investors with incremental FTRs as tradable instruments for recovering sunk capital costs and hedging market risks.

III. Forward markets and implications for merchant transmission investments

This project also develops a model of spot price behavior that allows for stochastic regime switching from a low-price to a high-price regime. This is an alternative to the quantile-based price model which leads to another reduced-form analytical framework for evaluating investment decisions. An important feature of this model allows factors such as the system load to affect the frequency of price spikes in the market, and as a result, the type of financial risk faced by participants in the market can be interpreted and evaluated. The effects of this spot price model on the electricity forward prices that provide the financial incentives for investment decisions are also investigated.

A fundamental complication for electricity is that congestion on the transmission system makes it infeasible to rely on a single market for one location as the primary source of price discovery for all locations. Consequently, trading some set of prices for different locations will be needed, but the number of locations must be small to ensure that there is enough liquidity in the market for reliable price discovery. An analytical framework is developed for evaluating the ability of three existing types of forward market in New York State to meet the financial needs of potential investors. It analyzes the premium that must be paid, in addition to having a forward contract to sell electricity, to get investors to build new peaking capacity, which can be extended to analyze the incentives for building new transmission capacity as well.

Potential uses

In conjunction with the stochastic electricity price models, the proposed power system simulation framework offers an important tool for modeling market signals and evaluating transmission and generation investments. For instance, this tool can be used by power merchants to evaluate opportunities in merchant transmission investments; by utility companies to value interruptible load contracts in light of meeting their generation adequacy requirements, and by system operators/regulators to examine how effective alternative incentive mechanisms are in inducing new investments for meeting transmission adequacy criterions. The stochastic-market-model component of our framework can be commercialized into a module which is to be integrated into existing commercial software packages for simulating power systems and market operations so as to make them capable of analyzing transmission adequacy issues.

Future work

Future research topics include applying the developed analytical framework for estimation of justifiable premiums paid above standard electricity forward prices to bring new generating capacity into the market, identification of price distortion, coordination of generation and transmission investments, and strategic interactions between transmission investors.

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1. Introduction

For decades, the electric power industry had been operating under the regime of regulated natural monopoly due to the extensive capital requirements for new entrants and the economy of scale in operations. While the evidence on the economic inefficiency of the regulated regime was mounting, rapid technology advancement made it viable to introduce competitions into the electricity supply industry. The deregulation in the U.S. was put forth by the Federal Energy Regulatory Commission (FERC) Orders No.888 and No.889 issued in 1996. The two orders aimed at ensuring open access to the transmission network and initiating structural changes in the generation, transmission and distribution sectors. The restructured business environment consists of primary wholesale markets for bulk energy trading, open transmission systems for physical electricity delivery, and ancillary service markets for reliable and secure operations of the power system. In summary, electric power systems are unbundled into horizontally separated segments of generation, transmission, and distribution to facilitate competition. It is expected that properly designed market mechanisms would drive economically efficient system operations and long-term capacity investments through price signals and economic incentives.

The on-going restructuring process of the electricity industry with a dynamic market environment and evolving regulatory rules has drastically affected the transmission network planning process. From the very beginning of the restructuring, a significant amount of attentions are attracted to the generation sector as the regulatory orders mandate large utility companies to divest their generation assets. This leads to substantial developments in valuation models for generating assets and a vast amount of experiences gained through the asset divesture process. In contrast, as for the transmission sector, while it is obvious that a highly reliable transmission system is a necessity for a workable power market, two important issues have not been adequately addressed. One is how well a market mechanism would work for charging transmission usage and efficiently utilizing a transmission network. The other one is whether there would exist a market mechanism based on existing electricity market signals that could induce efficient transmission investments for seeking merchandizing surplus or maintaining the bulk power system reliability. The lack of incentive in investing in new transmission facilities and the absence of effective cost recovery mechanisms for transmission investments has caused the serious problem of transmission inadequacy, especially in this market environment where generators respond to market opportunities by transferring larger quantity of power over longer distances more frequently. Statistics show a clear and increasing lag between new investments in transmission projects and generation developments in recent years. The inconsistency in transmission and generation investments as well as the mounting problems caused by the tight transmission capacity put the transmission adequacy issues under the center of attention and call for the creation of investment incentives and effective cost recovery mechanisms to alleviate the barely adequate transmission capacity conditions.

The introduction of the independent system operator of the transmission system, as has been implemented presently and for the foreseeable future, does not seem to provide enough incentives for efficient capacity expansion and maintenance for reliability of the transmission network. The central problems are the proper definition of market signals and the accurate valuation of transmission rights and facilities, which allow compensations for reliability enhancement and risk minimization of the system operations.

The electricity spot pricing scheme, as initially proposed by Schweppe et al (1980, 1985, 1988), Caramanis et al (1982), and Bohn et al (1984), and later extended with the introduction of financial transmission rights (FTRs) for transmission congestion hedging as illustrated by Hogan (1992), provides an economic basis for market transaction settlements and establishes a platform for revealing market signals for generation resource allocation and transmission capacity investment. Spot pricing is a natural extension of the classical market equilibrium theory. A central market agent (the power system operator) collects bids from market participants and, under the assumption that the submitted bids reflect marginal production costs and marginal consumption benefits, determines winning bids by solving an optimal power flow (OPF) problem and obtains the market-clearing locational marginal prices (LMPs) to settle electricity transactions. To hedge against LMP fluctuations induced by tight transmission capacity and provide cost certainty for transmission customers who pay for open access transmission services, FTRs are structured to entitle (and obligate) their holders (possibly negative) transmission revenues associated with specific congestions, which offset their congestion charges involved. FTRs can be allocated through auctions and bilateral transactions to market participants who value them the most. Based on the entitlement of potential revenues, FTRs are proposed as the property rights to be awarded to merchant transmission investors for capital recovery. Values of transmission rights should carry correct market signals to prompt demand responsiveness and to induce capital investments in generation and transmission sectors. It is crucial to understand the magnitude of the volatility of transmission prices under different market structures and how the volatility is affected by system reliability constraints. Financial Transmission Right (FTR) and Flow-Gate Right (FGR) are two common ways to define the value of transmission capacity of an electric power network.

Transmission adequacy criteria vary among utilities, even in the previously regulated era. Deregulation provides new challenges to define transmission adequacy criteria. There are also debates on the relationship between the short-term market signals, which are primarily responsible for promoting short-run efficient utilization of the scarce transmission capacity, and the long-term economic incentives for rewarding investment in transmission assets. Proper measurement benchmarks for transmission adequacy and control mechanisms for power system reliable operations are crucial to the viability of competitive markets in power generation. As the process continues to evolve, power grid operators (or regional transmission operators) and market participants all need accurate market signals to evaluate transmission adequacy and transmission capacity investments. The shortcomings of the ancillary services markets primarily (and to some extent reserve markets) in California, New England and New York have renewed the interests in the idea of “load as a resource” since the lack of demand side participation is viewed as one of the key attributes causing the market failures. On this aspect, proper market signals also enable system operators to design load contracts to induce active load participation to mitigate transmission congestion, which can play a significant role not only in substituting generation but also in mitigating transmission congestion.

This report identifies incentives and obstacles for transmission investments from various perspectives. By studying the central problems of modeling market signals for valuing and allocating transmission rights, this research investigates market mechanisms for compensating economically efficient transmission investment and system reliability enhancement as well as mitigating transmission risks. The proposed system simulation framework combined with the stochastic market price model provides a powerful tool for modeling the dynamic market signals and evaluating transmission investments. Numerical studies are carried out with the IEEE RTS24 system. The market signals for transmission investment are investigated under a specific pool-type market design. Under the pool market rules, while the fundamental system simulation approach provides (a.k.a. fundamental approach) more realistic modeling details under all system operating scenarios, it is computationally prohibitive due to the large number of scenarios that need to be considered. We combine the strengths of the fundamental approach and the technical reduced-form stochastic modeling approach. Using the market prices at all buses simulated from the fundamental power system model, we calibrate the stochastic spot price models to obtain reduced-form representations of the electricity market signals. This project focuses on integrating the fundamental approach with stochastic market price models for tackling issues such as evaluating transmission adequacy and valuing transmission rights/facilities utilizing simulation models of an underlying power system. In conjunction with the stochastic market models, the system simulation framework offers an important tool for modeling market signals and evaluating transmission investments. For instance, this tool can be used to examine how effective alternative incentive mechanisms are in inducing new investments for meeting transmission adequacy criterions. The stochastic-market-model component of our framework can be potentially commercialized into a module. It then can be integrated into existing commercial software packages, which simulate power systems and market operations, to make them capable of addressing transmission adequacy issues.

2. Transmission Inadequacy

The electricity supply industries in the U.S. were traditionally operated by vertically-integrated monopolies due to the facts that investments were capital-intensive and operations enjoyed economy of scale. Consequently, the electricity industries adopted cost of service regulation (COSR) for the monopolies to achieve a pre-approved rate of return. Although this structure achieved a balance in developments of generation and transmission as well as other operational aspects, COSR resulted in retarded innovation, obscure cost-reduction incentive, and improper decision on risk allocation. The mounting evidence on the flaws of the monopolistic industry structure led regulators to gradually introduce competition into the industry. The enactment of the Public Utility Regulatory Policies act (PURPA) in 1978 encouraged non-utility generation owners to supply power to the existing utilities. The movement toward more competitive wholesale electric power trading was accelerated by FERC’s Energy Policy Act (EPAct) of 1992, which opened the door of the previously monopoly franchised generation market to independent power producers (IPPs). The FERC Orders 888 and 889 in 1996 represent another major milestone by requiring non-discriminatory access to the transmission network. The open access to transmission network and the electricity wholesale market regardless of ownership of the generation unit triggered another building boom of power plants. Moreover, the frequent price spikes and extreme volatility in the late 1990s created profit and risk hedging incentives for independent and utility-associated power marketers to participate in generation development actively. Additional state and federal regulatory policies promoted the formation of independent system operators (ISOs), and, in some cases, the divestiture of generation assets. ISOs, where they were formed, separated operational control from ownership of the transmission and generation assets to increase efficiency and inhibit detrimental activities from conflicting interests. FERC’s Order 2000 continued this trend by promoting the voluntary formation of regional transmission organizations (RTOs) and transmission pricing reform.

Regulatory changes in the transmission system were accompanied by nationwide demand increases at an annual rate of 2-3% and substantial changes in the generation sector. New generation technologies, particularly gas-fired combined-cycle turbines, allowed electricity to be produced in more modular and flexible quantities with higher efficiency. A building boom ensued added over 200GW of new generation between the years of 1999 and 2004 (NERC 2004). In many cases, these units were located in convenience of construction or fuel resource accesses while taking adequate transmission connection capacity for granted. With the building boom reaching its end and the evolution to competitive markets well advanced, the transmission system is becoming increasingly vital. The importance of its new role of supporting market transactions is far beyond what is indicated by the relatively small capital cost it represents in the electric power industry.

Compared with the steady increase of demand and generation, however, transmission investment declined over the same time period. According to Hirst (2004), in 1972 approximately 30 GW generation was added and supported by $7.4 billion (in year 2004 dollars) in transmission investment. In 2001, 40.6 GW generation was added with only $4.6 billion in transmission. By year 2003, the numbers further diverged to having 52.4 GW of new generation versus $3.9 billion invested in transmission. Normalized transmission capacity measured in MW miles transmission facility per MW demand (or MW transmission facility per MW demand) declined at an annual rate of 1.5% (or 1.6%). The market environment strains the system further because merchant power plants competing for short and long-term contracts with multiple buyers are encouraged to transfer larger quantities of electricity over longer distance more frequently in capture interregional market opportunities, raising power flow patterns significantly different from the projected scenarios in system planning. Statistics by NERC on the number exercises of level 2 or higher transmission loading relief (TLR) from July 1997 to December 2005 as shown in Figure 2.1 illustrates the increasing frequency of transmission system challenges in recent years. Note that load seasonality is the primary factor for the TLR log fluctuations within a year.

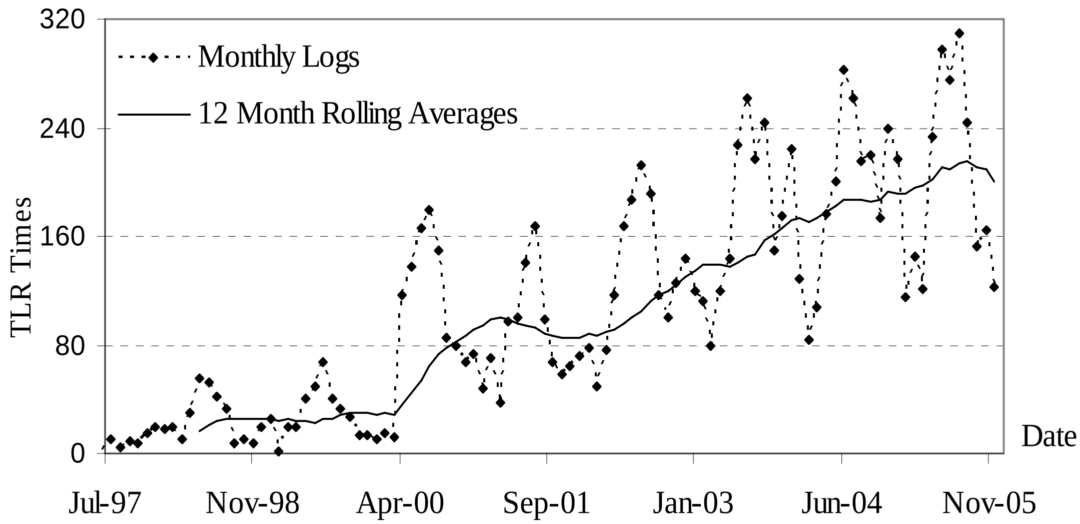

Figure 2.1 Statistics of level 2+ TLR from July 1997 to December 2005

It has been recognized that the lack of widely accepted regulatory rules and the absence of effective market mechanisms lead to vague signals for potential transmission investments by market participants. The identification of transmission investment incentives and obstacles in a market environment are essential for understanding and solving this problem. Traditionally, transmission investments are intended for enabling the delivery of low-cost power to consumers and enhancing system reliability. As the industry restructuring proceeds, a multitude of incentives for transmission investments can be identified.

1. **Economic efficiency**: transmission accesses to alternative power sources provide additional options to meet consumption at the lowest possible social cost.

2. **System reliability**: higher transmission reliability margin and diversified fuel accesses improve interconnection certainty by accommodating more fluctuating transactions, facility unavailability, and sudden disturbances.

3. **Financial stability**: transmission upgrades reduce system congestion and alleviate market participants' risk-hedging pressure incurred by volatile market prices.

4. **Market power mitigation**: electricity market is vulnerable to the exercising of market power which intentionally creates scarcity and manipulates prices. Market power can be mitigated by proper transmission expansions which facilitate competitions in generation.

5. **Environmental impact**: although people are concerned of transmission facilities' right-of-ways, given the more severe environmental impact of power plants, especially in highly populated regions, transmission connection to remote generation sources may provide a more environmentally sound alternative to meet demand (see Bloyd et al, 2002).

In spite of the benefits listed above, potential transmission investors face the following obstacles resulting from organization structure, physical nature, or economical characteristics that complicate the recovery of capital investments.

1. **Free riding**: as a public good with non-excludable benefit sharing, typical transmission investments are haunted with the free-riding problem due to the difficulty of isolating the benefits to the investor. Market participants would choose to be free riders expecting positive externalities induced by others' investments.

2. **Lumpiness**: transmission investments typically appear as addition of large blocks of capacity. The obscured linkage between expected benefit and marginal cost complicates the investment decisions.

3. **Market risks**: given the ever-changing electricity demands, generation portfolio, network topology, and market rules, it is impossible to predict with accuracy the future economic payoffs accruing from a transmission investment.

4. **Regulatory risk**: one key element for success of a transmission project is regulatory approval. In many cases, however, alignment of federal, state, and local regulations results in project delays and rejection is a very real possibility. Consequently, funds expended early in the project may be at substantial risk.

The obstacles listed above are confounded by fragmented ownership that easily leads to sub-optimal solutions. This chapter investigates the market-based incenting mechanisms to encourage transmission investments for economic efficiency, reliability enhancement, and market risk hedging while avoiding obstacles listed above such as the free riding problem.

A sound transmission network, with efficient incentive mechanisms to maintain and invest in capacity, is essential to the overall success of restructuring of the electric power industry. Transmission system operation is far more important compared with the relatively small percentage of the capital cost it represents (less than 10% (ABB, 2001)) in the industry. It is also far more important under the competitive environment than under traditional regulation regime because it needs to support a much larger range of transactions.

A transmission investment could be an independent expansion of the network, (that is, construction of separate new transmission facilities that are not physically intertwined with the incumbent network), or, could be network deepening investment (Joskow and Tirole, 2004), which involves physical upgrades of the facilities on the existing network without requiring extra right-of-way. These upgrades include replacing the existing cables with higher current-carry capability, installing static VAR compensators to provide dynamic reactive support, inserting series compensation to reduce the apparent impedance of long lines, and increasing transmission capacity by installing advanced control schemes such as power system stabilizers or inter-tripping schemes.

3. Transmission Pricing and Congestion Management

The inherent physical natures of electricity determine the unique characteristics of the evolving electricity market and impose unprecedented complexities for its management. First, the fact that electricity travels at close to the speed of light and is not economically storable in bulk requires the instantaneous balance between generation and load plus losses. Deprived of the buffering benefit of holding inventory, electricity markets are subject to temporary demand-supply imbalance which results in volatile locational marginal prices (LMPs). Second, without the widespread use of expensive control devices over the transmission network, electricity flows in accordance with the physical Ohm's and Kirchoff's Laws instead of on any contracted path. As a consequence, it impedes the free movement of electricity as envisioned by economics theory and physically connects the transactions delivered at various locations within the system. Third, various restrictions such as equipment capacities, voltage bounds, frequency requirements, and stability concerns should be adhered to for continuous production and delivery of electricity. Consequently, marginal generation cost, congestion rent, reliability and security cost altogether measure the market value of generation and demand, which further diversifies the LMPs. Generally, the dynamics of LMPs are in line with the ever-changing system conditions and reveal market opportunities accordingly. LMPs provide the basis for a market mechanism to guide the allocation of scarce generation resources and addition of new capacities. The same argument leads to the research work on evaluating financial transmission rights (FTRs), whose values reflect the transmission service conditions and can potentially offer market-based incentives for capital investment in the transmission sector. Similar to LMPs in the energy market and FTRs in the transmission right market, values of operating reserve services should be discovered accordingly to guide transactions in the ancillary service markets as well. Due to the physical constraints of electricity listed above and the embedded uncertainties of a competitive market, market dynamics cannot be foreseen before the market clears.

Electricity spot prices show strong mean-reversion phenomenon (namely, the prices tend to revert to a long-term mean level as time progresses). Mean-reversion is a common feature that can be found in the prices of many traded commodities. The reason for electricity price to exhibit mean-reversion is that when the price of electricity is high (e.g. higher than its long-run mean level), electricity supply tends to increase thus putting a downwards pressure on the price; when the spot price is low, the electricity supply tends to decrease thus providing an upwards lift to the price. Another salient feature in electricity spot prices is the presence of price jumps and spikes. Such jumpy behavior in electricity spot prices is mainly attributed to the fact that a typical regional aggregate electricity supply curve almost always has a kink at certain capacity level and the curve has a steep upward slope beyond that capacity level. Jumps and spikes resulting from limited amount of installed supply capacity coupled with low demand elasticity exacerbate the price volatility of electricity. Electricity prices also demonstrate stochastic volatility and regime-switching in some markets. Since the temperature is one of the dominating factors which influence the aggregate load level, the randomness in temperature implies that the volatility of spot prices can be a random factor. In markets where the majority of installed supply capacity is hydropower, such as the Nord Pool and the Victoria Pool, electricity spot prices exhibit regime-switching, namely, the prices alternate between high and low regimes corresponding to the respective low and high precipitation levels.

3.1. Transmission Pricing

For physically connecting geographically dispersed regions and transporting energy among them, a transmission network is critical. It enables electric power system functions and materializes the benefit of competitiveness and the economy of scale in the generation sector. In a competitive market environment, the transmission sector assumes a new role of supporting market trading. To ensure necessary maintenance and expansion in transmission facilities for maintaining system reliability and security, all transmission investments should be correctly valued and adequately compensated. The central problem involved is the market values of transmission capacities and effective pricing mechanism of transmission services. Transmission pricing mechanisms are designed for transmission cost recovery, which consists of initial capital investment and running operation and maintenance costs incurred. The challenging task of choosing a pricing methodology is determined by technical, economic and political factors. As the restructuring of power industry and the probing for effective market mechanisms continue, various methods have been proposed. The embedded cost and the marginal cost based methods are two most notable ones.

3.1.1 Embedded Cost Method

The embedded cost methods allocate the capital costs and the annual maintenance and operation costs of existing facilities to particular transmission service customers. Various forms of embedded cost have been proposed.

1. The **rolled-in-embedded method** assumes that the entire transmission system is used irrespective of the actual facilities that carry the transmission service. It is a straightforward MW and duration based charge. The use-of-transmission-system charges determined are independent of the transferring distance, source/sink points and the power flow distribution on different circuits caused by the transaction. It is also called the postage stamp method
2. The **contract path method** is based upon the assumption that the transmission flow is confined to a specified electrically continuous path. The resulting flow changes on facilities not along the fictional path are ignored. The recovery of costs is thus limited to those facilities along this assumed path
3. The **boundary flow method** takes into account the changes in MW boundary flows of the transmission system due to an underlying transaction, either on a power line flow basis or on a net interchange basis. Two power-flows with and without the transaction are calculated and compared to yield the changes involved
4. The **line-by-line method** is also known as the MW-mile method. It differs from the boundary flow method in that it considers the transferring mileage on each line as well. The MW flow on each transmission line is multiplied by the transferring mileage and summed up to measure the usage of the network in MW-miles. Transmission charges are allocated to different transactions in proportion to the usage of the grid.

In summary, the embedded cost methods are based on approximated power flow patterns that do not reflect actual system dispatching and do not follow the ever-changing system conditions. Because Kirchoff’s Laws, instead of economic expectations, govern the flow of electricity, the usage of the transmission network is difficult to trace as simplified in methods listed above. Transmission congestion costs and system externalities are not fully reflected in individual prices but spread over all network users.

3.1.2 Marginal Cost Method

In contrast, the marginal cost method measures market value of delivering an additional unit of electric power from the source to the sink bus. It is an extension of electricity locational pricing theory. In addition to defining the market-clearing electricity price at each location, locational prices provide an immediate answer to the otherwise intractable market-clearing value of transmission facility usages. Transferring of power between two locations is physically equivalent to sale (inject) at the source and purchase (withdrawal) at the destination. Therefore, the price of transmission should just be the difference between the locational prices of energy. When the system is constrained, marginal cost pricing reflect the opportunity cost of the constraints and provides the economic incentives that promote the allocation of the limited transmission capacity to the most cost-effective users.

The marginal cost method is an extension of electricity spot-pricing theory, which measures the change in costs due to an infinitesimal change in load. The spot prices are made up of components including marginal generating costs, losses, quality of generation supply, and quality of network service, etc. The marginal transmission price between two nodes equals the difference between the two electricity spot prices. It is a measure of how much it costs the transmission grid to deliver an additional unit of electric power.

3.1.3 Efficient Transmission Pricing for Congestion Managing

In the market environment, an efficient transmission pricing mechanism should promote access to all potential users. It should establish mechanisms that allow for recovery of fixed and variable costs, eliminate the pan-caking of rates, assign cost responsibility following cost causation consistent with the system usage, minimize cost shifting, provide adequate opportunity to attract capital investment, compensate for business risk, and promote service reliability and economic efficiency.

The embedded cost methods are based on assumptions of approximated power flow patterns that do not reflect actual system dispatching and do not follow the ever-changing system conditions. Transmission congestion and system externalities are not fully reflected in individual prices but spread over all network users. In comparison, the marginal cost based transmission pricing is primarily a cost recovering mechanism based on marker values of the transmission facilities.

The embedded cost method can be adopted prudentially to design a reasonable transmission tariff charge mechanism. And the marginal cost methods can be relied to calculate the spot prices changing over locations and over time. Locational marginal price (LMP) can be determined through a bid based, security constrained market-dispatch, which is in general a complicated non-linear and typically non-convex problem. The system operator dispatches the supply in the order of offered price, lowest to highest, based on the locational price-demand functions at the consumption nodes. When congestion occurs, lower-cost supply must be passed over for higher-cost supply, and different LMPs are generated. The difference between LMPs at any two nodes gives the cost of transmission between the two nodes.

3.2. Transmission Rights

The extraordinary price volatility creates strong demands for trading instruments with underlying related to transmission risks among risk-averse buyers and sellers of electricity for purposes of hedging market price and transmission risks. The transmission rights came up in response to such demands. A properly designed transmission-pricing scheme combined with well-defined transmission rights, if traded liquidly and competitively, can contribute to risk mitigation, reveal fair valuation of transmission facilities, and yield transmission investment incentives for power market participants. A transmission right can be defined as the priority to access to the underlying transmission facility or financial entitlement associated with the underlying capacity. Physical Transmission Rights (PTRs) and financial transmission rights are proposed correspondingly.

3.2.1 Physical Transmission Rights

The concept of Transmission Right (PTR) was proposed at the beginning of the restructuring, which was intended to realize decentralized congestion management by allocating the capacity of congestion-prone transmission interfaces to market participants. The physical capacity of each of the potentially congested interfaces is identified. Rights to use this capacity are defined, quantified, and allocated to suppliers and consumers. Power transfers over the congested interfaces are limited to those who possess the corresponding PTRs thus paying no transmission charge except for the acquisition cost of PTRs. However, the PTR mechanism makes the system operator’s role more passive. To a great extent, the allocation of PTRs through bilateral contracts or private auction markets determines the usage of scarce transmission capacity and determines the system dispatch as well. Some major potential problems with PTRs have been identified. The right of PTR holders to withhold access would contribute to market power that harms competition. In a design built on the centerpiece of a coordinated spot market, physical transmission rights with the associated scheduling priority would create perverse incentives and conflicts with priorities defined by the bids selecting mechanism employed in a security-constrained economic dispatch. What is more, if the system operator is excluded from accessing and controlling the withheld transmission capacity, the reliability and security of the system might be compromised. It has been argued that the physical interpretation of transmission rights was the principal complaint that buried the FERC’s original capacity reservation tariff. The attempt to match a large number of transaction schedules to a set of transmission rights creates a burden that hampers the trading flexibility needed to support a market and compromises the operating flexibility needed to maintain reliability.

3.2.2 Financial Transmission Rights

The financial transmission right mechanism is proposed for a centralized market dispatch paradigm. It separates the physical use priority of the transmission network from the ownership of the transmission rights but specifies financial entitlements that are connected to the congestion rents that the ISO collects in the presence of transmission congestion. The market-clearing prices determined through market dispatch determine the payments to FTR holders.

The definition of transmission rights depends on how transmission capacity is specified and measured: power flow carrying capacity for each link of the network, or the point-to-point power transfer capabilities. While point-to-point financial transmission rights (short as FTRs to distinguish from FGRs) are defined based on the power injection point to withdrawal point transfer capability, flowgate rights (FGRs) are structured on the basis of the link-based capacity measure. A flowgate can be a line, a transformer, or a set of lines and transformers with a certain capacity limit (Alvarado, 2003). The FTR mechanism has been adopted in the PJM interconnection since 1998, in New York since 1999, and in New England since 2003, while FGR approach was established in Texas system in February 2002. PJM has created FTR options, while similar evaluation is under investigation in New York and New England markets. Bushnell and Stoft (1996) show that under certain rules the transmission rights provide correct incentives for transmission investment.

A FGR represents a right to collect congestion rent by a portion of the capacity over a particular transmission flow-gate in a specified direction at a rate of the marginal values of capacity on the underlying flowgates at the time of congestion, i.e., shadow price of the underlying flowgate resulting from market dispatch. The theoretical basis is to associate congestion costs with the flowgates along the power flows. It assumes that a power transfer distribution factor (PTDF) matrix is ready to decompose a transaction into parallel power flows over a certain number of commercially significant flowgates (CSFs). A comparison of FGRs and FTRs is referred to (Chao, 2000) and the merits of the FGR mechanism are identified as: a flowgate's capacity is constant independent of power flows; only congested links require financial settlement; a portfolio of FGRs can replicate an FTR but not the other way around in general; it is a natural option-type market instrument with non-negative value presents bounded downside risk.

As implied above, the FGR approach simplifies the practices by focusing on transmission capacity limits only assuming a constant PTDF's structure. Particularly noteworthy, as it is consistently under-appreciated and recognized as the Achilles heel of FGR approach (Ruff, 2000), the system operations are constrained not only by the actual power flows but also by the projected power flows that would appear under postulated contingencies. One solution proposed is to introduce state-contingent FGRs. However, the nature of the problem suggests that each pair of flowgate and contingency should be treated separately with its own state-contingent FGR, transmission capacities, and PTDF matrix. A large number of FGR portfolios should be assembled to hedge embedded congestion risk of a transaction. The deep complexity and illiquidity would result so the applicability is doubted.

In contrast, the FTR approach is based on the application of an LMP pricing mechanism which incorporates the full set of normal and contingency constraints. An FTR entitles (or obligates) its holder the right to collect revenue at the difference of LMPs times the contractual volume specified ex ante. Therefore, an FTR provides a perfect hedge for a point-to-point power transaction against any set of binding constraints including postulated contingency events. Besides, defined as an obligation, an FTR between any two non-hub buses (e.g., from Bus A to Bus B) can be decomposed into two hub-involved FTRs. The unit payoff function of the FTR from bus A to bus B is $P_B - P_A = (P_B - P_{Hub}) + (P_{Hub} - P_A)$, where P_A, P_B, and P_{Hub} denote the LMPs at buses A, B, and the hub, respectively. FTR mechanism's support of the hub-and-spoke trading model provides the trading flexibility envisioned. However, a prudent market participant should be aware of the hidden problems with the FTR mechanism as well. Although FTRs are perfect for congestion hedging, the trading risks cannot be eliminated all at once. The holding volume of an FTR is based on the projected power transaction, which is contingent on the actual system conditions. Besides, the liquidity and price certainty of FTRs are questionable. Furthermore, extra strategic behaviors on FTRs may exist for the money streams represented.

In the presence of transmission losses and congestion, the LMB-based revenues collected from energy consumers would be greater than the payments to suppliers. The net revenue is referred to as the merchandising surplus or congestion rent. More precisely, under the framework of bid-based, security-constrained economic dispatch, the net revenue difference is simply the infra-marginal rent on losses and transmission constraints. If the system operator, as an authorized monopoly, keeps the congestion revenue, incentives arise to manipulate dispatch and prevent grid expansion to generate even greater congestion rentals, this incentive would work contrary to the goal of an efficient, competitive electricity market. A convenient solution to both problems – hedging against congestion and removing the adverse incentive for the system operator – is to redistribute the congestion rent through FTRs operating in parallel with the energy transactions.

Although LMPs provide short-term congestion signals only, the financial transmission rights translate LMPs into long-term investment signals. In the short term, the goal of transmission rights is to facilitate transactions in power markets by locking the transmission usage charge and avoiding congestion risk. In the long term, as widely expected, the objective is to give the market signals to motivate transmission investments.

3.2.3 Options on Financial Transmission Rights

Due to the downside risk associated with FTRs, FTR options (FTROs) are introduced. However, since FTROs cannot be straightforwardly decomposed to firm power injection and withdrawal at the source and sink buses, the complexity of simultaneous feasibility test (SFT) increases significantly and the virtual power transfer capacity of the system would be depreciated. Given these concerns, the adoption of FTROs in industry has been very slow in pace.

The FTR option definition seems to be a natural extension of FTR obligations. However, although workable in principle, under closer inspection, there are problems with the option mechanism. For example, point-to-point (PTP) FTR obligations can be easily reconfigured to support a system of trading hubs, whereas PTP options are inherently from one point to another and difficult to reconfigure. For similar reasons, because there exist a large number of possible realizations of the power transaction portfolios as implied by a set of FTR options, each of which requires a separate SFT, it is easy to decide on a simultaneously feasible allocation of FTR obligations setup but much more difficult to decide if a collective allocation of FTR options would be revenue adequate. And by construction, the option setup excludes the effects of counter-flow that relieves the network constraints, the aggregate available capacity of the grid would actually be reduced, consequently, fewer options than obligations would be recognized as feasible and be allocated. Given these complications, the adoption of FTR options in industry has been slow in pace.

3.2.4 Allocation of Financial Transmission rights

An FTR gives its holder a share of congestion rents that the ISO collects in the presence of transmission congestion. The amount of issued FTRs is decided ex ante. Allocation of FTRs typically occurs as an auction. The design of the auction is decided depending on the market structure. FTRs may also be allocated to market participants who pay the embedded costs of constructing the transmission facilities. The FTR market is operated in parallel with the spot market, to ensure revenue adequacy the FTRs must satisfy the simultaneous feasibility test (SFT) which incorporates all power system constraints, such as transmission capacity constraints.

Allocations of FTRs typically occur as auctions. Incremental FTRs from new transmission facilities can be allocated to their investors. To ensure revenue adequacy of the system operator, the configuration of FTRs should conform to a SFT which incorporates all credible constraints. Periodic FTR auctions and secondary bilateral markets provide opportunities for market participants to adjust their portfolios. While the energy market set the actual use of the transmission system, the parallel FTR settlements manage the financial congestion hedging.

The configuration and allocation of transmission rights should be subject to SFT conforming to the system capability and to ensure revenue adequacy for the system operator. Each time there is a change in the configuration of all outstanding FTRs, the SFT is necessary to ensure that the transmission system can support the transactions implied by the set of issued FTRs.

The simultaneous feasibility test problem for the configuration of FTRs is defined as follow: to ensure that all the FTRs$\left(\mathbf{P}^{\mathbf{FTR}}\right)$-represented power injections $\left(\mathbf{P}^{\mathbf{Inj}}\right)$ and withdrawals $\left(\mathbf{P}^{\mathbf{Eje}}\right)$ can be accommodated simultaneously by the system, a SFT is conducted to prevent the violation of system constraints. For example, the transmission network capacity constraints can be tested as follows,

$$\mathbf{F}\left(\mathbf{P}^{\mathbf{Inj}}, \mathbf{P}^{\mathbf{Eje}}, \mathbf{x}, \mathbf{u}\right) \leq \mathbf{T} \tag{3.1a}$$

$$\mathbf{F'}\left(\mathbf{P}^{\mathbf{Inj}}, \mathbf{P}^{\mathbf{Eje}}, \mathbf{x'}, \mathbf{u'}\right) \leq \mathbf{T'} \tag{3.1b}$$

where

$\mathbf{P}^{\mathbf{FTR}}$	the vector of power transfers underlying the configuration of FTRs $\mathbf{P}^{\mathbf{FTR}} = \left\{P_{i,e}^{FTR}\right\} = \left\{\left(P_i^{Inj}, P_e^{Eje}\right), i \in I, e \in \mathcal{E}\right\}$
$\mathbf{P}^{\mathbf{Inj}}$	the vector of power injections represented by $\mathbf{P}^{\mathbf{FTR}}$, $\mathbf{P}^{\mathbf{Inj}} = \left\{P_i^{Inj}, i \in I\right\}$
$\mathbf{P}^{\mathbf{Eje}}$	the vector of power withdrawals represented by $\mathbf{P}^{\mathbf{FTR}}$, $\mathbf{P}^{\mathbf{Eje}} = \left\{P_e^{Eje}, e \in \mathcal{E}\right\}$
$\{\mathbf{F}, \mathbf{F'}\}$	function of power flows on transmission facilities in postulated scenarios
$\{\mathbf{T}, \mathbf{T'}\}$	the transmission network capacity vectors in postulated scenarios
$\{\mathbf{x}, \mathbf{x'}\}$	the vectors of system state variables in postulated scenarios
$\{\mathbf{u}, \mathbf{u'}\}$	the vectors of system control variables in postulated scenarios
$\{I, \mathcal{E}\}$	the set of injection and withdrawals buses underlying the configuration of $\mathbf{P}^{\mathbf{FTR}}$

3.2.5 Revenue Adequacy

The revenue adequacy issue refers to a financial counterpart of physical feasibility of FTR-represented power transactions. It means that the total LMP-based congestion rent collection should be adequate for FTR entitlements for the same time period. This is a central issue in the provision of a financial transmission right mechanism. Financial transmission rights are contracts for financial payments that depend on the outcomes of the market dispatching. The analogous physical problem would be to define the available capacity for transmission usage rights such that the transmission schedules could be guaranteed to flow in any given period. Each time there is a change in the configuration of FTRs, the simultaneous feasibility test needs to be run to ensure that the transmission system can support the transactions implied by the set of issued

FTRs. It has been demonstrated that if the set of FTRs is simultaneously feasible, then revenue adequacy can be achieved.

The problem of system security arises from the concern that some unforeseen event, such as loss of a transmission line or a generator failure, may cause cascading outages throughout the network (Chao and Peck, 2001). For instance, when a line outage occurs in an interconnected system, the power flows will be redistributed throughout the network according to physical laws. As a consequence, this may cause overloading on another line, triggering additional line failures and may eventually jeopardize the entire system. To ensure that the reliability of the power system will not be endangered by such events, contingency analysis is regularly conducted to estimate the likely power flow patterns under a set of postulated equipment outages. An important implication of this practice is that it is no longer possible to define the capacity of each transmission facility independently. Another implication is that a more conservative dispatching usually results from these security constraints.

In the presence of electrical losses and transmission congestion, the revenues collected under an LMP model would be greater than the payments to participants. This net revenue is referred to as the merchandising surplus, congestion rent, or other similar terms. More precisely, under the framework of bid-based, security-constrained economic dispatch, the net revenue difference is simply the infra-marginal rent on losses and transmission constraints.

4. Market Dispatch

In a pool-based electricity market, congestion management is implicitly accomplished in the market-clearing process, and the LMPs are determined as outcomes of a centralized market dispatch, which is usually formulated as a network constrained optimal power flow (OPF) problem. To incorporate transmission losses into the market dispatch, instead of approximating the losses as a polynomial function of the power output of each unit and calculate a penalty factor for each generation unit, explicit power-flow equations are listed as essential constraints in the formal establishment of the optimal power flow problem. Note that the transmission losses are accounted for implicitly in the power flow equations and their market costs are embedded in the electricity locational marginal prices. OPF requires solving a set of linear or nonlinear equations and inequalities to obtain the optimal operational solution. Its general formulation is given as follows,

$$\mathit{Min}\ F(\mathbf{x},\mathbf{u},\mathbf{A},\mathbf{c}) \quad \mathit{s.t.} \quad \mathbf{g}(\mathbf{x},\mathbf{u},\mathbf{A})=0,\ \mathbf{h}(\mathbf{x},\mathbf{u},\mathbf{A})\le 0 \tag{4.1}$$

where

$\mathbf{A}$	a matrix of system parameters
$\mathbf{c}$	a vector of cost or economic efficiency related parameters (e.g., demand bids)
$F(\cdot)$	the objective representing the intended optimal operations, usually in the forms of generation cost, transmission loss, deviation from target schedule, control shift, and so on
$\mathbf{g}(\cdot)$	a set of power flow equations
$\mathbf{h}(\cdot)$	a set of inequality constraints on vector arguments $\mathbf{x}$ and $\mathbf{u}$ consisting of branch flow limits, bus voltage limits, generator output limits and so on
$\mathbf{u}$	a vector of control variables consisting of real and reactive power loads and generations, voltage settings and bounds, transformer tap settings and so on
$\mathbf{x}$	a vector of state variables consisting of bus voltage magnitudes and phase angles, and so on

4.1. Market Dispatch Model

Market dispatch in a power pool is conducted in a similar form to the traditional power system economic dispatch, with generation cost functions replaced by market bid functions. Bilateral and multilateral transactions can be modeled by configuring set of power injections and withdraws at corresponding source and sink buses. Given a specific system configuration, the system operator usually determines the optimal dispatch by solving an OPF, with a predefined objective and subject to given constraints. Alternative objectives such as maximizing social welfare or minimizing system operating cost, transmission losses, or customer costs can be adopted in the OPF formulation. The rational for choosing different objectives and the respective implications on market participants are discussed in (Alonso, 1999). Here social welfare maximization is defined as the objective. The optimization model is defined as follows.

By collecting I supply and J demand bids, the system operator conducts the market dispatch to maximize social welfare while accommodating all power flow balance and transmission feasibility constraints.

$$Max\, W\left(\mathbf{s}, \mathbf{d}, \mathbf{f}^{S}(\cdot), \mathbf{f}^{D}(\cdot)\right) \tag{4.2a}$$

$$s.t.\quad \mathbf{g}(\mathbf{x}, \mathbf{u}, \mathbf{s}, \mathbf{d}) = 0 \tag{4.2b}$$

$$\mathbf{h}_{\mathbf{T}}(\mathbf{s}, \mathbf{d}, \mathbf{x}) \le \mathbf{T} \tag{4.2c}$$

$$\mathbf{s} \le \mathbf{s}_{Max} \tag{4.2d}$$

$$\mathbf{d} \le \mathbf{d}_{Max} \tag{4.2e}$$

Specifically, according to the traditional formulation, the set of power flow equations (4.2b) consists of, for any bus n,

$$\begin{aligned} s_n - d_n &= v_n \sum_{m \in \psi_n} v_m \left[G_{nm} \cos(\theta_n - \theta_m) + B_{nm} \sin(\theta_n - \theta_m)\right] \\ &+ j v_n \sum_{m \in \psi_n} v_m \left[G_{nm} \sin(\theta_n - \theta_m) + B_{nm} \cos(\theta_n - \theta_m)\right] \end{aligned} \tag{4.2f}$$

where

$\mathbf{d}$	a vector of demand quantity dispatched, $\mathbf{d} = [d_j],\ j = 1,2,\cdots J$
$\mathbf{s}$	a vector of supply quantity dispatched, $\mathbf{s} = [s_i],\ i = 1,2,\cdots I$
$\mathbf{f}^{S}(\cdot)$	a set of supply bid functions, $\mathbf{f}^{S}(\cdot) = [f_i^{S}(\cdot)],\ i = 1,2,\cdots I$
$\mathbf{f}^{D}(\cdot)$	a set of demand bid functions, $\mathbf{f}^{D}(\cdot) = [f_j^{D}(\cdot)],\ j = 1,2,\cdots J$
$\mathbf{h}_{\mathbf{T}}(\cdot)$	a set of transmission line loading functions
$\mathbf{T}$	a vector of transmission line loading capacity, $\mathbf{T} = [T_k],\ k = 1,2,\cdots K$
$W(\cdot)$	social welfare as a function of supply and demand bid functions, and market accommodated supply and demand quantities
$\{G, B\}_{nm}$	conductance and susceptance of transmission line nm
v_m, θ_n	magnitude and phase angle of voltage on bus n
ψ_n	the set of buses with transmission lines connected to bus n

Among the constraints, (4.2b) matches generation and demand at each system node, (4.2c) maintains the transmission system feasibility, (4.2d, e) incorporate the bounds. The problem (4.2), with a convex objective function and linear convex constraints, is a convex programming problem. Its associated Lagrange function is defined as,

$$\mathcal{L}(\mathbf{s}, \mathbf{d}, \boldsymbol{\lambda}, \boldsymbol{\gamma}, \boldsymbol{\eta}, \boldsymbol{\mu}) = -W(\cdot) + \boldsymbol{\lambda}\mathbf{g}(\cdot) + \boldsymbol{\gamma}\left[\mathbf{h}_{\mathbf{T}}(\cdot) - \mathbf{T}_k\right] + \boldsymbol{\eta}(\mathbf{s} - \mathbf{s}_{Max}) + \boldsymbol{\mu}(\mathbf{d} - \mathbf{d}_{Max}) \tag{4.3}$$

where $[\boldsymbol{\lambda}, \boldsymbol{\gamma}, \boldsymbol{\eta}, \boldsymbol{\mu}]$ are vectors of Lagrangian multipliers associated with constraints (4.2b-e), respectively. In order for a point $(\mathbf{s}^*, \mathbf{d}^*, \boldsymbol{\lambda}^*, \boldsymbol{\gamma}^*, \boldsymbol{\eta}^*, \boldsymbol{\mu}^*)$ to be optimal, in addition to (4.2b-e), to guarantee the gradient of $W(\mathbf{s}, \mathbf{d})$ is normal to $\mathbf{g}(\cdot)$, $\mathbf{h}_{\mathbf{T}}(\cdot) - \mathbf{T}_k$, $\mathbf{s} - \mathbf{s}_{Max}$, and $\mathbf{d} - \mathbf{d}_{Max}$, it requires

$\nabla W(\mathbf{s},\mathbf{d})$ being normal to $\nabla \mathbf{g}(\cdot)$, $\nabla(\mathbf{h}_{\mathbf{T}}(\cdot)-\mathbf{T}_k)$, $\nabla(\mathbf{s}-\mathbf{s}_{Max})$, and $\nabla(\mathbf{d}-\mathbf{d}_{Max})$ being linearly dependent vectors,

$$\frac{\partial \mathcal{L}}{\partial \mathbf{s}}(\mathbf{s}^*,\mathbf{d}^*,\boldsymbol{\lambda}^*,\boldsymbol{\gamma}^*,\boldsymbol{\eta}^*,\boldsymbol{\mu}^*)=0 \tag{4.4a}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{d}}(\mathbf{s}^*,\mathbf{d}^*,\boldsymbol{\lambda}^*,\boldsymbol{\gamma}^*,\boldsymbol{\eta}^*,\boldsymbol{\mu}^*)=0$$

plus the complementary slackness condition,

$$\boldsymbol{\gamma}^*\left[\mathbf{h}_{\mathbf{T}}(\cdot)-\mathbf{T}_k\right]=0,\ \boldsymbol{\gamma}^*\geq 0 \tag{4.4b}$$

$$\boldsymbol{\eta}^*(\mathbf{s}^*-\mathbf{s}_{Max})=0,\ \boldsymbol{\eta}^*\geq 0$$

$$\boldsymbol{\mu}^*(\mathbf{d}^*-\mathbf{d}_{Max})=0,\ \boldsymbol{\mu}^*\geq 0$$

Due to the convexity of (4.2a-b), the second-order optimality conditions are satisfied. In the economical sense, the Lagrange multiplier λ_n associated with the power balance at the bus n can be interpreted as the optimal price because it quantifies the cost (or value, from demand side) for supplying (or consuming) an additional MW at the bus n of the network. On the other hand, the Lagrange multiplier γ_k associated with the power flow limit of the k^{th} transmission flowgate is interpreted as the variation in social cost if the transmission capacity is relaxed, called flowgate shadow price or congestion multiplier. By solving (4.4), LMPs can be read off the Lagrange multipliers associated with the corresponding constraints. The FTR values can be readily deduced from the price differences, while the FGR values are reflected by the Lagrange multipliers associated with the circuit loading capacity constraints in $\mathbf{h}_{\mathbf{T}}(\mathbf{x})\leq \mathbf{T}$. The non-zero shadow prices of binding transmission constraints are major factors which diverse the LMPs. Market uncertainties due to random supply and demand bids, fluctuating system loads, varying fuel price, and unexpected transmission line outages are incorporated by using random parameters $\left[\tilde{\mathbf{T}},\tilde{\mathbf{f}}^S(\cdot),\tilde{\mathbf{f}}^D(\cdot)\right]$ with certain distributional assumptions being made (see Sun et al., 2005). With a parametric optimal power flow formulation, the sensitivity of the optimal operating conditions with respect to any parameter under interest corresponding to a market participant's input or the system operator's control can be investigated and the corresponding economic values can be interpreted. For instance, we model the unexpected transmission line outage on a line T(A-B) in a power system by a Bernoulli random variable: the outage of T(A-B) occurs with probability p. Given an outage, the capacity of T(A-B) is 1/10 of its normal value. The different capacity levels of T(A-B) under the states of normal and outage may result in different LMPs across the system. Thus we can analyze the sensitivity of the distributions of LMPs and FTRs with respect to the probability parameter p.

4.2. Linearization of Market Dispatching Problems

Traditionally, to obtain the present system operating conditions for further analysis, the power flow of the system can be described using the voltage magnitude and phase angle at each bus, transformer tap, and so on. These traditional power flow (TPF) equations are formulated in terms of $\mathbf{g}(\mathbf{x},\mathbf{u},\mathbf{A})=0$ based on the fact that the sum of the injected power flows at a bus is zero. However, due to the high nonlinearity of some equations, the converging to the solution is usually slow. For market dispatch, a common practice in industry is to avoid the time-consuming iteration process of solving nonlinear AC power flow equations and adopt a DC formulation instead. DC power flow prompts a simple and fast solution of the market dispatch problem. In the characterization of transmission lines, the DC model usually ignores conductance and reactive power flows. It also assumes the voltage magnitudes at all buses are unit valued and the phase angles are close to each other. Specifically, the power flow equations can be simplified as follow in per-unit measures, not that only real power flows are modeled.

$$s_n - d_n = \sum_{m \in \psi_n} B_{nm} \left(\theta_n - \theta_m \right) \tag{4.5}$$

However, accuracy is sacrificed unless sophisticated transformations of all limits into energy or flow limits are made (see Alvarado, 2003).

Given the limitations of traditional power flow and DC power flow models, a quadratized power flow (QPF) model (see Meliopoulos, 2001 and Kang, 2001) is proposed based on modeling any power system component as a set of linear or quadratic equations (which can be achieved with the introduction of additional state variables). Application of connectivity constraints (Kirchoff's current law) at each bus yields the quadratized power flow equations:

$$\mathbf{G_Q}(\mathbf{x_Q}, \mathbf{u}) = [\mathbf{x_Q}, \mathbf{u}]^T \cdot \mathbf{\Pi} \cdot [\mathbf{x_Q}, \mathbf{u}] + \mathbf{\Gamma} \cdot [\mathbf{x_Q}, \mathbf{u}] + \boldsymbol{\beta} = 0 \tag{4.6}$$

where

$\mathbf{x_Q}$	the vector of the state variables for QPF
$\mathbf{u}$	the vector of control variables
$\mathbf{\Pi}, \mathbf{\Gamma}$	non-variable matrices
$\boldsymbol{\beta}$	a non-variable vector

The solution to the quadratic equations can be obtained by the Newton-Raphson method and iteration terminates when the norm of the QPF equations is less than the tolerance,

$$\mathbf{x_Q}^{k+1} = \mathbf{x_Q}^{k} - \mathbf{\Phi}\left(\mathbf{x_Q}^{k}\right)^{-1} \cdot \mathbf{G_Q}\left(\mathbf{x_Q}^{k}\right) \tag{4.7}$$

where

k	the step of iterations
$\mathbf{\Phi}(\mathbf{x_Q})$	the Jacobian matrix of the set of power flow equations at state vector $\mathbf{x_Q}$

For a large-scale system the number of equations is large, so is the dimension of the Jacobian matrix. However, the Jacobian matrix is highly sparse and the computational burden can be significantly alleviated employing sparsity techniques.

An extension of the co-state method to the QPF introduced in Meliopoulos (1988) and applied in (Bakirtzis, 1991 and Meliopoulos, 1994) can be employed to compute the sensitivity of a performance index $f_I(\mathbf{x_Q}, \mathbf{u})$ (such as total transmission loss, line loading, and bus voltage functions) to control variable $\mathbf{u}$. Differentiation of the QPF equations gives,

$$\frac{\partial \mathbf{G_Q}(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{u}} + \frac{\partial \mathbf{G_Q}(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{x_Q}} \cdot \frac{d\mathbf{x_Q}}{d\mathbf{u}} = 0$$

Therefore, we can get

$$\frac{d\mathbf{x_Q}}{d\mathbf{u}} = -\left(\frac{\partial \mathbf{G_Q}(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{x_Q}}\right)^{-1} \cdot \frac{\partial \mathbf{G_Q}(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{u}} \tag{4.8}$$

The derivative of the system performance index function with respect to u_c is given by:

$$\frac{df_I(\mathbf{x_Q}, \mathbf{u})}{d\mathbf{u}} = \frac{\partial f_I(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{u}} + \frac{\partial f_I(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{x_Q}}\left(\frac{\partial \mathbf{G_Q}(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{x_Q}}\right)^{-1}\frac{\partial \mathbf{G_Q}(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{x_Q}} = \frac{\partial f_I(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{u}} + \hat{\mathbf{x}}_\mathbf{Q}{}^T \mathbf{\Phi} \tag{4.9}$$

where $\hat{\mathbf{x}}_\mathbf{Q}$ is the co-state vector of the power flow equations,

$$\hat{\mathbf{x}}_\mathbf{Q}{}^T = \frac{\partial f_I(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{x_Q}} \cdot \left(\frac{\partial \mathbf{G_Q}(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{x_Q}}\right)^{-1}$$

For a function $f_I(\cdot)$ not explicitly dependent on control variable $\mathbf{u}$, we have $\frac{\partial f_I(\mathbf{x_Q}, \mathbf{u})}{\partial \mathbf{x_Q}} = 0$.

With the QPF and co-state method linearization, the solving of a market dispatch problem can be accelerated by linearizing the active and close-to-active constraints as follows and converting market dispatch into a linear programming problem,

$$Max\, W\left(\mathbf{s} + \Delta\mathbf{s}, \mathbf{d} + \Delta\mathbf{d}, \mathbf{f}^S(\cdot), \mathbf{f}^D(\cdot)\right) \tag{4.10a}$$

$$\text{s.t.} \quad \sum_{i=1}^{I} \Delta s_i - \sum_{j=1}^{J} \Delta d_j = 0 \tag{4.10b}$$

$$\sum_{i=1}^{I} \frac{\partial T_k}{\partial s_i} \Delta s_i + \sum_{j=1}^{J} \frac{\partial T_l}{\partial d_j} \Delta d_j \le T_k - h_T(\mathbf{s}) \tag{4.10c}$$

$$\Delta\mathbf{s} \le \mathbf{s}_{Max} - \mathbf{s} \tag{4.10d}$$

$$\Delta\mathbf{d} \le \mathbf{d}_{Max} - \mathbf{d} \tag{4.10e}$$

where Δ measures the deviations of a variable from its previous operating condition. Note that for any bus n, $\frac{\partial T_k}{\partial s_n} = -\frac{\partial T_k}{\partial d_n}$ denotes the impact on loading on flowgate k with one unit of incremental power injection at bus n. Since reactive power and voltage variation are accounted in AC power flow equations, $\frac{\partial T_k}{\partial s_n}$ reflects the system operating conditions more accurately compared with the PTDF coefficients derived by DC power flow equations. The detailed computational procedures are referred to Appendix B. Equation (4.10c) can be further extended to incorporate transmission losses as,

$$\sum_{i=1}^{I}\left(1 - \frac{\partial L}{\partial s_i}\right)\Delta s_i - \sum_{j=1}^{J}\left(1 + \frac{\partial L}{\partial d_j}\right)\Delta d_j = 0 \tag{4.10f}$$

where for $\forall n$, $\frac{\partial L}{\partial s_n} = -\frac{\partial L}{\partial d_n}$ can be calculated in a similar procedure as $\frac{\partial T_k}{\partial s_n}$.

By solving (4.10), the market clearing locational marginal prices and FTR values can be determined efficiently.

4.3. Incorporation of Reliability Constraints

While maintaining a highly reliable power system is technically challenging in practice, this goal needs to be achieved since the system reliability is crucial in keeping low-cost and qualified electricity supply accessible continuously over time and supporting competitive electricity markets. There has been substantial research done on the power system reliability issues under the regulated policy regime. However, under the restructured industry regime, the economic impact on market participants by system operators (SOs) imposing system reliability constraints has not yet been adequately investigated. Without a good understanding on the interplay between the imposed system reliability requirements and the resulting market price dynamics, it is difficult for SOs and market participants to estimate the economic impacts of reliability constraints, and for market participants to access market risks involved and then take on corresponding trading positions to manage the risks. As a result, people would refrain from making investments to maintain a necessary operational capacity margin for system reliability purpose. The lack of investments in maintaining an adequate generation reserve margin or transmission reserve margin would lead to crisis similar to the one occurred in California in 2000-2001. The lessons from California call for regional generation and transmission resource adequacy requirements for maintaining reliable and secure power system operations.

System planning criteria along with the operational requirement to balance electricity production and consumption are required to maintain system reliability. A common adequacy criterion for system planning is related to the probability of shortfall of installed generation capacity with respect to demand. Several inter-derivable criteria such as loss of load probability (LOLP), loss of load expectation (LOLE), and hourly loss of load expectation (HLOLE) have been used. System specific factors (such as the largest generating unit's capacity, forced outage rates, generation unit portfolio, load diversity, and transmission interface capability) determine a reserve margin, a measure of the amount of excess installed generating capacity as a percentage of peak load demand, ranging from 13% to 20% depending on conservatism of the planners (See US-Canada Power System Outage Task Force 2004).

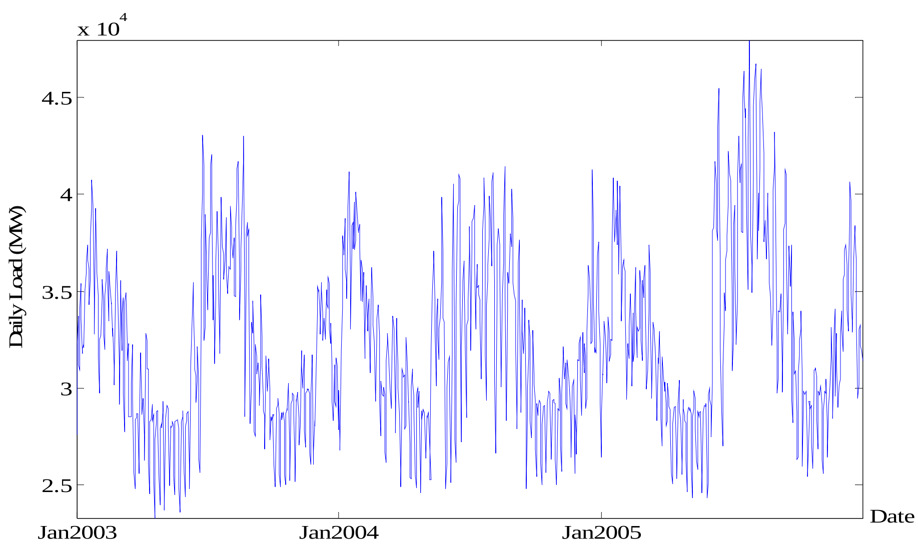

Figure 4.1 PJM East system load seasonality with winter/summer peaks

Figure 4.1 shows the daily average load in PJM East from January 2003 to December 2005. The seasonality of load gives rise to the tendency to take generating units and transmission components out of service during the spring and the fall for maintenance. The practice leads to more constant reserve margin than would be suggested by the seasonal load shape.

On the aspect of system operation, however, with increased competition encouraged by the market opportunities, more generation units and transmission facilities are operated closer to the edge for economic efficiency, which leads to higher risks of system failures and impaired reliability. Functions such as monitoring of bus voltages, conformance to transmission limits, procurement of capacity reserves, and accommodation of creditable contingencies without loss of system function are coordinated continuously. To prevent the occurrence of cascading outages throughout the network triggered by unforeseen events, such as forced outages of a transmission line or a generator unit, which jeopardize the entire system, contingency analysis is conducted regularly. The practice leads to a conservative market dispatch to ensure all facilities stay within normal or emergency ratings with normal and contingency operating procedures in effect, so that the systems can absorb the dynamics over swings and remain stable following a credible disturbance. Besides, spare capacity in generation and transmission facilities is used to hedge against disturbances such as load spikes (see Bobo, 1994 and McCalley, 1991). Generation operating reserves are procured by market participants or system operators to prevent energy market distortion and support real-time transactions. They are characterized by the deliverability and categorized as follows,

1. Automatic generation control capacity which can be adjusted by the system operator's automatic generation control (AGC) signals to offset normal supply and demand fluctuations.

2. Spinning reserve which consists of synchronized units that can be brought online within 10 minutes upon request.

3. Non-spinning reserve which consists of hydroelectric or quick start combustion turbine units not synchronized to the grid but can be brought online within 10 minutes.

4. Backup reserve which consists of generation capacity that can be brought online within 30 minutes.

Usually, reliability is deemed as a public good which benefits all market participants. Reliability enhancement and LMP-determining market dispatch are economically separated activities. As a consequence, there lacks a market mechanism to value reliability and the costs involved are spread among all consumers. However, economic value of reliability can be discovered at least partially with a properly designed market mechanism. A reliability-differentiated pricing scheme (see Siddiqi, 1993) can be constructed correspondingly.

Market dispatch OPF formulation (4.2) can be augmented to a security constrained optimal power flow (SCOPF) problem by incorporating constraints addressing system reliability concerns, including system feasibility test under postulated contingency scenarios and generation and transmission capacity reserves, as follows,

$$\mathbf{g}(\mathbf{x'}, \mathbf{u'}, \mathbf{s}, \mathbf{d}) = 0 \tag{4.11a}$$

$$\mathbf{h}_{\mathbf{T}}(\mathbf{x'}) \leq \mathbf{T'} \tag{4.11b}$$

Note that $\mathbf{A'}$, $\mathbf{x'}$, and $\mathbf{T'}$ represent the changed system admittance matrix, state variables, and transmission capacity under contingencies respectively. The $N-1$ criterion is widely adopted in industry for postulated credible contingencies. Adjusted capacity of generation units $\mathbf{s}_{Max}$ and transmission facilities $\mathbf{T}$ leaving reserve margins, voltage magnitude lower/upper bounds $\{\underline{\mathbf{V}}/\overline{\mathbf{V}}\}$, and reactive power generation lower/upper bounds $\{\underline{\mathbf{f}}(\mathbf{p})/\overline{\mathbf{f}}(\mathbf{p})\}$ reflecting generation feasible operation region as functions of real power generation $\mathbf{p}$ which can be approximated by constants $\{\underline{\mathbf{q}}/\overline{\mathbf{q}}\}$ for simplicity should be incorporated. By taking more conservative values for $\lfloor \mathbf{s}_{Max}, \mathbf{T}, \underline{\mathbf{V}}, \overline{\mathbf{V}}, \underline{\mathbf{q}}, \overline{\mathbf{q}} \rfloor$, certain reliability criteria, such as generation reserves, transmission reliability margin (TRM, the margin between transmission facilities' capacity and their commitment), capacity benefit margins (CBM, the transmission transfer capability reserved by load serving entities to ensure access to generation from interconnected systems), and voltage security bounds, can be incorporated correspondingly. The specification of the market dispatch model actually reflect the openness of the competitive market as market mechanisms instead of regulation determines the service values and allocate the costs involved. As the restructuring continues, further details can be incorporated into the market dispatch model with the evolving market design.

By solving the market dispatch problem, following the market-driven approach, various price premiums can be read off the Lagrange multipliers associated with various binding constraints as components of nodal price signals (see Alvarado, 2003 and Chen, 2002). As more reliability constraints become active, the LMPs become further differentiated across space and time. The impact of contingency tests, generation operating reserves and transmission reliability margin requirements on electricity price behaviors and electricity derivative values will be investigated in section 6.

With the recognition of potential disturbances and other persistent uncertainties, market participants expect a high level of system reliability to support power transactions. On the transmission network, the assessment of reliability levels can be converted to quantifying indices such as TRM and CBM. Conceptually, the economic values associated with the differentiated TRM and CBM provide a mechanism for assessing reliability investment that could serve as a basis for justifying cost recovery. The basic idea behind this is to sell reliability as a quality factor of the service. Reliability requirements of consumers can be collected, aggregated and transformed to these indices on the underlying transmission facility, and reflected in the valuation and beneficiary identification of the investments. Since investment in the transmission sector alone cannot achieve a desirable system reliability level, similar mechanisms should be established for the generation and distribution sectors to achieve the coordination.

As suggested above, reliability benefits can be represented by a value curve rather than a threshold requirement. The recovery of investment costs incurred can be accomplished through augmented transmission prices as discussed above.

5. Transmission Investments for Adequacy

In a bulk electric power system, reliability means providing customers with the amount of electricity they need when they want it. Reliability exists when the electric system is in balance between load and generation or can be rapidly brought into balance following any disruption. The ability of an electric system to recover from a disturbance depends on the relative size and responsiveness of the remaining system generation. Generally, operating through an interconnected system provides larger and more stable supply of reserves than can be achieved by individual utilities alone. In the planning of a system, the reliability concern includes adequacy and security aspects. Adequacy is the assurance of sufficient supply of electricity to meet customers' maximum needs. Adequacy exists when the system has sufficient generation and purchased power available to meet the load and reserve requirements. Reserves must be sufficient to accommodate planned and unexpected unit unavailability and errors in load forecasts. Security is the operation of a power system to withstand sudden large and unanticipated disturbances. Security exists when those responsible for operational control of the system can monitor system conditions, and anticipate and successfully rapidly respond to disturbances.

It is ideal to envision a unique electricity price for all market participants regardless of the exact location within the system. In that case, loads can always be met by the cheapest generation units, the merit-order generation, so that minimum social cost is incurred. However, when transmission congestion occurs, generation units out of merit-order have to be dispatched. Although congestion costs may represent a small portion of the total energy procurement cost as cleared in the market, the incidence on market efficiency and economic incentives for transmission and generation investment in the long run should be addressed. Economically, for electricity buyers, the impact of transmission congestion mimics what is caused by suppliers' exercise of market power by withholding generation. A net loss of consumers' surplus is induced. The inefficiency involved (known as the net deadweight loss) represents the social cost of the inadequate transmission capacity (see Figure 5.1).

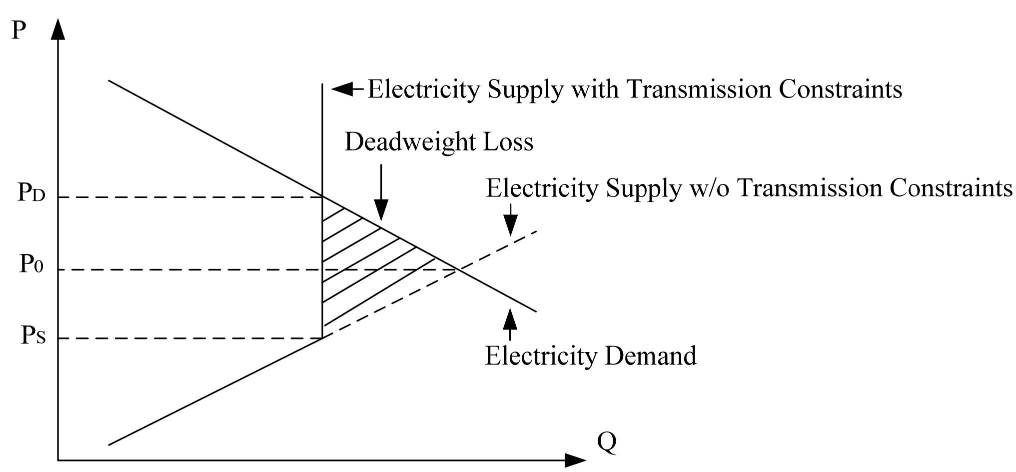

Figure 5.1 Deadweight loss due to transmission congestion

5.1. Alternative Transmission Investment Mechanisms

Since various incentives drive capital investment for transmission capacity, we cannot rely on a single mechanism for cost-recovery. Some transmission upgrades may be proposed by the system operator for reliability enhancement, while others may be proposed by one, or a group of, market participants in response to market signals. Prevailing investment forms can be identified as follows:

1. System-wide reliability enhancing and economic efficiency improving transmission upgrades

The Regional Transmission Organizations usually prepare regional transmission expansion plans which consolidate reliability or improve system-wide economic efficiency. Since these projects bring widespread benefits to most system customers, the cost involved tend to be allocated over a large group of consumers. A request for proposals (RFP) process is preferred since the competitive RFP process promotes minimal cost while assigning the project related risks to the winning respondent instead of to the end consumers. Investments in this category are limited to those projects the direct economic benefits of which are non-significant to any market participant. This approach can be refined by allocating project costs through a cost-benefit analysis among sub-regions and a non-uniform portion of the cost can be allocated accordingly (Rotger, 2001).

2. Voluntary transmission investment

Projects in this category include generation interconnection requests to increase electricity delivery to the market, load connection request to get access to desired resources, and capacity expansions that reduce congestion energy costs for consumers, for example, in a load pocket such as New York City. These investments are initiated by and benefit market participants. The free-rider problem is less bothering here since the economic benefits of the projects to potential investors are more exclusive, although they usually introduce more competition to mitigate the existing market power of others. Voluntary transmission investment projects are sponsored by those who would gain the benefits. It is necessary, however, to assure that the projects do not degrade system reliability nor create additional opportunities for the exertion of market power.

3. Merchant transmission projects

In the context of this study, merchant transmission investors rely on the LMP-based transmission service pricing mechanism and seek financial transmission rights to pay for the transmission investment. Three components are essential to this category of market-motivated transmission investments. First, the spatially-differentiated electricity price signals provide approximate economic signals for determining where to invest; second, FTRs hedge against congestion-risks or, as tradable financial instruments, entitle investors the rights to collect revenues in the future; third, an efficient financial transmission rights identification and allocation mechanism is expected to assign right amount of rights to the right investors, which include eliminating the opportunities of free-riding on public good benefits. The merchant investment mechanism relies on free entry and competitive power markets. It places the risks of investment inefficiencies and cost overruns on investment decision-makers instead of on the consumers.

For whatever form of the transmission investment proposal, the impact of network externalities should be examined. Network externalities in electric power system originates from

Kirchhoff's Laws which govern power flows over the interconnected AC system. A certain transmission investment may have positive or negative impacts on the transfer capacity between other locations and therefore, on the financial position of other transmission owners/investors. As a crucial issue regarding trade-offs between cooperation and competition in the long run, the negative externality impact degrades system reliability and undermines fair competition. Generally, the feasible power injection/withdrawal set changes after the implementation of such an investment. An example is given in Figure 5.2 as an illustration.

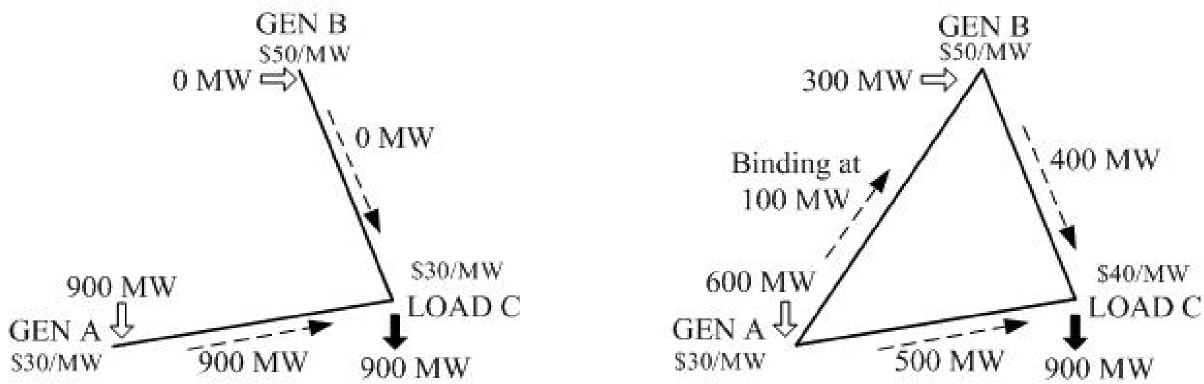

Figure 5.2 Detrimental impacts due to network externalities

The expansion of this simple network by the addition of low-capacity 100 MW transmission line AB actually decreases the transfer capacity from node A to node C. In this example, the network externality brings benefits to GEN B but affects GEN A and LOAD C negatively.

A typical network-deepening project that only increases the transmission thermal capacities of existing facilities does not reduce the size of the set of feasible dispatches, but it is not necessarily the case for an independent expansion of the network. Generally, the feasible power injection/withdrawal set changes after the implementation of an independent expansion investment. A small expansion of the network does not necessarily have a small effect. Unfortunately, the complexity of the effects on the feasible dispatch set grows with the network size. In a practical power system, it is the transmission owners' responsibility to conduct such a study based on complete network information.

5.2. Cost Allocation Mechanisms

Transmission cost allocation is a complicated problem due to the nature of transmission

1. Transmission infrastructure provides a public good for society.

2. Transmission provides network access for competitive generators, and it is also a potential competitor for inefficient generators.

3. It can impact market prices and asset values significantly in a negative or positive way, to different parts.

4. Externalities are generated by the physical laws guiding the power flows.

Cost allocation and recovery policies clearly influence transmission investment. The goal of encouraging investment will have to be balanced with equity and fairness considerations.

Although the reliability expectations of consumers within a zone vary, it is hard to allocate costs of reliability-enhancing transmission investments within a local zone because the reliability enhancement essentially applies to everyone within the electric vicinity and beneficiary boundaries are very difficult to draw. Consequently, a political process rather than a pure economic assessment is needed to endorse the cost socialization. However, for system-wide reliability enhancing and economic efficiency improving transmission investments, cost allocation generally can follow the principle of having the beneficiaries pay, which applies either to the entire control area, or to a group of identified zones. A flow-based method can be applied to determine the beneficiary distribution factors. Depending on the scale and scope of the transmission project, a representative backbone network can be identified according to the voltage level with each generation group, load of each load serving entity (LSE), and each through-transfer contract being represented by a power injection or withdrawal and aggregated at the corresponding node on the transmission network. The beneficiary distribution factors are calculated based on power transfer distribution factors of the representative injections and withdrawals. These beneficiary distribution factors shall be normalized to prevent over or under cost coverage. A number of representative system loading scenarios should be identified to calculate the beneficiary distribution factors. And the factors need to be updated over time with the changing of transmission network topologies.

The cost allocation among investors in a voluntary transmission investment seeking economic benefits can be conducted in proportion to the economic impacts. A reasonable projection of market price dynamics over the investment time horizon is essential for the quantitative assessment of economic benefits. Two competing approaches are available for market price modeling: a fundamental approach that relies on power system simulation; and a technical approach that models uncertainty directly. While the fundamental approach provides more realistic representations under specific scenarios, it is computationally prohibitive due to the large number of scenarios to be considered. The method presented in this report is to combine the strengths of the two approaches by calibrating the stochastic price process models using probabilistic system simulation results.

As identified in the previous section, locational marginal prices, financial transmission rights, and efficient financial transmission rights identification and allocation mechanisms are necessary to incent merchant transmission investments. The theoretical basis of LMP and FTR has been discussed. This section intends to address the identification and allocation of incremental transmission rights induced by a potential merchant transmission investment. Mathematically, it can be reduced to the sensitivity analysis of a linear programming problem.

A transmission investment, regardless of network-deepening or independent expansion of the network, always induces incremental transmission rights. Therefore, a transmission investment increases the quantity or expands the portfolio of feasible FTRs that can be issued. With incremental transmission rights identified and allocated to the investors, the incentives for transmission investment can get stronger.

Note that the structuring of incremental transmission rights to be issued is limited by the simultaneous feasibility test procedure, which verifies that the transmission system could simultaneously accommodate injections and withdrawals representing all outstanding transmission rights. It also ensures that the congestion rents collected by the system operator will be sufficient to fund the amounts it must pay to the holders of transmission rights. This means the system operator is always revenue adequate and no cost becomes socialized from this aspect.

In case a new transmission project unavoidably violates existing FTRs, theory of public economics suggests that the investor shall buy back the disabled FTRs or be allocated reverse FTRs representing counter-flows to make the total FTR portfolio simultaneously feasible based upon the new network structure. Or, the system operator should retain some transmission rights during the long-term FTRs auction to avoid jeopardizing FTRs held by market participants when a new transmission project comes. However, this induces additional overheads to be socialized to all consumers.

Long-term transmission rights can also be evaluated based on probabilistic power flow. The value and availability of transmission rights are defined in terms of the probability of the occurrence of transmission congestion. Monte Carlo approach with importance sampling techniques can be employed to compute the probability distribution of a circuit flow based on given load curve and generation characteristics. Likely the value of a transmission right is established by different levels of firmness, which is helpful for valuing all the transmission rights.

6. Simulation of Electricity Market Operations

Market simulation is the imitation of a real-world market operation over time, to describe and analyze the behavior of the system. It involves the generation of artificial system operating conditions representing the practical characteristics of the market. It is a powerful methodology for the solution of many real world problems. Simulation allows the testing of market designs without acquiring actual resources, which usually turn out to be extremely expensive. Interested details can be thoroughly investigated by focusing on related phenomena. Simulation can help in exploring various possible outcomes due to certain operating procedures, which is hard to accomplish in a real system because we cannot see its entirety in a relatively short time horizon. It can also be used to visualize the possible scenarios, and to further understand the effects of changing certain factors. Statistical analysis is often used to interpret and evaluate the simulation results.

This section presents a case study of using the market dispatch model specified in Section 4.1 to simulate a pool-type electricity market. It describes the electric load model used, the power transaction model, the network model, and the Monte Carlo simulation method. The following pseudo algorithm is implemented for computing the distributions of LMPs and values of FTRs/FGRs.

Step 1. Loop: 1 to N_simulation

Step 2. Monte Carlo sampling of the random system parameters: (***A, c, T***) where ***A, c*** are defined in (4.1), and ***T*** is defined in (4.2 c).

Step 3. Solving the following OPF problem (given by 4.2 a - 4.2e) with the sampled parameter (***A, c, T***)

$$Max\ W\left(\mathbf{s}+\Delta\mathbf{s},\mathbf{d}+\Delta\mathbf{d},\mathbf{f}^{S}(\cdot),\mathbf{f}^{D}(\cdot)\right)$$

$$\text{s.t.}\quad \sum_{i=1}^{I}\Delta s_i-\sum_{j=1}^{J}\Delta d_j=0$$

$$\sum_{i=1}^{I}\frac{\partial T_k}{\partial s_i}\Delta s_i+\sum_{j=1}^{J}\frac{\partial T_l}{\partial d_j}\Delta d_j\le T_k-h_T(\mathbf{s})$$

$$\Delta\mathbf{s}\le\mathbf{s}_{Max}-\mathbf{s}$$

$$\Delta\mathbf{d}\le\mathbf{d}_{Max}-\mathbf{d}$$

Step 4. Get LMPs and the values of FTRs/FGRs from the solution in Step 3.

Step 5. End of Loop.

6.1. Monte Carlo Simulation

Monte Carlo simulation is the art of approximating an expectation by the sample mean of a function of simulated random variables. The essence of the method can be described as invoking the Laws of Large Numbers to approximate expectations.

Monte Carlo simulation has been adopted to conduct the analysis for this project. As sequential simulation requires more calculation time, we use quasi-sequential simulation instead which generates realistic system states and obtains distributions of indices of interest. More detailed information can be obtained than a simple state sampling approach. Monte Carlo simulation can become more efficient by implementing importance sampling. Importance sampling is choosing a good distribution from which to simulate one's random variables. The importance sampling is by identifying the important samples via the contingency ranking described in Appendix B. Using the important samples, the results have to be appropriately weighted in order to obtain the correct distributions and expectations of the involved results.

Monte Carlo simulation was first used by Ulam and von Neumann as a Los Alamos code word for the stochastic simulations applied to building better atomic bombs. Mathematically, consider a random variable X with probability mass function or probability density function $f_X(x)$ for $x \in \chi$, the expected value of a function $g(X)$ is, for the discrete case,

$$E[g(X)] = \sum_{x \in \chi} g(x) f_X(x) \tag{6.1a}$$

or, for the continuous case,

$$E[g(X)] = \int_{x \in \chi} g(x) f_X(x) dx \quad . \tag{6.1b}$$

If $E[g(X)]$ exists, the Weak Law of Large Numbers indicates that for any arbitrarily small number ε, we have,

$$\lim_{n \to \infty} P\left(\left|\tilde{g}_n(X) - E[g(X)]\right| \geq \varepsilon\right) = 0 \tag{6.2}$$

where $\tilde{g}_n(X) = \frac{1}{n} \sum_{i=1}^{n} g(x_i)$

The dimension of many practical problems is high and requires very involved numerical methods for analytical studies on the distribution of interest to reach a satisfactory approximation in such integration. A natural alternative is to use Monte Carlo techniques to exploit the probabilistic properties of the integrands rather than their analytical properties. Given the absence of an analytical method in evaluating market price behaviors, Monte Carlo simulation provides an alternative to mimic actual processes and random behavior of the system. Monte Carlo simulation in this project consists of randomly sampling system states, testing them for acceptability, and aggregating the contribution of loss of load states to the reliability until the coefficients of variation of these indices drop below pre-specified tolerances. The basic approach can be applied for each hour of a year in chronological order (sequential approach) or the hours of the study time can be considered at random (random approach). In order to obtain an acceptable level of accuracy of the indices, several variance reduction techniques, (such as control variates, importance sampling, stratified sampling, and antithetic variates), have been adopted to reach a pre-specified precision with less computing time.

Since load variations are the most fundamental drivers for market dynamics, a load chronological curve (LCC) can be drawn to represent the load conditions for a system over a time horizon. However, to get probabilistic distribution of market economic measures, it is not necessary to simulate the system performance by maintaining the chronology of the load model.

A load duration curve (LDC) can be derived based on LCC, and a quasi-sequential simulation framework of the system can be constructed.

6.2. Case Study with the IEEE-RTS 24 System

The experiments with the IEEE RTS-24 system shown in Figure 6.1 are presented in this section to empirically illustrate differences between AC/DC power flow based market dispatch models and the impact of reliability constraints on market prices and risks. This section focuses on the electricity price and market risk assessment in pool-based markets according to various market dispatch models. Different optimal power flow problems reflecting AC/DC power flow modeling differences and various reliability considerations are formulated. Corresponding market impacts are investigated comparatively. Due to the complexity of the problem, it is difficult to predict the consequence of imposing reliability constraints. The paper provides empirical observations obtained through numerical experiments with the IEEE RTS-24 system**.**

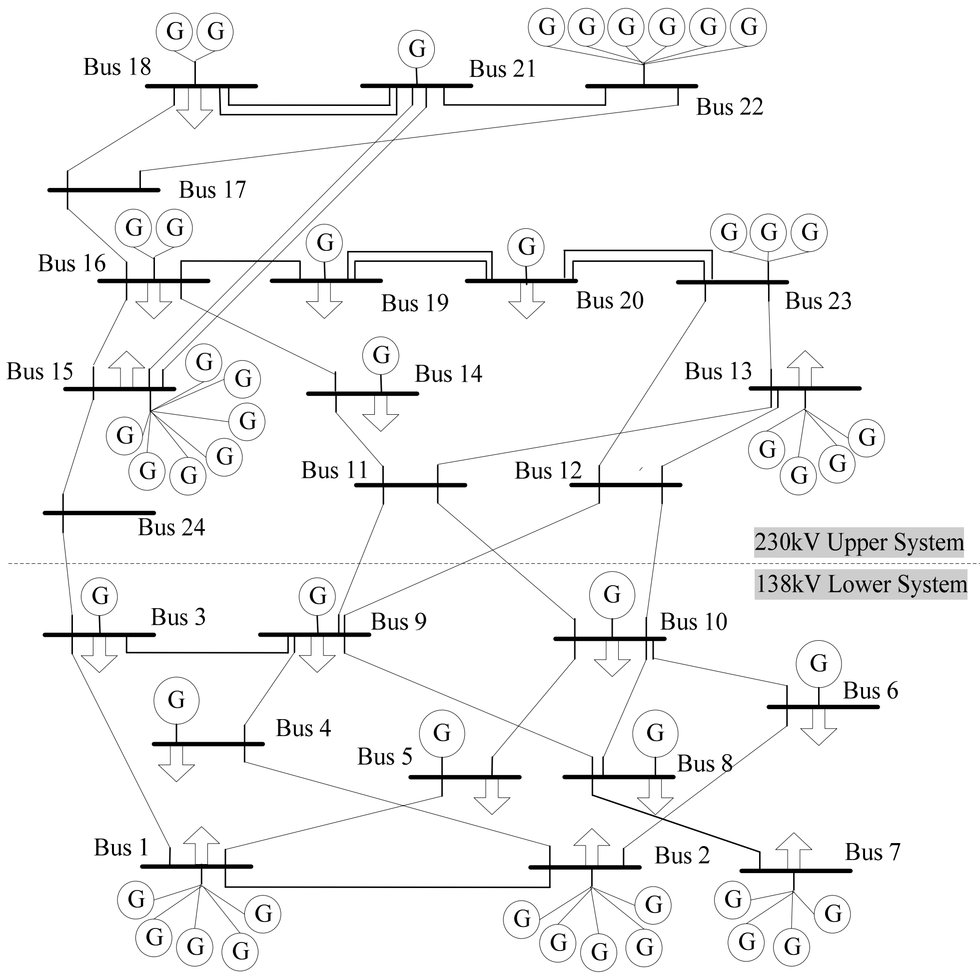

Figure 6.1 The IEEE RTS24 system

Each "G in a circle" represents a generation unit, and each arrow represents a native load. System yearly peak load L^{Peak}, weekly, daily, and hourly loads in percentages of L^{Peak}, admittance matrix $\mathbf{A}$, upper and bounds of real and reactive power generation parameter $\lfloor \overline{\mathbf{p}}, \mathbf{p}, \underline{\mathbf{q}}, \overline{\mathbf{q}} \rfloor$, and transmission capacities $[\mathbf{T}, \mathbf{T}']$ are referred to Billinton (1994). Voltage magnitude bounds $\underline{\mathbf{V}}/\overline{\mathbf{V}}$ are set to be 0.95/1.05 per-unit. A per-unit value is defined as a relative number in percentage to a base number, which reflects the nominal value. Coefficients of generation cost functions $\mathbf{C}(p) = \mathbf{a} + \mathbf{b}\mathbf{p} + \mathbf{c}\mathbf{p}^2$ are referred to (Meliopoulos, 1990) with vectors $\mathbf{a}$, $\mathbf{b}$, $\mathbf{c}$ having been doubled to reflect recent fuel cost increases. To stress the impact of transmission in stead of generation capacity constraints on market dynamics, we modify the RTS-24 system by setting transmission line capacities to be $0.6\overline{\mathbf{T}}$ and $0.6\overline{\mathbf{T}'}$ in normal and contingency scenarios, respectively. Correspondingly, the system peak load level is reduced to be $0.6L^{Peak}$. Due to the daily pattern of the load levels, we follow the NERC (North American Electric Reliability Council) definition of on-peak hours H^{on} being the 16 hours beginning at 7 am and ending at 11:00 pm for Monday through Saturday of each week, with the exception of some national holidays. All remaining hours are defined as off-peak H^{off}. The forced outage rates of most thermal units are set as 10%.

The load chronological curve (LCC) and load duration curve (LDC) of the system are shown as bellow in Figure 6.2. Note that as the load level bin of the LDC gets smaller, the LDC converges to be a smoother curve. The coarseness of the curve is determined by the tradeoff between computational burden and the accuracy of simulation.

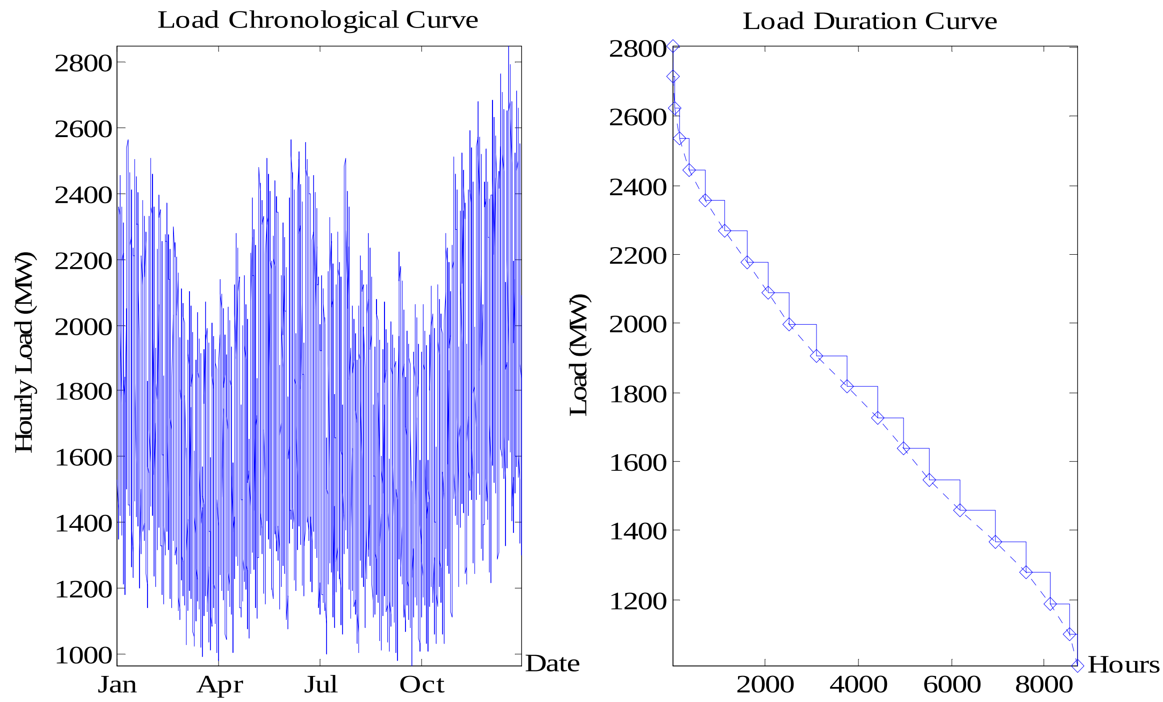

Figure 6.2 IEEE RTS24 load chronological (left) and the load duration (right) curves

By adopting different market dispatch models, we study comparatively the expectations of electricity prices and financial transmission rights values and their volatilities. Also investigated are the values-at-risk (VaRs) of market portfolios, generation owners' profits, load payments, and system congestion rents etc. For the convenience of illustration, notation $M^{C_1C_2C_3}$ denotes various market dispatch models with C_1 being A/D denoting using AC/DC power flow equations, C_2 being C/N denoting with/without contingency test, and C_3 being R/N denoting with/without generation reserve and transmission reliability margin requirements, $D^{C_1C_2C_3}$ denotes relative difference between models $M^{C_1C_2C_3}$ and M^{ACN} using M^{ACN} result as the base value. Note that only one representation of system conditions is assumed for calculation of hourly market prices. System condition changes within the hour are ignored. If the mechanism of an actual system, for example the PJM market, were adopted, where market prices are calculated every 5 minutes, the difference between models would have been more measurable, especially during resource-tightened and demand surging hours.

6.2.1 Single Scenario LMPs

Assume a low-load $(0.25L^{Peak})$ scenario in which no transmission line is congested and no generation unit reaches its capacity bound, the LMPs on all buses according to models M^{ANN} and M^{DNN} are illustrated in Figure 6.3.

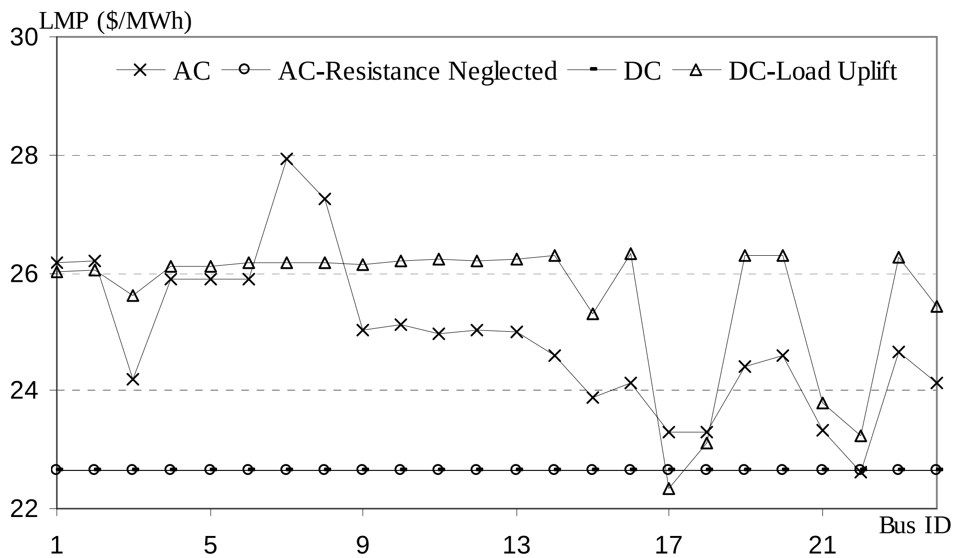

Figure 6.3 LMPs (in low load scenario) by models without contingency test

We observe that M^{DNN} gives a uniform LMP for all buses while LMPs from M^{ANN} are differentiated across buses. The differences come in part from consideration of transmission losses. By ignoring line resistances and, therefore, transmission losses, in M^{ANN}, exactly the same LMP can be obtained as by M^{DNN}. This equivalence remains as long as no other constraint becomes active. For M^{DNN}, following (Overbye, 2004), if we uplift load by 7%, the amount of transmission loss in percentage of system load according to M^{ANN}, which is equivalent to allocating loss in proportion to loads, the resulting LMPs get differentiated and closer to what M^{ANN} gives. However, differences remain since the loss allocation embedded in M^{ANN} is not uniform. The differences between M^{ANN} and M^{DNN} also come from possible active voltage bounds. For a transmission line connecting bus i and j with series resistance/reactance R/X, real/reactive power flows P/Q, the voltage decrease V_{ij} along the line is approximately

$(R+jX)\cdot\left(\overline{(P+jQ)e^{-j\delta_i}/V_i}\right)$, with V_i/δ_i being voltage magnitude/phase angle on bus i. For a system with many high impedance transmission lines, or in the case of high-load scenarios, the impact of transmission losses and voltage bounds tends to be more significant and the uniform load uplifting can not necessarily improve accuracy of M^{DNN}. Furthermore, if reactive power related services are priced explicitly, the economic incentive of voltage regulation can be significant.

Next we adopt the security constrained market dispatch models to simulate outages of lines 5-10 & 18-21. Assuming the installment of VAR compensation and voltage regulation equipments, the voltage bounds under a contingency are relaxed to be [0.90, 1.10] p.u. as used in (Milano, 2003). As illustrated in Figure 6.4, the LMPs in model M^{DCN} remain spatially uniform at a higher value as compared with those in Figure 6.3. Also increased are most of the LMPs according to M^{DCN} with uniform uplift of load which accounts for transmission losses. However, just as expected, the LMPs in model M^{ACN} are further spatially differentiated.

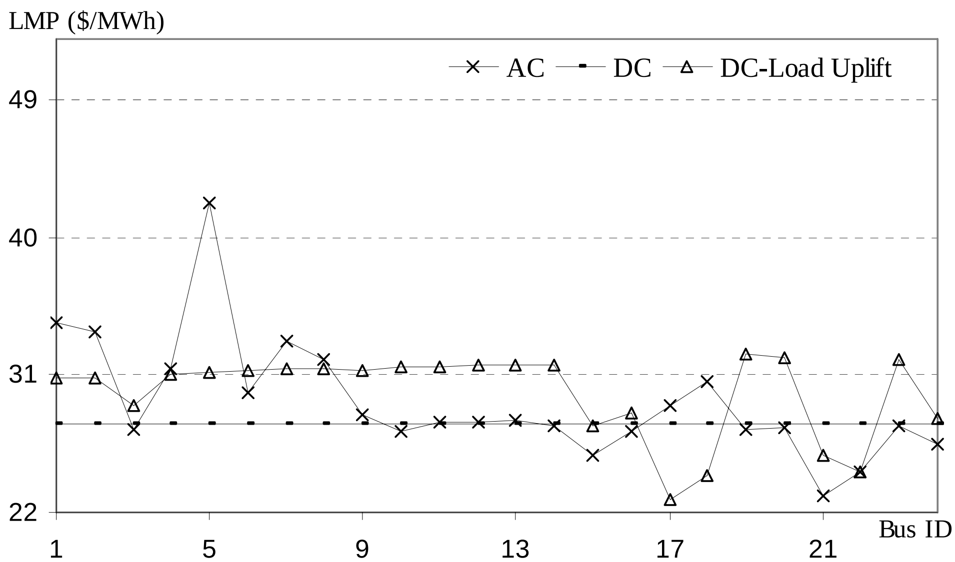

Figure 6.4 LMPs (in low load scenario) by models with contingency test

In a high load $\left(0.55L^{Peak}\right)$ scenario, as Figure 6.5 shows, both models M^{DCN} and M^{ACN} get differentiated LMPs reflecting transmission congestion. Actually, due to active voltage bounds, the discrepancy of LMPs at several buses such as 7, 8, and 21 becomes magnified.

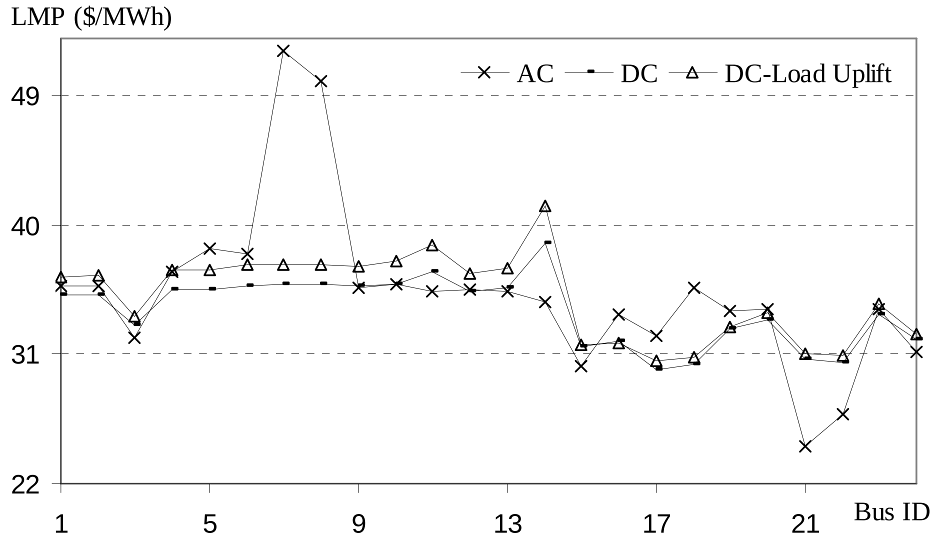

Figure 6.5 LMPs (in high load scenario) by models with contingency test

It is also foreseeable that with a different contingency list, different LMPs will result. By postulating the outages of lines 16-14 and 21-15 in high load scenario, the LMPs as illustrated in Figure 6.6 can be quite different as compared with those in Figure 6.5, especially for buses connected with the facilities in the list.

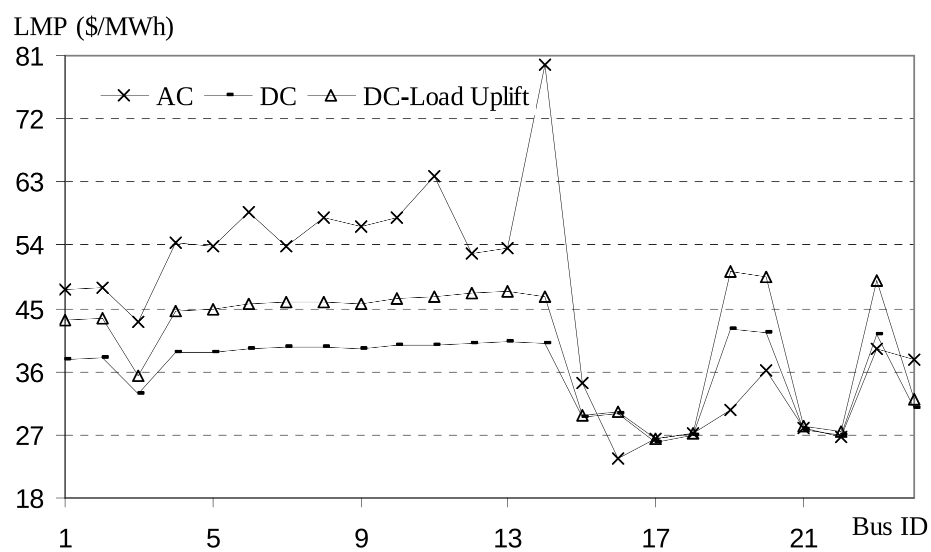

Figure 6.6 LMPs (in high load scenario) by models with contingency test
using different contingency lists

Accordingly, the contingency list shall be made available as public information to market participants for their understanding of market dynamics. In the following numerical experiments, we consider line outages of 5-10 and 18-21 for contingency tests.

6.2.2 Statistics of LMPs, FTR, and FTR Options

Intuitively, LMPs in a power market are higher in on-peak hours H^{on} than the prices in off-peak hours H^{off} since loads are generally higher in H^{on}. This pattern is clearly illustrated by the LMPs computed from either model M^{DCN} or model M^{ACN}. Figure 6. plots the probability density functions (PDFs) of LMPs at two typical buses. On the left panel, LMPs at Bus 4 obtained in model M^{ACN} are higher than those obtained in model M^{DCN}. Similar relationships are observed at Buses 1, 2, 5, 6, 7, 8, and 18. On the right panel, LMPs at Bus 21 computed in model M^{ACN} are lower than those computed in model M^{DCN}. Similar price profiles are also observed at Buses 10, 12, 15, 22, 23, and 24.

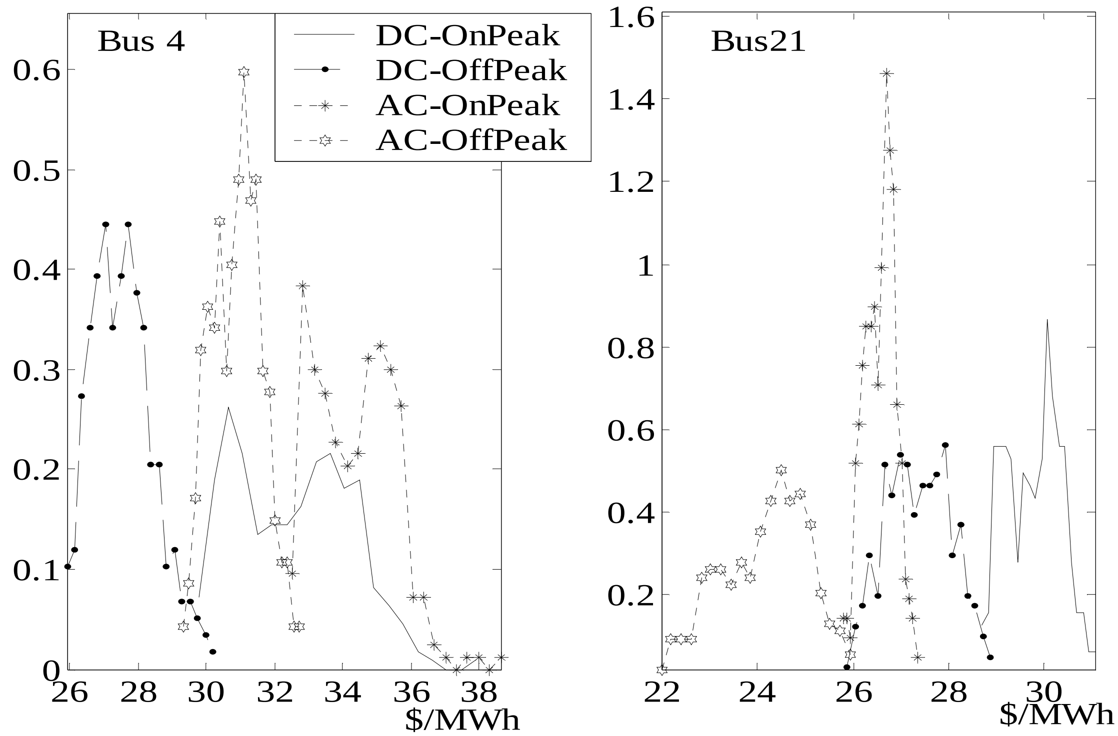

Figure 6.7 Comparison of PDFs of LMPs in on/off-peak hours in different models

While the LMPs in H^{on} are generally expected to be higher than those in H^{off}, LMPs at Bus 5 computed from the model M^{ACN} provide a counter-example where the PDF of the on-peak LMP distribution is to the left of the off-peak distribution, as shown in Figure 6.8. This is an example of the potentially erratic behavior of LMPs at a bus directly involved in a postulated contingency.

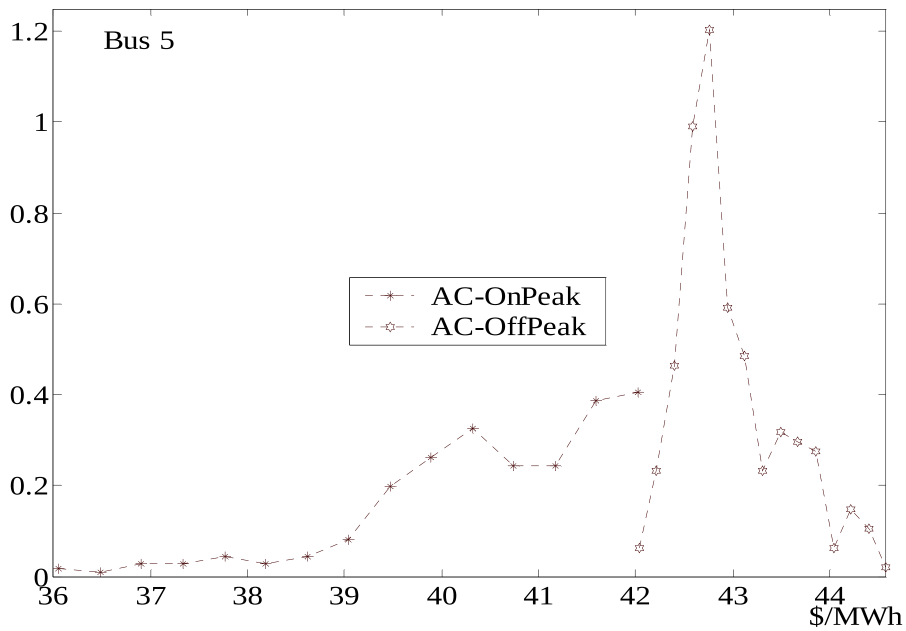

Figure 6.8 Comparison of the PDFs of LMPs at Bus 5 in on/off-peak hours

To illustrate the impact of incorporating contingency tests and the differences between the DC and AC models, comparative statistics of daily averaged on/off-peak LMPs are shown in Table 6.1. Note that the selected buses are identified as having high volumes of power injection or withdrawals (e.g., major generation or load sites, or both).

Table 6.1 Comparative statistics of LMPS

Bus	Model	Mean		Volatility	
		H^{on}	H^{off}	H^{on}	H^{off}
7	M^{ACN}	44.5	31.4	4.9	2.2
	D^{DCN}	-26.6%	-12.4%	-62.8%	-58.9%
	D^{ANN}	0.6%	10.0%	-19.7%	-21.4%
15	M^{ACN}	29.4	25.9	0.9	0.9
	D^{DCN}	5.0%	6.3%	-38.6%	-11.7%
	D^{ANN}	4.4%	6.6%	-16.3%	-21.1%
18	M^{ACN}	32.1	28.6	0.9	0.9
	D^{DCN}	-8.7%	-4.5%	-35.4%	-30.9%
	D^{ANN}	-8.3%	-5.2%	-38.0%	-23.0%
23	M^{ACN}	31.4	27.0	1.5	1.0
	D^{DCN}	2.3%	2.2%	-22.7%	-8.2%
	D^{ANN}	2.4%	5.6%	-20.5%	-21.4%

The relative differences in the risk measure of volatility between different LMP models are significant in general, especially in the peak hours. In most cases, the market risks generated by the LMP dynamics are underestimated by the DC models. For the mean value of LMPs, while the approximation errors are modest at Buses 15 and 23, the errors can be as large as $D^{DCN} = -26.6\%$ at Bus 7 and $D^{ANN} = -8.3\%$ at Bus 18. For the load payment (defined by load quantity multiplying the LMP at the load bus) side, the comparative statistics of daily on/off-peak load payments at Buses 7 and 18 are shown in Table 6.2.

Table 6.2 Comparative statistics of load payments

Bus	Model	Mean		Volatility	
		H^{on}	H^{off}	H^{on}	H^{off}
7	M^{ACN}	2402.5	1145.6	592.9	250.5
	D^{DCN}	-27.1%	-12.9%	-44.8%	-32.8%
	D^{ANN}	0.3%	9.7%	-9.2%	-3.6%
18	M^{ACN}	4558.2	2756.6	702.9	451.5
	D^{DCN}	-8.8%	-4.6%	-14.6%	-12.1%
	D^{ANN}	-8.4%	-5.3%	-14.7%	-9.8%

Note that the approximation errors of load payment means are comparable to those of LMPs. However, the approximation errors of volatilities are lower in absolute values, due to the fact that high LMP volatility appears in high load scenarios. Volatilities of load payments are equivalent to volatilities of LMPs multiplied by time varying weights, which reduces the relative differences.

As risk-management instruments, FTRs offer the ability to hedge against uncertain congestion rents associated with forward transactions. The value of an FTR equals the difference of LMPs at the power injection and withdrawal buses but its volatility also depends on the correlation of the two LMPs. The PDFs of two FTR values in on-peak hours H^{on} based on different market dispatch models are shown in Figure 6.9.

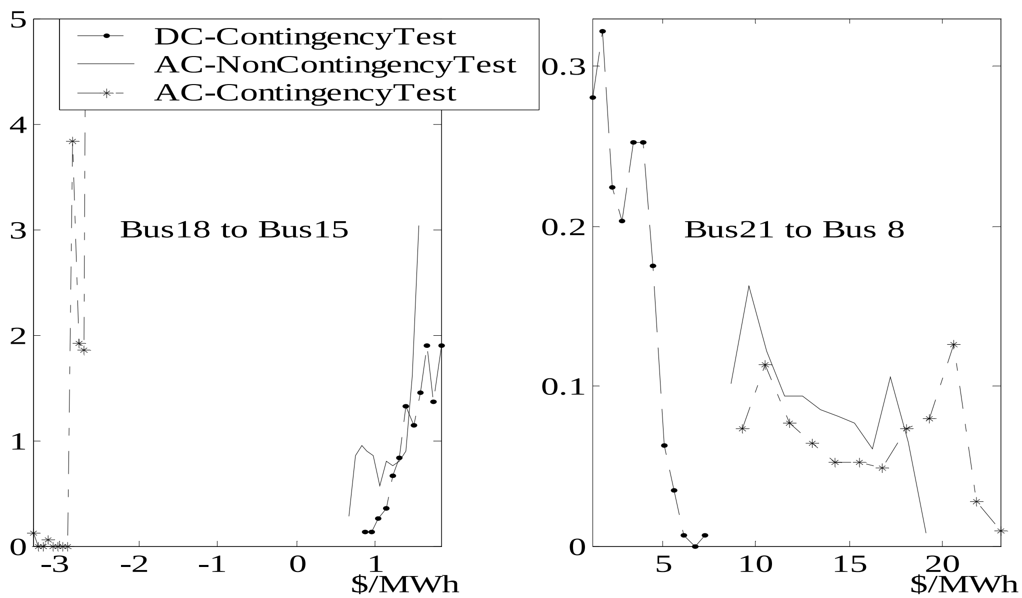

Figure 6.9 Comparisons of the PDFs of FTRs in on-peak hours under different models

The value of FTR 18->15 is negative in model M^{ACN} but positive in models M^{DCN} and M^{ANN}. Similar contrast exists for FTR 2->6 (numbers not reported here). In the right panel of Figure 6.9, the value of FTR 21->8 is higher in model M^{ACN} than it is in the other two models. More comparisons of the mean and volatility of the FTR values in H^{on} and H^{off} in M^{DCN}, M^{ANN}, and M^{ACN} are shown in Table 6.3.

Table 6.3 Comparative statistics of FTR values

FTR	Model	Mean		Volatility	
		H^{on}	H^{off}	H^{on}	H^{off}
18->10	M^{ACN}	-0.42	-2.11	1.02	0.26
	M^{DCN}	3.46	0.25	1.27	0.33
	M^{ANN}	4.40	2.25	1.19	0.22
21->3	M^{ACN}	4.95	3.17	1.00	0.09
	M^{DCN}	1.71	0.15	0.43	0.19
	M^{ANN}	1.99	1.02	0.47	0.10
22->6	M^{ACN}	7.21	4.34	1.94	0.22
	M^{DCN}	3.30	0.24	1.21	0.31
	M^{ANN}	6.92	4.38	1.45	0.36
23->8	M^{ACN}	10.57	3.46	3.01	0.95
	M^{DCN}	0.61	-0.01	0.71	0.01
	M^{ANN}	10.32	4.87	2.47	0.76

Note that the expected values of FTRs can be quite different in the three models. As for the volatilities which reflect the risks of FTRs, the values computed from model M^{ACN} are in general higher than those computed from the other two models. Also, because LMPs have low volatility in H^{off}, so do the FTRs.

As hinted by the high demand and popularity for the financial options in financial markets, FTR options have been constructed and their practices are under investigation in PJM, California, and Texas electricity markets (Deng, 2005). FTR options offer the right to claim congestion compensation but avoid the obligation to pay congestion costs in adverse conditions. The impact of various market dispatch models on FTR option pricing is examined as follows. For an underlying FTR with mean μ and volatility σ for its value distribution, two strike prices of the option are set to be $K_1 = \mu + \sigma$ and $K_2 = \mu + 2\sigma$. Corresponding to FTRs listed above, Table 6.4 shows the statistics of FTR options in H^{on}.

Note that the differences in FTR option values among different electricity market models can be significant as well. Lower FTR values do not necessarily yield lower FTR option values, and vice versa. Abnormally high electricity prices due to extreme scenarios such as facility outages and load spikes have crucial effects on the FTR option valuation. For example, although the value of FTR 18->10 is negative in most scenarios, the corresponding FTR option has a substantially positive value due to scattered LMP spikes.

Table 6.4 Comparative statistics of FTR option values

FTR Option	Model	Mean		Volatility	
		K_1	K_2	K_1	K_2
18->10	M^{ACN}	0.10	0.04	0.42	0.28
	M^{DCN}	0.13	0.01	0.32	0.12
	M^{ANN}	0.18	0.04	0.45	0.21
21->3	M^{ACN}	0.09	0.01	0.17	0.05
	M^{DCN}	0.02	0.01	0.06	0.03
	M^{ANN}	0.06	0.00	0.13	0.03
22->6	M^{ACN}	0.27	0.10	0.90	0.55
	M^{DCN}	0.12	0.01	0.31	0.11
	M^{ANN}	0.15	0.05	0.73	0.56
23->8	M^{ACN}	0.10	0.04	0.42	0.28
	M^{DCN}	0.13	0.01	0.32	0.12
	M^{ANN}	0.18	0.04	0.45	0.21

6.2.3 Impact of Generation Capacity Reserve and Transmission Reliability Margin

For each group of generation units connected to a bus, we impose a requirement of generation reserve at 20% of total capacity or the largest single unit capacity, whichever is higher (Bobo, 1994), to approximate the operational reserve margin.

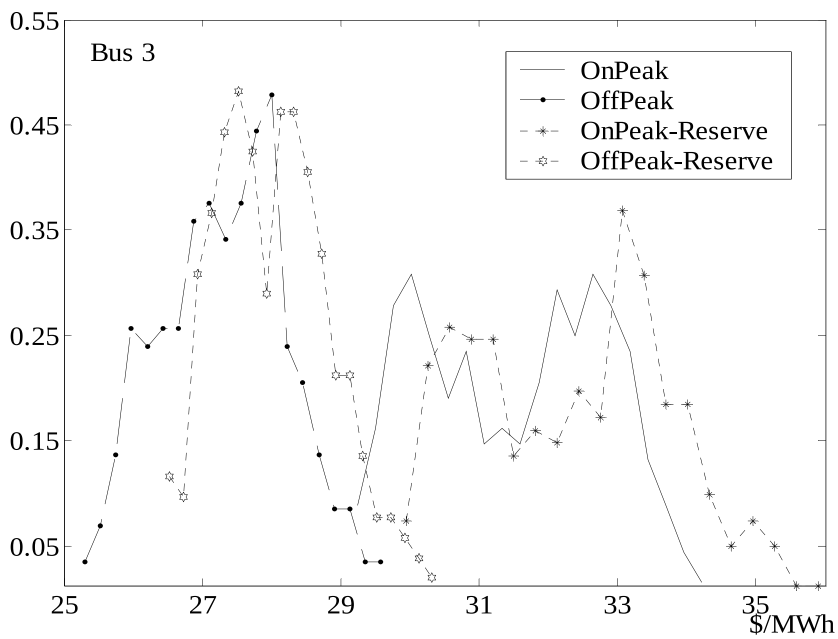

Figure 6.10 Comparison of PDFs of LMPs at Bus 3 in on/off-peak hours by different models

The largest unit capacity is also set for generation reserve in the upper and lower systems to protect from unit outages. A 15% transmission capacity margin is reserved for each transmission facility (McCalley, 1991). At most buses, the generation and transmission capacity reserve constraints induce approximately a modest right shift to the PDFs of LMPS. We pick Bus 3 as a representative case and show the distributions of LMPs obtained in models M^{ACN} and M^{ACR} over on-peak/off-peak hours H^{on}/H^{off} in Figure 6.10.

The left panel shows significant increases of LMP at Bus 13 in H^{on} after imposing system reliability constraints in the market dispatch model, while the right panel shows that the off-peak LMPs on Bus 21 actually decreases after imposing reliability constraints, and the tail of the off-peak LMP PDF is also thinner than that computed from model M^{ACN}.

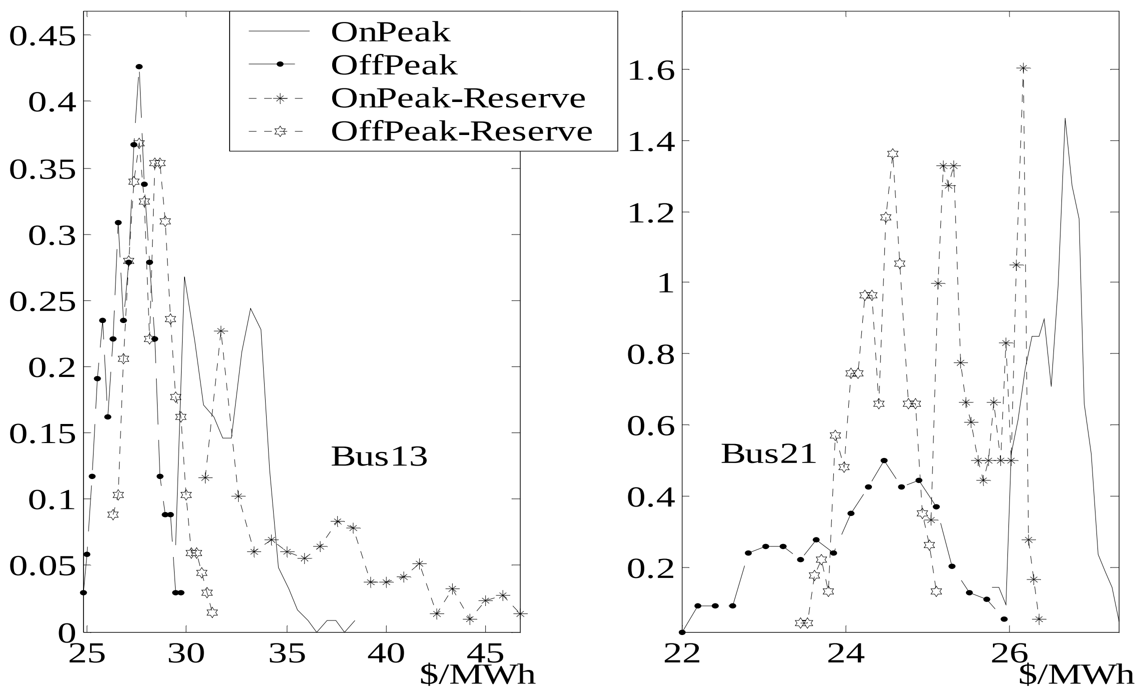

Figure 6.11 Comparison of PDFs of LMPs on Bus 13 and Bus 21
in on/off-peak hours by different models

From Figure 6.11, we reach a general conclusion that the impact of imposing system reliability constraints is more significant in on-peak hours when more system constraints tend to be binding than in off-peak hours.

6.2.4 Statistics of Portfolio Value, Generation Owners' Profit, System Load Payment, and System Congestion Rent

Value-at-Risk (VaR) is a powerful measure for assessing market risk (Dahlgren, 2003 and Denton, 2003). Unlike market risk metrics such as the asset beta value and the durations of bonds (Hull, 2002) which are applicable to only certain asset categories or certain sources of market risks, VaR is based on the probability distribution of a portfolio's market value, which reflects the contribution of all sources of market risk. Therefore, VaR is an all-encompassing measure of market risk. Let VaR^{α} denote the VaR of a portfolio at level $\alpha \in (0,1)$, a quantity that equals the $1-\alpha$ quantile of the distribution of the portfolio value. Namely, $VaR^{\alpha} = \sup_x \{x : P[X \le x] \le 1-\alpha\}$. Suppose a power generator has units at Buses 2, 18, 21, and 23 and has load contracts at Buses 6, 14, 3, and 5 in peak hours H^{on}. A portfolio can be constructed to include FTR 21->3, FTR option 2->6, and physical power supply forward contracts with load serving entities (LSEs) at Buses 5 and 14 all in H^{on}. Suppose the forward prices equal the seasonal mean value of the LMPs in H^{on} and the FTR, FTR option, and the forwards are all of the quantity of 30 MW. The portfolio also contains the generation revenues/costs of the excess/inadequate generation capacity after serving the load obligations, which are settled at spot prices. The daily mean, volatility, and the one-day VaRs of the portfolio value based on different market dispatch models are shown in Table 6.5.

Table 6.5 Comparative statistics of portfolio values (unit: $\$10^3$)

Model	Mean	Volatility	$VaR^{0.95}$	$VaR^{0.90}$
M^{DCN}	11.79	8.19	2.84	3.58
M^{DCR}	10.56	10.74	0.14	0.85
M^{ANN}	12.13	8.62	2.85	3.66
M^{ANR}	11.28	11.02	-0.97	-0.18
M^{ACN}	16.30	8.87	6.52	7.64
M^{ACR}	15.23	12.47	1.96	2.86

Although the differences in the mean portfolio value obtained from different market dispatch models are modest, the differences in the VaR estimations are quite significant. The importance of employing an appropriate market dispatch model for the risk management practices of power market participants is endorsed by this fact as it demonstrates that the correct assessment of a risk measure such as VaR depends critically on how the power market is modeled.

The statistics of generation owners' profits, defined as the generation owners' revenue minus generation cost, are shown in Table 6.6,

Table 6.6 Comparative statistics of system generation owners' profits (unit: $\$10^3$)

Model	Mean	Volatility	$VaR^{0.95}$	$VaR^{0.90}$
M^{DCN}	143.95	13.49	124.26	125.83
M^{DCR}	113.80	17.28	94.72	96.01
M^{ANN}	140.69	14.68	120.43	121.82
M^{ANR}	112.46	14.95	92.12	93.49
M^{ACN}	133.21	14.88	112.36	113.94
M^{ACR}	109.01	18.92	85.30	86.68

We also define the VaR^{α} metrics of daily load payment in hours H^{on} as the α-quantile of its distribution, that is, $VaR^{\alpha} = \sup_x \{x : P[X \le x] \le \alpha\}$, since the right tail is of concern to consumers. The one-day VaR of daily payments for total system loads are shown in Table 6.7.

Table 6.7 Comparative statistics of system load payments (unit: $\$10^3$)

Model	Mean	Volatility	$VaR^{0.95}$	$VaR^{0.90}$
M^{DCN}	622.32	90.18	735.42	772.82
M^{DCR}	651.44	99.90	764.13	830.69
M^{ANN}	653.95	96.13	776.69	818.07
M^{ANR}	681.64	108.21	815.36	859.41
M^{ACN}	649.74	97.94	772.16	810.37
M^{ACR}	687.88	123.66	850.87	913.82

System congestion rent is a proper measure for price disparity, transmission adequacy, and competitiveness of a market as well. The statistics of means, volatilities, and one-day VaRs (defined in the same way as those of load payments since the right tail is of concern to system operators) of total system congestion rents are shown in Table 6.8.

Table 6.8 Comparative statistics of system congestion rents (unit: $\$10^3$)

Model	Mean	Volatility	$VaR^{0.95}$	$VaR^{0.90}$
M^{DCN}	32.16	13.17	14.51	16.12
M^{DCR}	62.47	17.90	41.33	44.51
M^{ANN}	41.18	14.78	23.77	25.15
M^{ANR}	71.54	23.60	40.04	41.95
M^{ACN}	40.00	16.55	17.89	19.54
M^{ACR}	77.44	34.80	37.15	39.31

From Tables 6.5-6.8, we observe that the adoption of various market dispatching models has various impacts on each participant's financial positions. The risk metrics are more volatile, and the means and VaRs tend to take less favorable values if AC-based instead of DC-based power flow formulation is adopted, if contingency tests is incorporated, or, most significantly, if generation capacity reserve and transmission reliability margins are imposed. Of course, the significance of the impact depends on how these factors are imposed and on the system specific conditions. The imposing of generation/transmission reserve requirements causes increase in load payments and decreases in generation profits, which implies the cost sharing between generation owners and consumers.

6.2.5 System-Wide LMP Volatilities

We introduce a system-wide LMP volatility measure

$$Vol^{Sys} = \sqrt{E\left[\sum_{n=1}^{N}\left(LMP_n - \overline{LMP}\right)^2 \Big/ (N-1)\right]} \tag{6.3}$$

where $\overline{LMP} = \frac{1}{n}\sum_{n=1}^{N} LMP_n$, with expectation being taken over the distribution of system loads. Vol^{Sys} reflects the dispersion of LMPs across the entire system. The values of Vol^{Sys} averaged over all hours in H^{on} and H^{off} in each model are given in Table 6.9.

Table 6.9 Comparative statistics of system-wide volatilities

Model	H^{on}	H^{off}
M^{DCN}	1.46	0.16
M^{DCR}	3.28	1.06
M^{ANN}	3.82	2.01
M^{ANR}	5.04	2.41
M^{ACN}	4.39	3.97
M^{ACR}	5.50	3.70

According to Table 6.9, with more constraints incorporated into the market dispatch problem, the LMPs over the system get spatially more dispersed. This observation coincides with our intuition.

6.3 Summary

Through simulation studies, this section compared alternative market dispatch models which differ from each other in DC or AC power flow formulations and in the set of reliability constraints considered. Their impacts on market dynamics are investigated and a few observations can be made,

1. Even during off-peak hours when system load is low and few constraints of the OPFs are binding, higher levels of variation in the LMPs across the test system are observed in the AC-based market dispatch models than in the DC-based market dispatch models. This discrepancy is caused by their different treatments of transmission losses. In DC models, the aspects of transmission line resistances and transmission losses are absent, which requires exogenous loss functions or LMP uplifts for transmission loss allocation. By contrast, AC-based market dispatch models incorporate losses in the power flow equations in the optimization. As the result, the economic impact of transmission losses is reflected through a component of LMPs.

2. In the AC-based market dispatch models, control of bus voltages with respect to pre-specified upper and lower bounds causes further spatial variations of the LMPs and makes the LMPs more sensitive to load peaks as compared to the DC models, where no voltage constraint is imposed. This is especially true for buses connected to transmission lines with high impedance or buses distant from VAR support. It suggests that the economic incentives for voltage regulation could be more significant if reactive power related services were explicitly priced as advocated by some researchers.

3. The volatilities of LMPs, FTR values, suppliers' revenues, consumers' payments, and consequently, market participants' market risks, are underestimated by the DC-based market dispatch models as compared with the AC model, especially during on-peak hours when system load is high and more constraints of the OPFs tend to be binding. It brings significant deviations in valuing market instruments like FTR options since extreme system scenarios, such as facility outages and load spikes, are essential in determining their values.

4. The contingency list considered by the system operator in the security-constrained market dispatch model is crucial to the determination of LMPs, especially to buses with direct connection with the transmission facilities appearing in the list. Therefore, the contingency list

should be made available as public information for market participants for their understanding of market dynamics.

5. Generally, the imposing of generation reserve or transmission reserve margin requirement lifts the LMPs, although exceptions do exist on generation redundant buses or load pockets. The increase of load payments and decrease of generation profits induced result in a cost sharing between generation owners and consumers for enhanced system reliability.

The choice of the market dispatch model is crucial. The discrepancy between the respective market estimations by different models would be more significant if market prices were calculated more frequently, as the 5-minutes interval adopted by the northeast ISOs in the U.S. instead of the 1-hour interval adopted in our simulation studies. It is also foreseeable that to establish economically driven mechanisms for ancillary services, market dispatch models should be enhanced to increase the transparency of market pricing and cost allocation rules. More information regarding the dispatch should be disclosed to market participants for better market assessments. Due to the complexity of the problem, the observations are preliminary and system-specific. However, an analytical framework is established and the importance of the problem is revealed. More analytical results are expected in our further research.

7. Stochastic Electricity Price Models

Two approaches are widely employed in studying the electricity price behaviors: a fundamental approach that relies on simulation of system operations, and a technical approach that attempts to model the stochastic behavior of market prices from historical data and fundamental analysis. Along the line of the technical approach, pricing models developed for non-storable commodities tend to fall short in capturing the erratic characteristics of electricity prices such as spikes and negative values. There is a growing literature on modeling electricity prices in the restructured electricity industry with models utilizing reduced-form stochastic processes, fuzzy regression combined with neural network, and Fourier Hartley transform-based techniques. However, it is challenging for these models to reveal the impacts of bulk power system constraints on price volatility. Moreover, the constantly changing market rules make the technical models difficult to calibrate using market data. As an alternative, we consider the approach of combining the fundamental approach with the technical models for modeling electricity prices and apply it to transmission rights valuation.

7.1. Class-I Quantile Based GARCH Model

Due to the unique characteristics of electricity (such as non-storability, transmission capacity constraints, and inelasticity of electricity consumption), unparalleled volatilities are exhibited in electricity prices. Other observations of empirical electricity prices, including volatility clustering and the heavy tails, have been revealed in the literature. Motivated by the flexibility of quantile-based probabilistic models in capturing stylized features of empirical data, we implement the quantile-based probabilistic model proposed in Deng and Jiang (2004) for modeling the unconditional distribution and fitting the marginal distributions of hourly log-return of electricity prices (log-return is defined as the logarithm of the ratio of each hourly electricity price in two consecutive days). The electricity prices obtained by simulation are used to calibrate the model parameters to make the model applicable to the specific electric system configuration and conditions. A non-Gaussian Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model using a quantile-specific distribution is constructed. In contrast to the traditional time series analysis which focuses on modeling the conditional first moment, the GARCH model incorporates the conditional second moments explicitly to better interpret the dynamics.

To characterize a probabilistic distribution of a univariate random variable X, the monotonically increasing quantile function $q(y)$, $y \in (0,1)$, as opposed to the probability distribution function $F(x)$, can be defined as the generalized inverse:

$$q(y) = F^{-1}(y) = \inf\{x : F(x) \geq y\} \tag{7.1}$$

where the infimum is taken over the range of X.

The following class I distribution $Q(\alpha, \beta, \delta, \mu)$ is constructed in Jiang (2000) and is described by the following quantile function:

$$q(x;\alpha,\beta,\delta,\mu)=\delta^{\frac{1}{\alpha}}\left\{\ln\frac{x^{\beta}}{1-x^{\beta}}\right\}^{\left(\frac{1}{\alpha}\right)}+\mu \tag{7.2}$$

where $\alpha,\beta,\delta\in\mathbf{R}_{+}$, $\mu\in\mathbf{R}$ and the superscript (α) for $\alpha>0$ represents the operation:

$$x^{(\alpha)}=\begin{cases}x^{\alpha} & x>0\\ 0 & x=0\\ -(-x)^{\alpha} & x<0\end{cases}$$

and the probability density function of $Q(\alpha,\beta,\delta,\mu)$ is:

$$f(x;\alpha,\beta,\delta,\mu)=\frac{\alpha\dfrac{(x-\mu)^{(\alpha)}}{(x-\mu)}\exp\left(-\dfrac{1}{\delta}(x-\mu)^{(\alpha)}\right)}{\delta\beta\left(1+\exp\left(-\dfrac{1}{\delta}(x-\mu)^{(\alpha)}\right)\right)^{1+\frac{1}{\beta}}}\ \text{for}\ x\in(-\infty,\mu)\cup(\mu,+\infty). \tag{7.3}$$

The intuitive interpretations for the parameters of a class I distribution are given as follows. Parameter α indicates the tail order with the smaller the value of α, the fatter the tail of the distribution; β depicts the balance of distribution tails with $\beta=1$ means a balanced tail and $\beta<(>)1$ means a fatter left (right) tail compared with the other; δ scales the point probability density, and μ determines the central location of the distribution. The versatile capability of the class I quantile-based distributions are illustrated in Jiang (2000).

The time series of the log-return ρ_h of electricity prices can be calculated as:

$$\rho_h=\log\left(P_h\big/P_{h-1}\right)=\log(P_h)-\log(P_{h-1}) \tag{7.4}$$

where h denotes the index of hour, and

P_h denotes the electricity price in hour *h*.

Given the distributions defined by the quantile function, we turn to the time series models based on these quantile-defined distributions. In particular, the non-Gaussian GARCH model with class I error distributions with the following specification is adopted to model the log return of electricity prices ρ_h $(h=1,2,\cdots,H)$,

$$\rho_h=\sigma_h\ \varepsilon_h \tag{7.5}$$

$$\sigma_h^2=\kappa_0+\kappa_1\ \rho_{h-1}^2+\kappa_2\ \sigma_{h-1}^2\ ,\ \kappa_0\geq 0,\kappa_1\geq 0,\kappa_2\geq 0$$

where $\varepsilon_t \sim i.i.d.\ Q_I(\alpha,\beta,\delta,\mu)$ random variables and ε_t 's are independent of $\{\rho_{h-k},\mathrm{k}\geq 1\}$ for $\forall t$.

Compared with the normal distribution based GARCH model, the model above has the following merits:

1. The closed-form quantile function of ρ_h leads to an explicit likelihood function and makes the maximum likelihood estimation an alternative approach for the inference of model parameters.

2. The diversity of tail patterns of the conditional distribution of ρ_h with respect to the model parameters α and β provides to the flexibility in accommodating various tail behaviors embedded in the empirical data.

3. The GARCH model provides inherent ability to capture the volatility clustering.

In addition to the approach of directly matching quantile functions to minimize the L_n norm distance between the theoretical quantile function as a function of model parameters and the empirical quantile function (see Jiang, 2000), the explicit quantile function and probability density function of the class-I distributions make the maximum likelihood estimation (MLE) a viable approach for parameter inference in the Class I quantile GARCH model.

The time series of ρ_h modeled in (7.5) can be rewritten as

$$\rho_h = \sqrt{\kappa_0 + \kappa_1 \ \rho_{h-1}^2 + \kappa_2 \ \sigma_{h-1}^2} \ \varepsilon_h \qquad (7.6a)$$

or,

$$\rho_h = \sigma_h \ \varepsilon_h, \text{ where } \sigma_h = \sqrt{\kappa_0 + \kappa_1 \ \rho_{h-1}^2 + \kappa_2 \ \sigma_{h-1}^2} \text{ and } \varepsilon_h \sim f(\rho; \alpha, \beta, \delta, \mu). \qquad (7.7b)$$

By a property of the class I distribution,

$$\rho_h \sim f(\rho; \alpha, \beta, \sigma_h^\alpha \delta, \sigma_h \mu). \qquad (7.8)$$

The joint probability distribution for the H hour price log returns is:

$$f(\rho_1, \rho_2, \cdots, \rho_H) = \prod_{h=1}^{H} f(\rho_h \mid \rho_{h-1}). \qquad (7.9)$$

The log-likelihood function φ can be expressed as,

$$\varphi = \ln\left(f(\rho_1, \rho_2, \cdots, \rho_H)\right) = \ln\left(\prod_{h=1}^{H} f(\rho_h \mid \rho_{h-1})\right) = \sum_{h=1}^{H} \ln\left(f(\rho_h \mid \rho_{h-1})\right) \qquad (7.10)$$

$$= \sum_{h=1}^{H} \ln\left(f(\rho_h; \alpha, \beta, \sigma_h^\alpha \delta, \sigma_h \mu)\right).$$

To estimate the parameters $[\kappa_0, \kappa_1, \kappa_2]$ for the GARCH model and the parameters $[\alpha, \beta, \delta, \mu]$ of the class I distributions, the maximum likelihood estimation (MLE) is applied. The MLE method solves the problem of maximizing the log-likelihood function $\varphi\left(\{\rho_h\}_{h=1}^{H}; \alpha, \beta, \delta, \mu, \kappa_0, \kappa_1, \kappa_2\right)$, which is formulated as:

$$\text{Max} \ \ \varphi\left(\{\rho_h\}_{h=1}^{H}; \alpha, \beta, \delta, \mu, \kappa_0, \kappa_1, \kappa_2\right) \qquad (7.11a)$$

$$\text{s.t.} \qquad \sigma_0 = 0 \qquad (7.11b)$$

$$\sigma_h^2 = \kappa_0 + \kappa_1 \ y_{h-1}^2 + \kappa_2 \ \sigma_{h-1}^2, \mathrm{h} = 1, \cdots, H \qquad (7.11c)$$

$$\kappa_0, \kappa_1, \kappa_2 \geq 0 \qquad (7.11d)$$

$$\kappa_1 + \kappa_2 < 1 \qquad (7.11e)$$

$$\alpha, \beta, \delta \geq 0 \qquad (7.11f)$$

where the constraints (7.11d and 7.11e) are for ensuring the stochastic process stationary.

Due to the high nonlinearity of the problem (7.11a-f), the convergence to optimum is very slow and difficult to achieve. Since it is proved in Hall and Yao (2003) that the distributional assumption of ε_t does not affect the inference of GARCH model parameters $[\kappa_0, \kappa_1, \kappa_2]$, the problem (7.11a-f) can be decomposed into two steps by relaxing the distributional assumptions on ε_t. In the first step, we find the GARCH model parameters $[\kappa_0, \kappa_1, \kappa_2]$ by replacing the parametric distribution with a normal distribution $N(\tilde{\mu}, \tilde{\sigma})$. This particular distribution $n(x; \tilde{\mu}, \tilde{\sigma}) = \frac{1}{\sqrt{2\pi}\tilde{\sigma}} \cdot e^{-\frac{(x-\tilde{\mu})^2}{2\tilde{\sigma}^2}}$ has two parameters $\tilde{\mu}$ and $\tilde{\sigma}$ only, and the estimation for $[\kappa_0, \kappa_1, \kappa_2]$ can be obtained relatively easier by replacing (7.11a) with the following:

$$\text{Max} \quad \varphi\left(\{\rho_h\}_{h=1}^{H}; \tilde{\mu}, \tilde{\sigma}, \kappa_0, \kappa_1, \kappa_2\right)$$

$$= \sum_{h=1}^{H} \ln\left(f\left(\rho_h; \sigma_h \tilde{\mu}, \sigma_h^2 \tilde{\sigma}\right)\right) = \sum_{h=1}^{H} \left(\ln(\sigma_h \tilde{\sigma}) + \frac{(\rho_h - \tilde{\mu})^2}{2\sigma_h^2 \tilde{\sigma}^2} + C \right) \tag{7.12}$$

where the constant C can be ignored in the objective function.

In the second step, we solve the $Q(\alpha, \beta, \delta, \mu)$ distribution parameters $[\alpha, \beta, \delta, \mu]$ using the values of $[\kappa_0, \kappa_1, \kappa_2]$ obtained above. The optimization problem here is:

$$\text{Max} \quad \varphi\left(\{\rho_h\}_{h=1}^{H}; \alpha, \beta, \delta, \mu\right) = \sum_{h=1}^{H} \ln\left(f\left(\rho_h; \alpha, \beta, \sigma_h^{\alpha}\delta, \sigma_h \mu\right)\right) \tag{7.13}$$

$$= \sum_{h=1}^{H} \frac{\alpha \dfrac{(\rho_h - \sigma_h \mu)^{(\alpha)}}{(\rho_h - \sigma_h \mu)} \exp\left(-\dfrac{1}{\sigma_h^{\alpha}\delta}(\rho_h - \sigma_h \mu)^{(\alpha)}\right)}{\sigma_h^{\alpha}\delta \cdot \beta \cdot \left(1 + \exp\left(-\dfrac{1}{\sigma_h^{\alpha}\delta}(\rho_h - \sigma_h \mu)^{(\alpha)}\right)\right)^{1+\frac{1}{\beta}}}$$

s.t. $\quad \alpha, \beta, \delta \geq 0$

$\sigma_0 = 0$

where $\sigma_h^2 = \kappa_0 + \kappa_1 \ \rho_{h-1}^2 + \kappa_2 \ \sigma_{h-1}^2, (h = 1, .., H)$.

7.2. Parameter Calibration

The class I quantile based GARCH model can be applied to the simulated IEEE RTS24 system electricity prices reported in the previous chapter. For illustration purpose, we use the electricity prices simulated from the AC market dispatch model with transmission constraints but no reliability constraints or contingency tests for parameter calibration.

Following the quantile function based parameter estimation procedures described above, the estimated model parameters for the class I distribution that fit the simulated RTS24 electricity prices are given in Table 7.1.

Table 7.1 Estimated model parameters

	α	β	δ	μ
Bus 05	0.864	0.998	0.0189	0.000908
Bus 18	0.858	0.961	0.0223	0.00145

Figure 7.1 illustrates the quantile-quantile (Q-Q) plots of the empirical quantile versus the respective theoretical quantiles where the theoretical quantiles are plotted on the x-axis and the empirical quantiles on the y-axis. Each of the two Q–Q plots in Figure 7.1 forms a relatively straight line, which indicates a good fit between the empirical quantile function and the theoretical quantile function, except for several outliers.

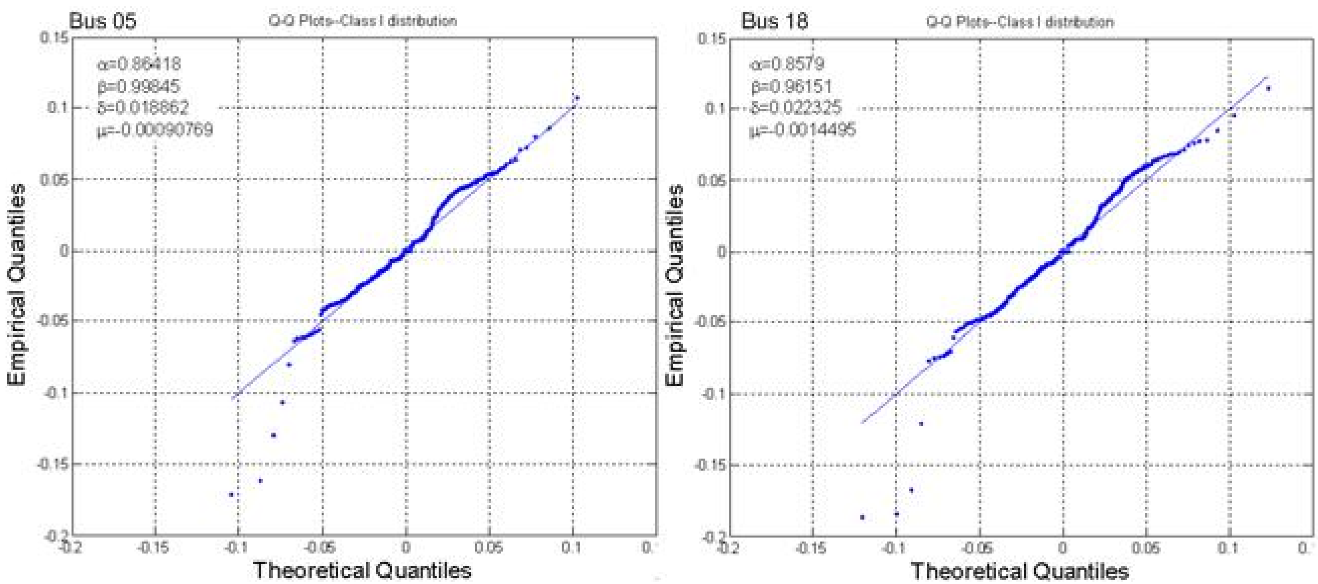

Figure 7.1 Q-Q plots based on class I quantile based GARCH(1,1) model applied to electricity prices on Bus 05 and 18

From the estimated values of $[\alpha, \beta, \delta, \mu]$, we see that the distributions of electricity prices at Buses 05 and 18 exhibit similar tail fatness. $\beta < 1$ indicates that the left tails of both price distributions are fatter than the respective right tails. The electricity prices simulated from other market dispatch models can be employed to calibrate the price model parameters to study the sensitivity of $[\alpha, \beta, \delta, \mu]$ with respect to various market model assumptions. The simulated LMPs can also be fitted to jump-diffusion and regime-switching price models.

With the parameters of the stochastic price models calibrated against the simulated LMPs from a based case and certain postulated cases with planned transmission investment projects, the resulting electricity price models can be employed to value economic incentives and financial transmission rights, which provide a market-based approach for evaluating investment decisions on where and how much to invest in generation and transmission. Investment opportunities on transmission capacity such as maintenance, upgrade and construction of new lines can be evaluated based on the projection of future market conditions using the reduced-form electricity price models calibrated through the power system simulation model.

8. Evaluation of Interruptible Load Contracts

In a power system, due to fluctuations in load, scheduled facility maintenance, and contingency events such as unexpected facility outages, capacity margins in generation and transmission are reserved for system reliability and security concerns. However, if the redundant capacity installed is economically unworthy, or, if sufficient reserved capacity cannot be achieved in a timely manner, the system operators and load serving entities have to resort to alternative approaches to avoid jeopardizing the system's operation. Methods such as rotating outages and reducing voltage are used in emergency contingency scenarios (Gedra and Varaiya, 1993). In a market environment, corresponding ancillary services, such as regulation up/down services and spin/non-spin reserves, are established. However, the adjusting effect is limited, especially in extreme scenarios when inadequate capacity can be acquired on a customer-willing basis to meet the demand. Interruptible load contracts combine direct load control for the system operator with monetary incentives to consumers.

In an interruptible load contract, the customer enters into a contract with the system operator or a load serving entity (LSE) to reduce its demand when requested. Interruptible load contracts offer consumers a range of rate-reliability choices. Customers who choose to buy interruptible energy, can do so by communicating the reliability level they want so that all usage above that level is at the interruptible price. Under the contracts, customers reduce their demand when requested by the utility. The system operator or load serving entity benefits from this by way of a reduction in its peak load, which helps it to restore its voltage profile, provide real and reactive power relief, and therefore, saving costly reserves and maintaining quality of service to the remaining consumers. The customers benefit from reduced energy costs and other benefits specified by the contract. The acquirement of interruptible load contracts provides an on-line reserve which can respond promptly to help maintain reliability when short-term emergency operating conditions are encountered.

This chapter provides preliminary studies on the sensitivity of system reliability indices with respect to the influential factors including the capacity and availability of generation, and transmission facilities. The effect of interruptible load contracts on system reliability indices is evaluated through comparative experiments.

8.1. Reliability without Interruptible Load Contracts

A 2-Bus example system is shown in Figure 8.1. Assume there are three identical generation units connected to Buses A and B respectively. The generation cost at Bus A is higher than that at Bus B. Two parallel transmission lines connect Buses A and B. The mean time to failure (MTTF), mean time to repair (MTTR), and forced outage rate (FOR) of all generation units and transmission lines are given in Figure 8.1.

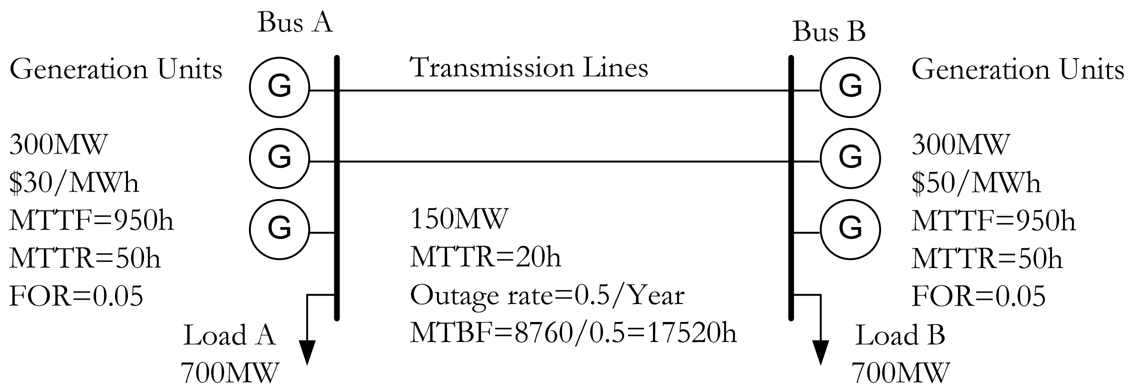

Figure 8.1 A 2-Bus Example with Constant Loads

By enumerating the possible generation and transmission facility availability states, the probabilities of discrete transmission capacity margins and loss of load are calculated and illustrated in Figure 8.2.

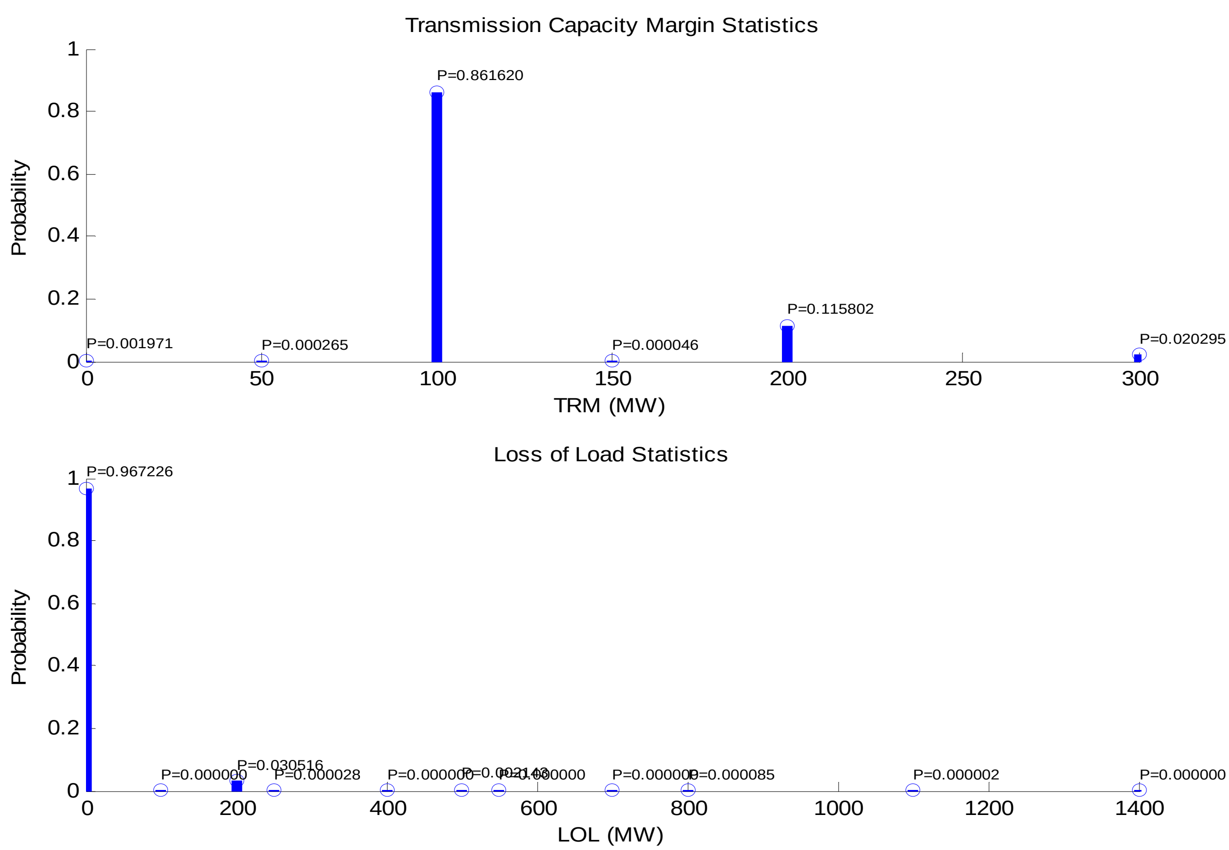

Figure 8.2 Probability of transmission capacity margin and loss of load

Figure 8.3 shows the sensitivity of reliability indices, including loss of load probability (LOLP), expected loss of load (LOL), expected transmission reserve margin (TRM), and expected transmission reserve margin in percentages, with respect to generator and transmission line outage rates. Note that the forced outage rate of generation units is essential to the reliability level as the reliability indices indicate. Changes in the forced outage rate of transmission lines in this particular system configuration have little impact on these reliability measures.

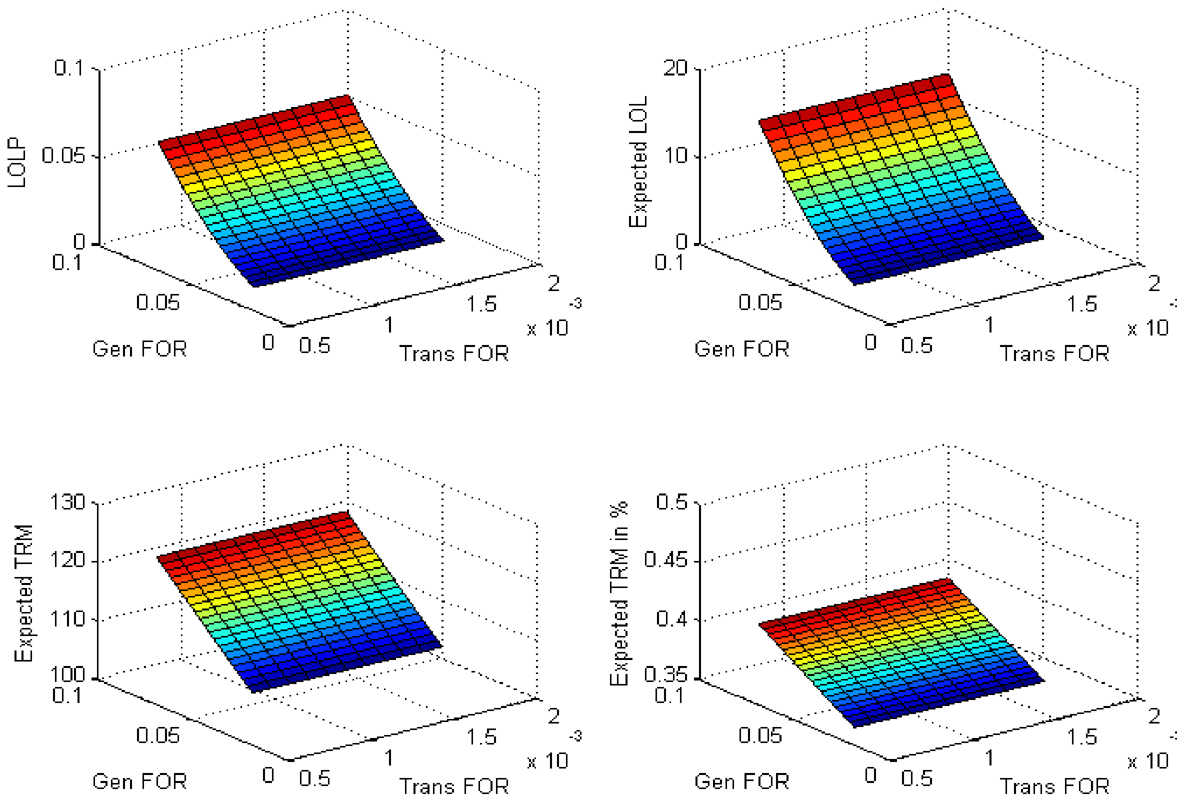

Figure 8.3 Reliability Indices with respect to generator and transmission line outage rates

However, as illustrated in the left panel of Figure 8.4, the expected generation margin at Bus A highly depends on the forced outage rate of transmission lines, although it is not the case with Bus B (shown in the right panel of Figure 8.4). This is due to the fact that generation at Bus A is of lower cost compared with that at Bus B. More generation at Bus A is dispatched according to the merit-order by the system operator in normal scenarios. The outage of transmission lines prevents the transfer of generation from A to B would equivalently increase the idle generation capacity at Bus A.

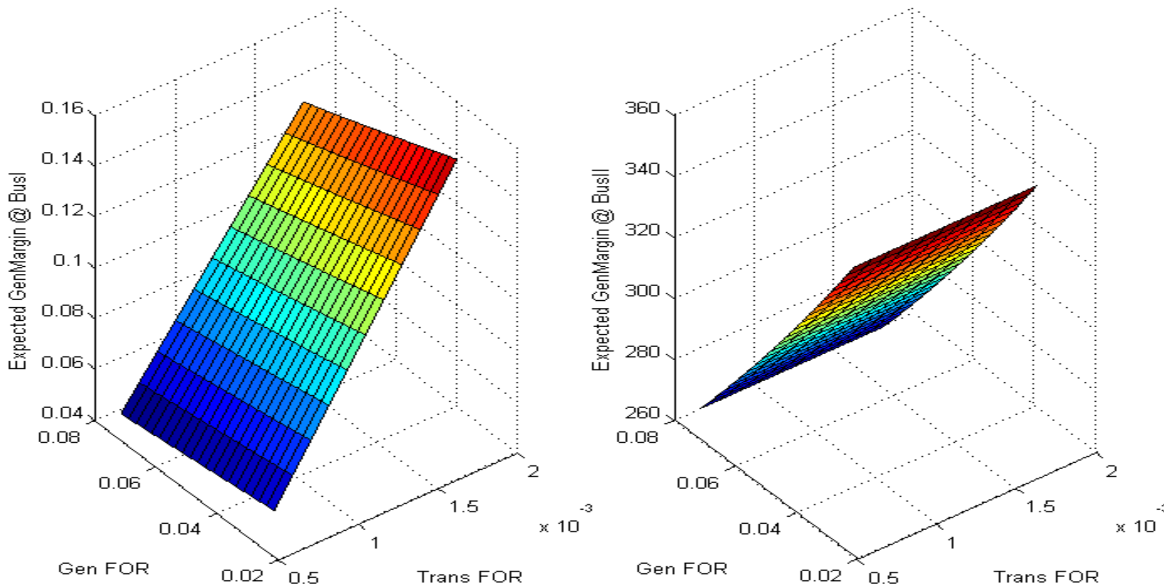

Figure 8.4 Expected locational generation margins
with respect to generator and transmission line outage rates

To investigate the impact of generation unit and transmission line capacity on the system reliability indices, market prices, and value of market instruments such as FTRs, the following experiments are carried on the 2-Bus system shown in Figure 8.5 while considering the generation costs as a function of generation output level.

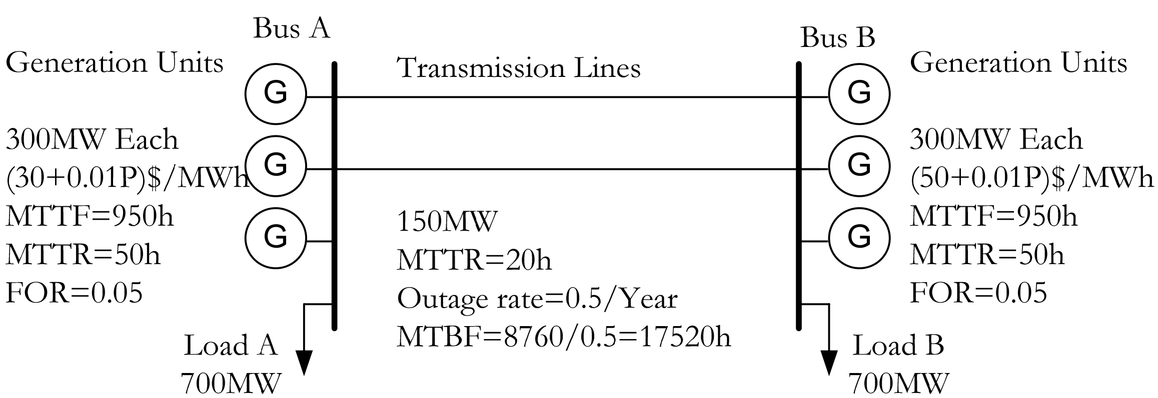

Figure 8.5 2-Bus system with constant loads and generation bids

If the transmission capacity constraint is ignored, the sensitivities of locational prices at Buses A and B, and the expected generation cost per unit load over the system, and the reliability indices such as LOL and LOLP are illustrated in Table 8.1 and Figure 8.6.

Table 8.1 Sensitivity of LMPs, FTR value, and unit generation cost with respect to generation unit capacity – without transmission congestion

Generation Unit Capacity	Expected LMP at Bus A	Expected LMP at Bus B	Expected Value of FTR A->B	Expected Generation Cost Per Unit Load
250	62.78	62.78	0	46.33
275	61.88	61.88	0	45.78
300	60.75	60.75	0	45.22
325	59.39	59.39	0	44.66
350	58.03	58.03	0	44.25

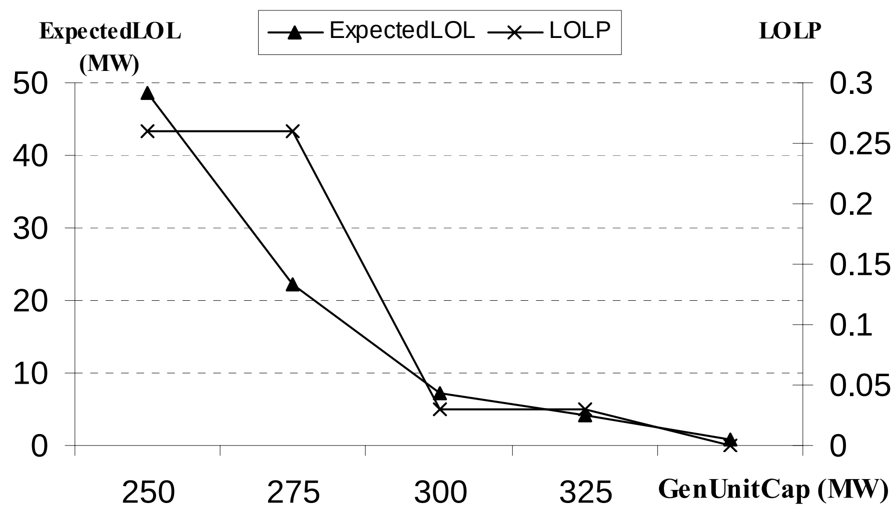

Figure 8.6 Sensitivity of expected LOL and LOLP with respect to generation unit capacity without transmission congestion

Similarly, the sensitivities for transmission capacity being 100 MW are illustrated in Table 8.2 and Figure 8.7. Note that although the expected LOL given limited transmission capacity is higher, especially when the generation unit capacity is high.

Table 8.2 Sensitivity of LMPs, FTR value, and unit generation cost with respect to generation unit capacity - transmission capacity 100 MW

Generation Unit Capacity	Expected LMP at Bus A	Expected LMP at Bus B	Expected Value of FTR A->B	Expected Generation Cost Per Unit Load
250	55.27	60.42	5.15	44.74
275	55.49	60.63	5.14	44.79
300	55.06	60.24	5.18	44.56
325	54.55	59.73	5.18	44.31
350	48.31	59.41	11.1	44.15

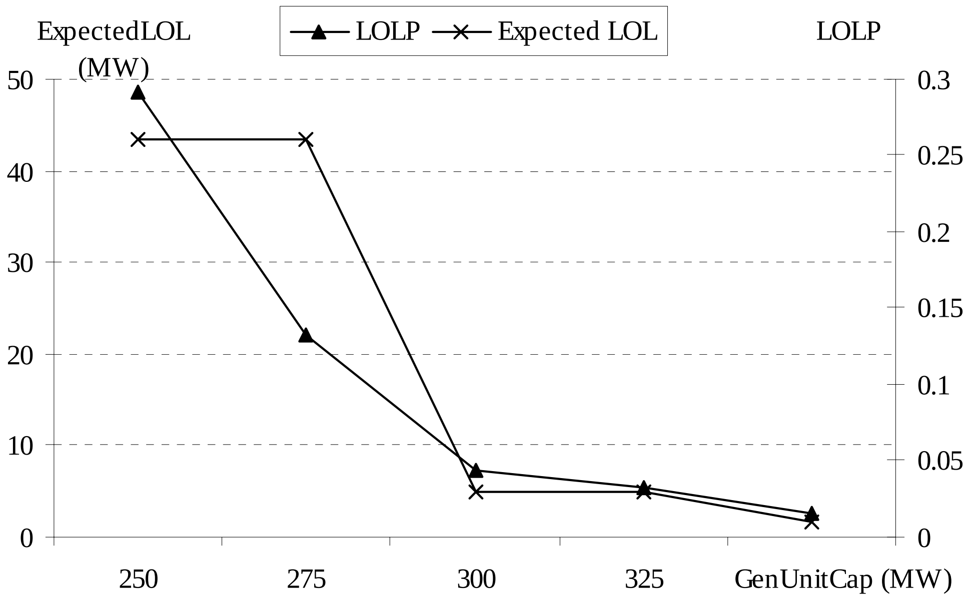

Figure 8.7 Sensitivity of expected LOL and LOLP with respect to generation unit capacity with transmission capacity being 100 MW

On the other side, by fixing the generation unit capacity at 300 MW and varying the transmission capacity, we calculated the sensitivities of locational prices at Buses A and B, the expected generation cost per unit load over the system, and the reliability indices (such as LOL and LOLP), as given in Table 8.3 and Figure 8.8.

Table 8.3 Sensitivity of LMPs, FTR value, and unit generation cost with respect to transmission line capacity - generation unit capacity 300 MW

Transmission Unit Capacity	Expected LMP at Bus A	Expected LMP at Bus B	Expected Value of FTR A->B	Expected Generation Cost Per Unit Load
50	46.43	61.09	14.66	45.15
75	54.63	60.67	6.04	44.84
100	55.06	60.24	5.18	44.56
125	55.52	59.82	4.3	44.33
150	55.95	59.39	3.44	44.13

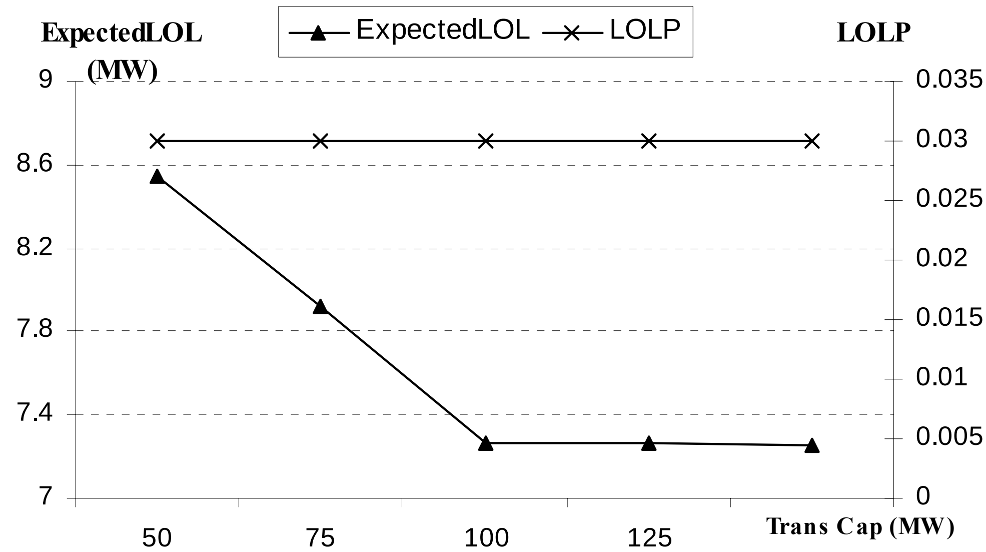

Figure 8.8 Sensitivity of expected LOL and LOLP with respect to transmission capacity (generation unit capacity = 300 MW)

From the experiments above, we make the following observations:

1. Since the forced outage rates (FOR) of generation units are much higher than those of transmission lines, the reliability indices (such as expected loss of load (LOL), loss of load probability (LOLP), and expected transmission capacity margin (TCM)) depend mainly on the FOR of generation units. The change of FOR of transmission lines within a certain region has little effect on these reliability indices when there is ample transmission capacity.

2. Expected loss of load and loss of load probability are either negatively or not correlated with transmission capacity margins.

3. The generation capacity margin (GCM) of a low-priced generation unit mainly depends on the FOR of transmission lines which export their generation. In contrast, the GCM of the high-priced generation unit mainly depend on its own FOR.

8.2. Interruptible Load Contracts

To investigate the impact of interruptible load contracts on system reliability, the follow experiments are carried out on the study 2-Bus example shown in Figure 8.9.

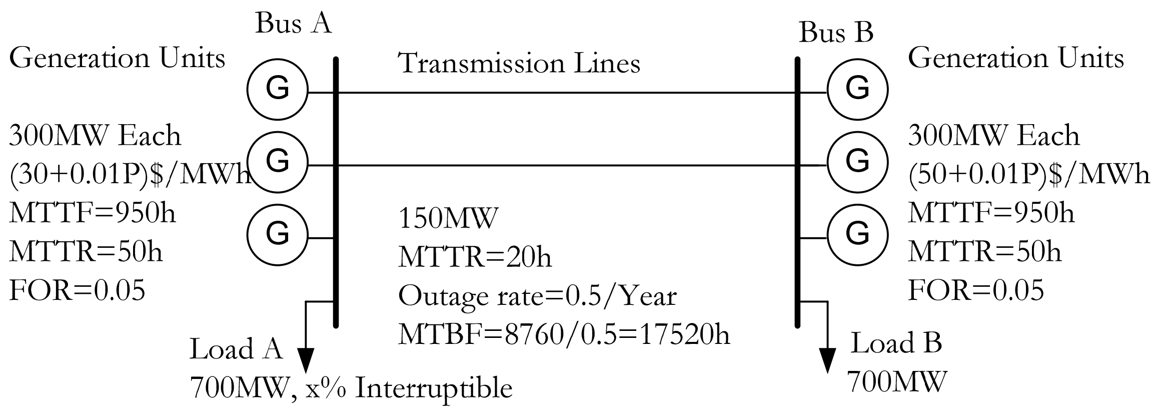

Figure 8.9 2-Bus system with 20% interruptible load contract at Bus A

We assume 20% of the load at Bus A is under an interruptible load contract. We redo the sensitivity of system reliability indices with respect to generation unit capacity and transmission line capacity. The results are shown in Table 8.4, Table 8.5, Figure 8.10, Figure 8.11, Figure 8.12, and Figure 8.13. The effect of interruptible loads can be read off through comparisons.

Figure 8.10 and Figure 8.11 show respectively that increased generation unit capacity reduces expected loss of load on both buses and the loss of load probability, and decreases the expected load interrupted.

Table 8.4 Sensitivity of LMPs, FTR value, and unit generation cost with respect to generation unit capacity with interrutible load contract - transmission capacity 100 MW

Generation Unit Capacity	Expected LMP at Bus A	Expected LMP at Bus B	Expected Value of FTR A->B	Expected Generation Cost Per Unit Load	Expected Load Interrupted at Bus A
250	62.77	62.78	0.01	46.33	37.07
275	61.88	62.00	0.12	45.85	10.44
300	50.47	60.76	10.29	45.22	4.59
325	50.37	60.67	10.3	45.14	3.85
350	50.28	60.57	10.29	45.06	2.02

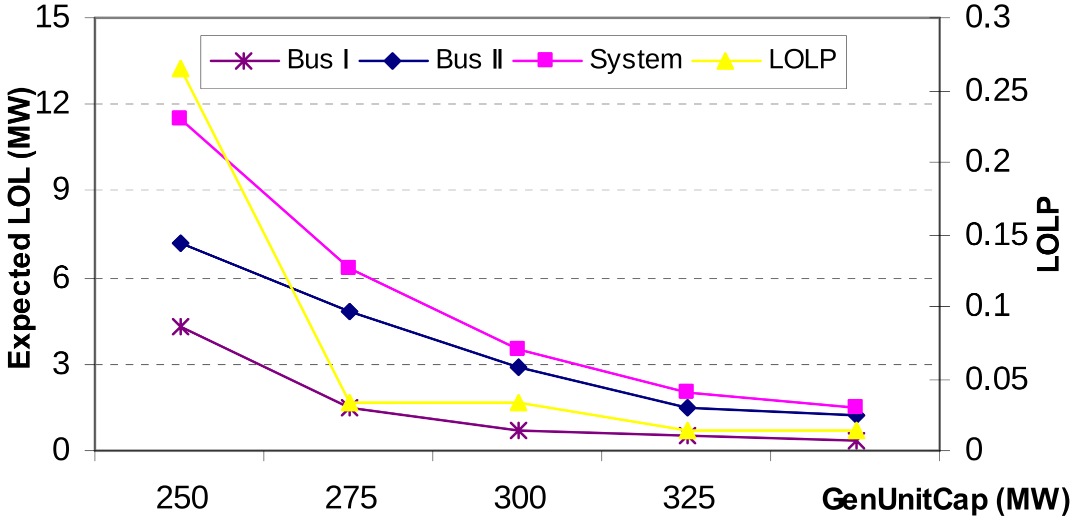

Figure 8.10 Sensitivity of expected LOL and LOLP with respect to generation unit capacity

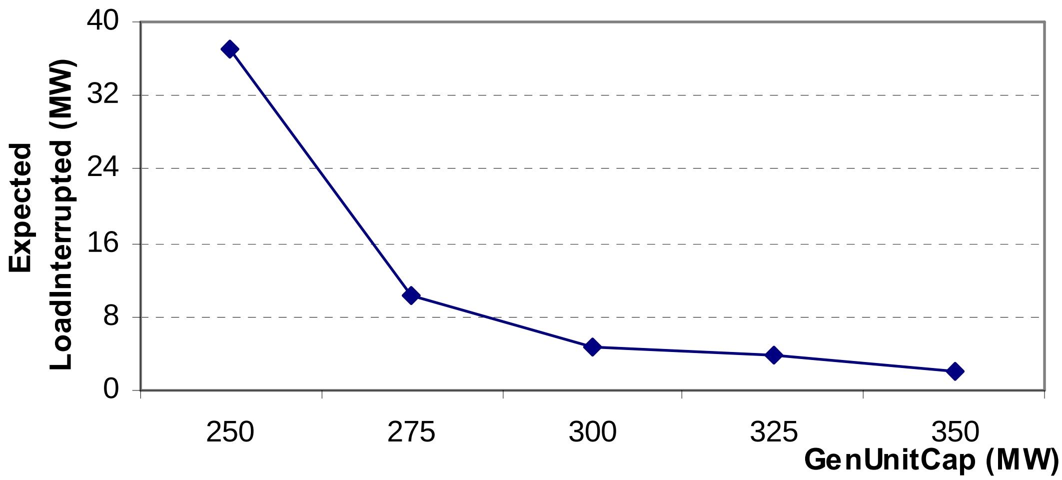

Figure 8.11 Sensitivity of expected load interruptible load
with respect to generation unit capacity

As shown in Table 8.5, Figure 8.12, and Figure 8.13, increased transmission line capacity decreases the per unit load generation cost, makes the LMP differences diminish, and decreases the expected loss of load on both buses.

Table 8.5 Sensitivity of LMPs, FTR value, and unit generation cost with respect to transmission line capacity with interruptible load contract - generation capacity 300 MW

Transmission Line Capacity	Expected LMP at Bus A	Expected LMP at Bus B	Expected Value of FTR A->B	Expected Generation Cost Per Unit Load	Expected Load Interrupted at Bus A
50	48.75	62.45	13.7	46.06	4.38
75	49.6	61.6	12	45.61	4.63
100	50.47	60.76	10.29	45.22	4.59
125	60.65	60.76	0.11	45.22	4.59
150	60.66	60.76	0.1	45.22	4.59

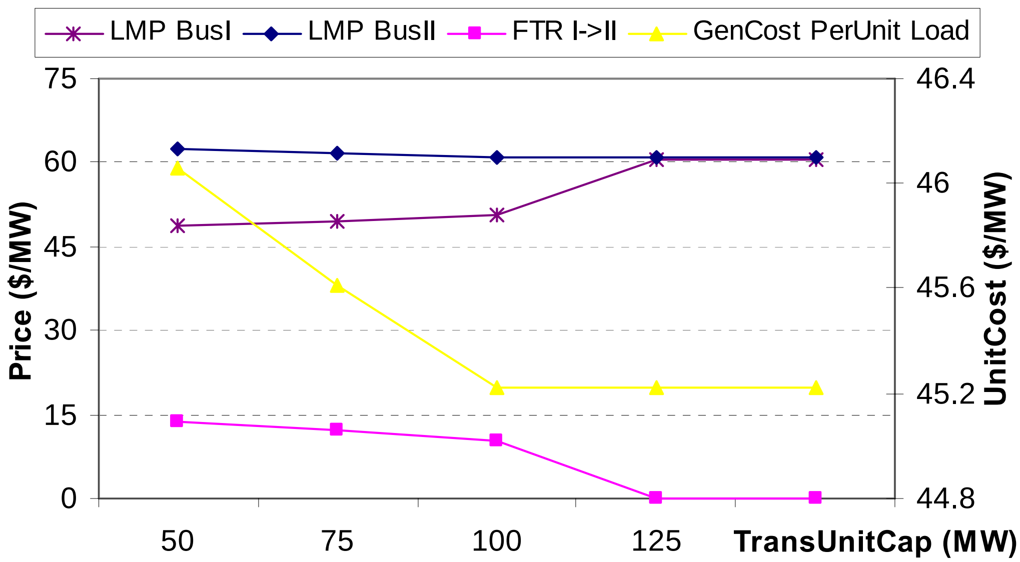

Figure 8.12 Sensitivity of LMPs, FTR values, and unit generation costs with respect to transmission line capacity

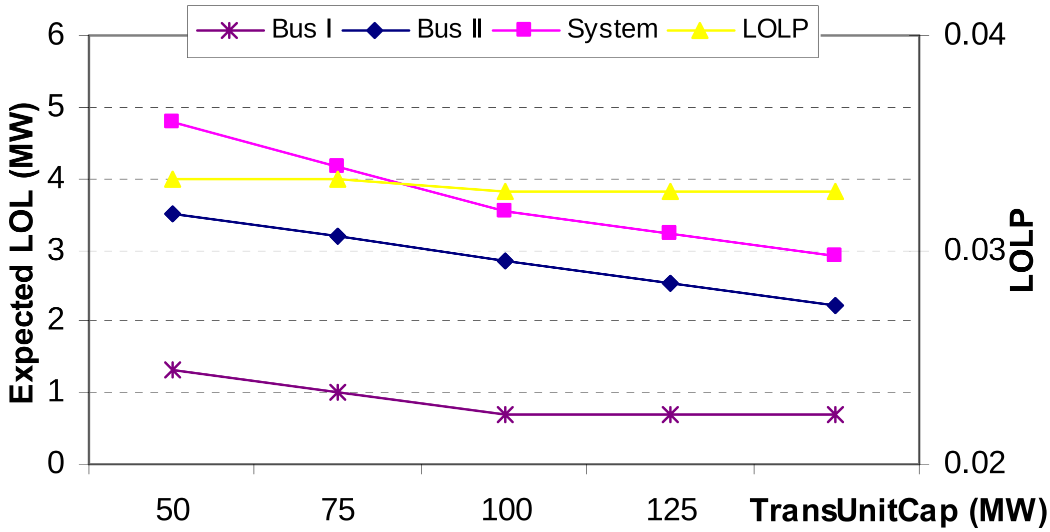

Figure 8.13 Sensitivity of expected LOL and LOLP with respect to transmission line capacity

Next we fix the transmission line capacity at 100 MW, generation unit capacity at 300 MW, and the transmission lines' FOR at 0.002 and examine the sensitivity of reliability indices with respect to generation units' FOR. The results are shown in Table 8.6 and Table 8.7. They are also plotted in Figure 8.14, Figure 8.15, and Figure 8.16.

Table 8.6 Sensitivity of LMPs, FTR value, and unit generation cost with respect to FOR of generation units with interruptible load contract

FOR of Generation Units	Expected LMP at Bus A	Expected LMP at Bus B	Expected Value of FTR A->B	Expected Generation Cost Per Unit Load
0.02	49.04	60.34	11.3	44.94
0.03	49.53	60.49	10.96	45.04
0.04	50.01	60.63	10.62	45.13
0.05	50.47	60.76	10.29	0.03
0.06	50.91	60.88	9.97	45.3
0.07	51.34	60.98	9.64	45.38
0.08	51.74	61.08	9.34	45.45

Table 8.7 Sensitivity of expected LOL, LOLP and load interruptible with respect to FOR of generation unit with interruptible load contract

FOR of Generation Units	Expected LOL at Bus A	Expected LOL at Bus B	Expected LOL	LOLP	Expected Load Interrupted at Bus A
0.02	0.09	0.46	0.54	0.0057	0.80
0.03	0.21	1.03	1.24	0.012	1.74
0.04	0.41	1.83	2.24	0.022	3.02
0.05	0.68	2.86	3.54	0.033	4.59
0.06	1.04	4.11	5.15	0.046	6.43
0.07	1.50	5.59	7.09	0.061	8.51
0.08	2.05	7.30	9.35	0.077	10.82

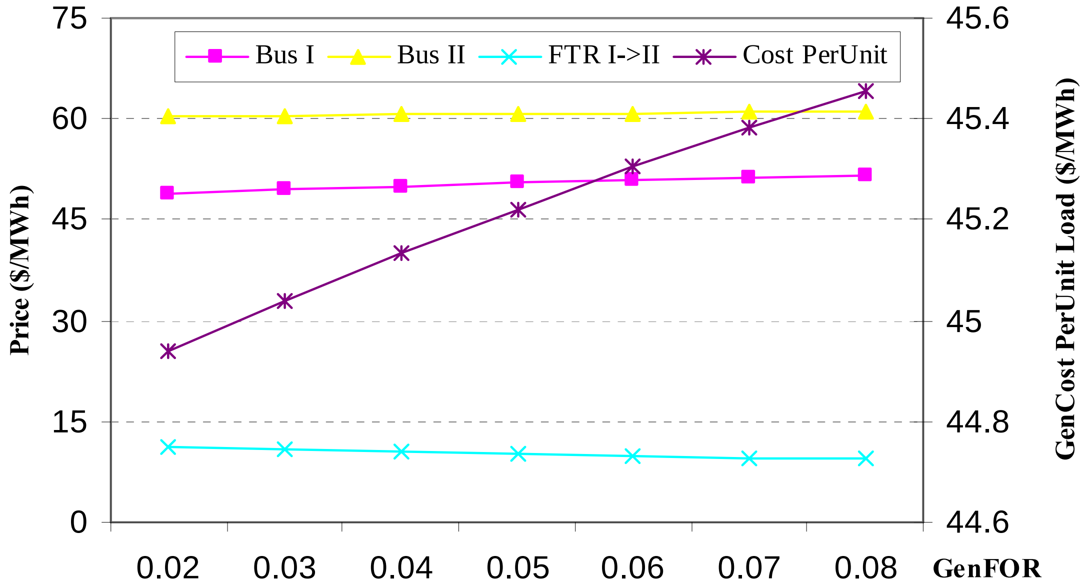

Figure 8.14 Sensitivity of LMPs and unit generation cost with respect to FOR of generation units

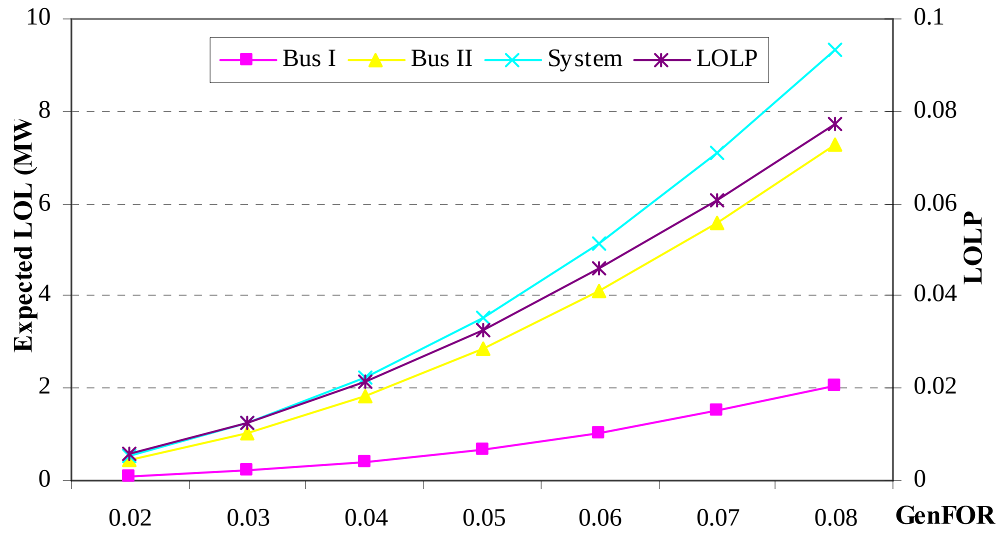

Figure 8.15 Sensitivity of expected LOL and LOLP with respect to FOR of generation units

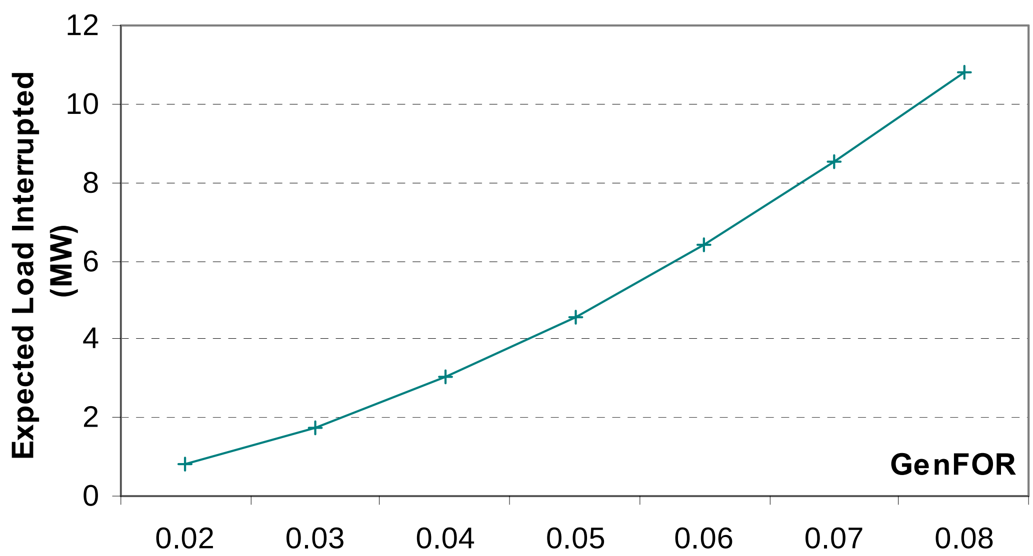

Figure 8.16 Sensitivity of expected load interrupted with respect to FOR of generation units

The increased forced outage rate of generation units increases the per unit load generation cost, increases the LMPs on both buses, increases expected loss of load and LOLP significantly, and increases the expected load interrupted.

Similarly, by fixing the transmission line capacity at 100 MW, generation unit capacity at 300 MW, and the generation units' FOR at 0.05, the sensitivity of reliability indices with respect to transmission lines' FOR are shown in Table 8.8 and Table 8.9.

Table 8.8 Sensitivity of LMPs, FTR value, and unit generation cost with respect to FOR of transmission lines with interruptible load contract

FOR of Transmission Lines	Expected LMP at Bus A	Expected LMP at Bus B	Expected Value of FTR A->B	Expected Generation Cost Per Unit Load
0.001	50.47	60.76	10.29	45.22
0.002	50.47	60.76	10.29	45.22
0.003	50.46	60.76	10.3	45.22
0.004	50.46	60.77	10.31	45.22
0.005	50.46	60.77	10.31	45.23
0.006	50.45	60.77	10.32	45.23
0.007	50.45	60.78	10.33	45.23

Table 8.9 Sensitivity of expected LOL, LOLP and load interruptible with respect to FOR of transmission lines with interruptible load contract

FOR of Transmission Lines	Expected LOL at Bus A	Expected LOL at Bus B	Expected LOL	LOLP	Expected Load Interrupted at Bus A
0.001	0.686	2.854	3.535	0.0328	4.588
0.002	0.682	2.855	3.537	0.0328	4.587
0.003	0.683	2.857	3.540	0.0328	4.587
0.004	0.684	2.858	3.542	0.0328	4.587
0.005	0.686	2.859	3.545	0.0328	4.586
0.006	0.687	2.861	3.547	0.0328	4.586
0.007	0.688	2.862	3.550	0.0328	4.585

Since the value of FOR of transmission lines is much lower than the FOR of generation units, the impact of transmission line FOR on system reliability and market prices is not as significant as the generation unit FOR, which can be seen from Table 8.6 to Table 8.9.

By fixing the transmission line capacity at 100 MW, generation unit capacity at 300 MW, and the generation units' FOR at 0.05 and transmission lines' FOR at 0.002, the sensitivity of reliability indices with respect to the component of interruptible loads at Bus A are shown in Table 8.10, Table 8.11, and Figure 8.11.

Table 8.10 Sensitivity of LMPs, FTR values, and unit generation costs with respect to ratio of interruptible load at Bus A

Ratio of Interruptible Load	Expected LMP at Bus A	Expected LMP at Bus B	Expected Value of FTR A->B	Expected Generation Cost Per Unit Load
10%	50.48	60.76	10.28	45.22
20%	50.47	60.76	10.29	45.22
30%	50.46	60.76	10.30	45.22
40%	50.46	60.76	10.30	45.22
50%	50.45	60.76	10.32	45.22
60%	50.45	60.76	10.32	45.22
70%	50.44	60.76	10.32	45.22

Table 8.11 Sensitivity of expected LOL, LOLP and load interrupted with respect to ratio of interruptible load at Bus A

Ratio of Interruptible Load	Expected LOL at Bus A	Expected LOL at Bus B	Expected LOL	LOLP	Expected Load Interrupted at Bus A
10%	1.77	3.63	5.40	0.033	2.30
20%	0.68	2.86	3.54	0.033	4.59
30%	0.24	1.69	1.92	0.008	6.57
40%	0.15	1.62	1.77	0.008	6.72
50%	0.073	1.60	1.67	0.008	6.82
60%	0.014	1.58	1.59	0.008	6.90
70%	0.005	1.51	1.51	0.008	6.98

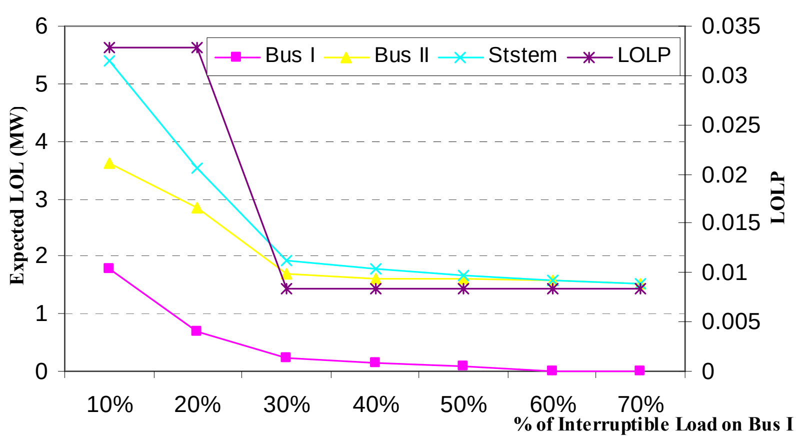

Figure 8.17 Sensitivity of expected LOL and LOLP with respect to ratio of interruptible load on Bus A

As more load on Bus A get involved with the interruptible program, the expected loss of load on Bus B decreases and so does the system LOLP. By comparing Table 8.11 with Table 8.2, in terms of holding the expected loss of load for the system below a required level, to increase the quantity of increased interruptible load contracts have comparable effect as to increase generation capacities.

Finally, by assuming a compensation rate for interrupted firm load at $1500/MWh (Leite da Silva et al, 1999) from the reduced expected compensation payment by introducing more interruptible load contracts, as long as the compensation for interruptible flexible load is lower than the last column shown in Table 8.12, the interruptible load contracts are beneficial to utilities.

Table 8.12 Expected LOL, load interrupted, LOL compensation and acceptable interruptible load prices with respect to ratio of interruptible load at Bus A

Ratio of Interruptible Load	Expected LOL	Expected Load Interrupted	Reduced Expected LOL	Expected LOL Compensation	Acceptable Interruptible Load Price
10%	5.40	2.29	1.86	2795.75	1218.61
20%	3.54	4.59	3.72	5584.33	1217.33
30%	1.92	6.57	5.34	8006.69	1217.98
40%	1.77	6.72	5.49	8231.72	1224.27
50%	1.67	6.82	5.59	8381.61	1228.31
60%	1.59	6.90	5.67	8501.43	1231.45
70%	1.51	6.98	5.76	8621.27	1234.53

Of course, since the contracted energy price for interruptible load is generally lower than the otherwise firm load, the reduced expected payment from these consumers should be taken into account for setting the compensation rates, which should be lower than the last column shown in Table 8.12.

9. Forward Markets and Investment Risk

9.1. Introduction

Every decision about investment in new generators, transmission, distributed energy resources and load management is based on expectations about future market conditions. Consequently, it is important to understand how the spot price of electricity behaves and how this behavior affects the forward prices that provide the financial incentives for investment decisions. The research conducted at Cornell University has focused on the following sequence of topics:

1. Modeling spot price behavior using stochastic regime switching to capture the infrequent price spikes that are an important feature of deregulated markets. These models predict the likelihood of observing a price spike on the following day conditionally on the forecasted system load.
2. Modeling the relationship between spot prices and forward prices during the "energy crisis" in California. The results show that the risk premium in the forward market was relatively small when high spot prices first occurred during the summer of 2000 compared to the winter of 2001 after the FERC had intervened in the market.
3. Using simulation to generate different stochastic realizations of daily summer temperatures and the corresponding levels of load and spot price. These realizations determine the risk of the expected income stream from selling electricity in the spot market by a merchant GENCO and the corresponding expected cost of purchasing electricity by a regulated DISCO over a typical summer.
4. Using stochastic annealing to derive an optimum portfolio of forward contracts between the GENCOs and the DISCOs in a market based on call options for peaking capacity (i.e., pay a fixed price to purchase the option of buying up to G MW at a specified "strike" price). In general, the strike prices are relatively close to the production costs except for the most expensive generators in the portfolio that are used infrequently to meet peak loads.
5. Determining the premium that must be paid, in addition to having a forward contract to sell electricity, to get investors to build new peaking capacity. For example, using 2004 spot prices for New York City as the basis for simulating spot price behavior, the income stream in a forward contract only provides about a third of the earnings needed to cover the capital cost of a new peaking unit.
6. Determining the potential for merchant investment in new transmission. The general conclusion is that merchant transmission is only viable in limited situations because the major role of a network is to maintain the reliability of supply when equipment failures occur. Merchant investment is potentially feasible for DC inter-ties and on a radial network. However, the many interdependencies that exist among transmission lines in a meshed network make it highly unlikely that decentralized decisions by merchant transmission owners will be sufficient to maintain reliability. Some type of formal planning process will be needed to identify the future upgrades that are needed on a network.

9.2. Modeling Price Spikes and Financial Risk in Forward Markets

A paper on "Predicting Price Spikes in Electricity Markets Using a Stochastic Regime-Switching Model with Time-Varying Parameters" (Mount et. al., 2006) shows that a stochastic regime-switching model with time-varying parameters can capture the type of volatile price behavior observed in many deregulated spot markets for electricity. The mean prices in two price regimes and the transition probabilities are specified as functions of the offered reserve margin and the system load. The high-price regime corresponds to the observed price spikes that typically occur during the summer months. In addition, the structure of the model is consistent with the actual "hockey stick" shape of the offers submitted by suppliers into the PJM market. Most capacity is offered at relatively low prices, and a few units are offered at much higher prices up to the price cap ($1000/MWh in PJM). Specifying Markov-switching in the model allows the high-price regime to be more persistent than is the case with a simple binomial jump process. Using on-peak daily data for PJM, the analysis shows that the model replicates the observed price volatility well. Consequently, this type of model is potentially useful for evaluating the financial risk of forward contracts and investment decisions in electricity markets. Standard financial models of price, such as geometric Brownian motion with jumps, do not allow for the unusual asymmetric type of volatility (i.e., infrequent price spikes) found in deregulated electricity markets.

From a policy perspective, it is important to predict price spikes. The probability of switching to the high regime is negatively and significantly related to the offered reserve margin (the amount of rejected generating capacity offered into the market). Our model showed that whenever the level of reserve margin is lower than 20% in the day-ahead market, a price spike is likely to occur. There were 13 price spikes in the PJM data set with prices higher than $100/MWh, and 11 of them correspond to switching probabilities greater than 0.5. Two other observations have probabilities greater than 0.5 but do not correspond to price spikes. Overall, the price spikes can be predicted accurately using correct market information. However, the accuracy of these predictions is sensitive to the accuracy of the explanatory variables. Using 1-day-ahead forecasts of the load and reserve margin leads to fewer correct predictions. To predict price spikes effectively, accurate information about the offered reserve margin, in particular, is needed.

A second paper on "The Effects of the Dysfunctional Spot Market for Electricity in California on the Cost of Forward Contracts" (Mount and Lee, 2003) reaches two major conclusions. First, the spot prices at different hubs in the Western Interconnection (or WECC) are highly interrelated. Consequently, the problem of high spot prices in California when the market was dysfunctional was transferred almost immediately to other trading hubs. In addition, the effects of structural changes in the CAISO market, associated with regulatory intervention by the FERC in December 2000, were reflected by similar changes in spot prices at all trading hubs. The first conclusion is that the effects of the energy crisis were not limited to the central market in California.

Second, the high spot prices in California resulted in high forward prices due to high risk premiums when the market was dysfunctional. These premiums were estimated conditionally on the forward prices of natural gas. In this respect, the FERC made the situation in California worse by failing to reestablish just and reasonable prices when the problem of high prices was first recognized in the fall of 2000. After introducing a new type of auction in the CAISO market in December 2000, spot prices were allowed to remain at high levels that were truly unprecedented for winter months. The risk premiums in the forward market after FERC's intervention were much higher than they had been in the summer of 2000, and these high premiums were built into the many forward contracts that were initiated in the winter of 2001.

Spot prices did not return to normal levels until the summer of 2001, and by this time, the risk premiums in the forward market had fallen back to zero.

9.3. Determining the Optimal Portfolio of Forward Contracts

A paper on "Incentives for New Investment in a Deregulated Market for Electricity" (Mount and Cai, 2004) establishes an equilibrium framework for trading between merchant GENCOs and regulated DISCOs in a forward market for electricity. There are a number of characteristics of electricity markets that make it difficult to use standard economic models to link forward prices to spot prices. Nevertheless, understanding the behavior of the forward prices of electricity is essential for analyzing investment decisions. Relatively long-term forward contracts will be needed by any investor to secure financing and commit to building new generation capacity. Unfortunately, the inherent risk of price spikes in deregulated markets and the difficulty of diversifying this risk make risk premiums high and hard to predict. The proposed trading model recognizes that there is a basic asymmetry between the relatively small risk faced by a GENCO and the relatively large risk faced by a DISCO that has a mandate to meet load at a regulated rate. This asymmetry of risk in the market implies that GENCOs can extract a substantial risk premium from the DISCOs. The analytical framework uses a Linex utility function that exhibits strong aversion to financial losses. This function represents an important improvement over standard mean/variance models. The equilibrium conditions for forward trading between the GENCOs and the DISCOs determine the optimum portfolio consisting of a fixed price/fixed quantity contract for base load and two-part contracts for peaking load.

The second objective of the paper was to evaluate investment decisions and determine the minimum level of profit needed to make an investment in new peaking capacity financially viable in a risky market. The analytical framework was applied to the New York City region because there is growing concern that the amount of installed capacity will be insufficient to maintain adequacy in the near future. The results show that the profit from the spot market provides only one third of the profit needed for a GENCO to invest in new peaking capacity. This is true even though the average price paid by a DISCO in a forward contract is substantially higher than the average spot price and the simulation assumes that price spikes occur more frequently than they do in the actual New York market.

We also evaluate three different procedures for increasing the incentives for investing in new peaking capacity. The first procedure requires the DISCOs to include a direct contract for new capacity in their portfolio of forward contracts. The second augments the payments to generators using a capacity auction to cover the capital cost of peaking capacity (corresponding to the procedure adopted in New York). The third allows price spikes to be higher but keeps the average spot price unchanged (corresponding to the energy-only markets in Australia and Alberta). Direct contracts are much less expensive than the other two procedures because the premium in the contract is only paid for the new capacity. In addition, a direct contract specifies that new capacity will be built. The other two procedures are much more expensive because in one case higher capacity payments are paid to all installed capacity, and in the other case, higher spot prices are paid for all on-peak load. In contrast to a direct contract, there is no requirement with either of these two alternative procedures that any of the extra money paid to generators will be used to build new peaking capacity. In spite of the high cost of these two alternative procedures, it is still risky to rely on market forces to maintain the required standard of system adequacy. Keeping the regulatory option of using a direct contract to build new capacity is the most secure way to ensure that system adequacy will be maintained in the future.

9.4. Implications for Merchant Transmission

The delivery of natural gas through pipelines to final customers supports a market structure based on allocating the capacity of a pipeline to different suppliers. Measuring the amount of gas supplied by each pipeline and the cost of transporting this gas is straightforward. In fact, the oversight of gas pipelines in the USA in support of a competitive market is the responsibility of the Federal Energy Regulatory Commission and the Department of Transportation. Applying the same sort of rules to the supply of electricity is feasible in a few limited circumstances, but in general, it is simply not appropriate. The main reason why the analogy to a pipeline does not work is that a network provides the infrastructure for maintaining the reliability of supply and makes the supply system relatively robust to a wide variety of equipment failures. Nevertheless, the rules established by the FERC for governing physical bilateral transfers of real energy are more appropriate for a pipeline than a transmission network. If there is enough "unused" transmission capacity, a physical contract is allowed under these rules, subject to meeting standards of operating reliability. This type of contract is supported even if the actual increased flows on the network are substantially different from the pathways on the network that are identified in the contract.

A paper on "Testing the Effects of Power Transfers on Market Performance and the Implications for Transmission Planning" (Mount and Thomas, 2006) describe a series of tests of the performance of an electricity market when there are changes in the quantity of transfers of real energy through an AC network (supported on the Cornell software platform POWERWEB). Using graduate students to represent suppliers in a uniform price auction, the results show that the market prices were substantially above competitive levels. Prices were higher when there was more congestion on the network due to transfers because the market was easier to exploit. For example, load pockets can occur when transmission lines reach their thermal or voltage limits, and this effectively reduces the number of suppliers competing in a region. Students have no difficulty identifying when they have the potential to exploit market power without understanding the physical causes of congestion.

The most important result from the market tests is that interactions between the level of transfers and individual suppliers explain a large part of the variability in earnings among firms. The effects of changing the level of transfers are very different at different locations on the network. Even though a fixed amount of energy is transferred from a single source to a single sink on the network, the consequences are surprisingly complicated. There is no consistent pathway for the transfers when the levels of native load vary, as they do in our experiments. Hence, it is misleading to assume that the transfers of electricity on a network can be treated in the same way as the transfers of natural gas on a pipeline.

Overall, the results show that experimental economics is an effective way to evaluate the effects of transfers of electricity on a network. Using POWERWEB, the market outcomes are determined by the combined effects of changes in the physical characteristics of the network and changes in the behavior of suppliers. The behavior of suppliers adapts to changes in the characteristics of the network, and the students were able to exploit market power effectively whenever the opportunity occurred. Both types of change affect how well a market works, and in a more elaborate experiment, it would also be possible to demonstrate how transfers affect the reliability of the supply system. Most economic models of deregulated electricity markets simplify the physical characteristics of a network, and most planning models used by electric utilities simplify the adaptive behavior of suppliers. However, the physical properties of any particular AC network impose real limits on the performance of a deregulated market. This poses a major challenge for any analysis of market performance, but it is essential to consider both the physical characteristics of the network and the realistic behavior of suppliers in the market simultaneously to get a full understanding of the role of transmission. Experimental economics, using a platform like POWERWEB, is a practical way to accomplish this objective.

A second paper on "Transmission System Planning – The Old World Meets the New" (Thomas et. al., 2005) evaluates the growing concern about underinvestment in new transmission facilities in the USA over the last decade. This has resulted in a transmission system that is loaded to a much higher degree than in the past with little hope of improvement in the foreseeable future. The transmission planner's world has changed from the simpler times of mainly worrying about load growth and generation adequacy to one that is much more complex. Now, a planner must worry about voltage problems, and transient and voltage stability in order to plan a reliable supply system that can operate closer to the 'edge'.

The dual roles of the transmission network for maintaining reliability and enabling inter-regional transfers of real energy are highly interdependent. Given the growing uncertainties that now exist about which organizations have the responsibility for meeting load and maintaining the reliability of the supply system, the analysis concludes that transmission owners should still be eligible to receive a regulated rate of return for all transmission services. However, better performance-based incentives and planning procedures are needed to direct investment into the best places to maintain the traditional high reliability of the network. While the analytical framework of market-based mechanisms can be used to evaluate transmission proposals (e.g. for a regulatory test) as well as merchant projects, the major part of the responsibility for maintaining the reliability of a transmission network rests with the regulators. It may be unrealistic to completely rely on decentralized decisions by transmission owners and load-serving entities to maintain reliability.

Federal regulators should be more proactive in encouraging the conversion of physical bilateral contracts to financial contracts for inter-regional transfers. Facilitating the establishment of viable forward markets for electricity throughout the country would be an important step in the right direction. There is no economic justification for continuing to support the accounting procedures used to legitimize short-term transfers based on physical bilateral contracts. Some of these contracts may increase net social benefits for all users of a network, but there is no guarantee that a financially attractive bilateral contract produces a net gain for all users of a network. This is particularly true when the transmission system is congested.

The increased loadings of transmission capacity have led to concerns about reactive power utilization because reactive losses and concerns about voltage stability greatly increase when congestion occurs. While the power flow and transient stability programs are still the primary tools used for transmission planning, new tools have been made available to improve planning, such as enhanced Optimal Power Flow (OPF) models. Nevertheless, new tools are still needed to study many more scenarios more efficiently as planners consider more uncertainties. Data such as machine data, exciter and governor models, power factors, and generator reactive capabilities have become more important and new tools must be made available to verify these data and models. These are the responsibilities undertaken through a traditional planning process, and there is no evidence to justify a greater dependence on decentralized decision as a replacement for transmission planning at this time. In addition, today's transmission planners must communicate closely with real time operations to better understand how the system is being operated and how the new challenges posed by markets are being managed in today's changing world. Although many improvements in the regulation of transmission can be made, it is important to determine what deregulated markets really can do before transferring the responsibility for system reliability to market forces.

This research sponsored by PSERC on transmission has resulted in ongoing efforts to extend the analytical framework described in Section 9.3 to evaluating the financial risk of the differences in the spot prices between two locations on a network. This is a fundamental step towards measuring the financial risk of congestion and the economic value of reducing bottlenecks between un-congested and congested regions on a network. However, an important parallel effort is to develop an analytical framework that deals with both congestion and reliability simultaneously. Our expectation is that considering this combination is the best way to develop the next generation of planning models for maintaining system adequacy.

10. Conclusions and Future Work

10.1. Conclusions

Transmission investment in a competitive market environment remains an open and challenging problem which constantly becomes a subject of debate among academic and industrial researchers. This project tackles the issues of modeling market signals for inducing transmission-adequacy-driven investments and valuing load participation contracts. First, the incentives and obstacles associated with existing mechanisms for allocating transmission costs and compensating transmission investments are documented. This project then investigates the modeling of market signals through integrating fundamental power system simulation models with reduced-form stochastic electricity price models and examines the valuation of transmission capacity subject to congestion and system reliability requirements through a Locational Marginal Price (LMP)-based transmission pricing framework. Economic incentives for transmission investment based on financial transmission rights are evaluated through stochastic electricity price models calibrated to the proposed fundamental power system simulation model.

Specifically, to establish reduced-form stochastic models for electricity market price signals reflecting transmission adequacy requirements, a fundamental power system simulation framework was adopted. It incorporated transmission network operational constraints, supply/demand fluctuations, power system contingencies, and system reliability requirements. Under this framework, market price behaviors resulting from DC and AC power flow based market dispatch models were studied through computational experiments with an IEEE Reliability Test System. Although the expected values of the simulated LMPs in the DC dispatch models approximate those in the AC models well during the off-peak hours, clear differences are documented during the on-peak hours. Such differences in the price behavior result in significant discrepancies in valuing market instruments (e.g., FTRs and options on FTRs) under extreme system conditions such as facility outages and load spikes. More importantly, it was found that the volatilities of LMP, FTR value, suppliers' revenue, and consumers' payment (in other words, the market risks of all market participants) are underestimated if a DC-flow based market dispatch model is employed. Market prices obtained through the power system simulation models are used to calibrate a specific class of reduced-form stochastic electricity price models which are termed as quantile-based GARCH models. The sensitivity of model parameters to system conditions is investigated and quantitative relationships between model parameters and system reliability requirements are established. Heuristic methods for identifying incremental FTRs resulting from typical network-deepening or network-expanding transmission investment projects are illustrated. It is then demonstrated that the market-based transmission investment compensation mechanisms, such as the one rewarding investors with incremental FTRs as tradable instruments for recovering sunk capital and hedging market risks, do provide economic incentives for transmission investments aiming at capitalizing on inefficiency and enhancing system reliability.

This project also investigates the role of forward markets in maintaining system reliability. All decisions about investment in new generators, transmission, distributed energy resources and load management are based on expectations about future market conditions. Consequently, it is important to have reliable sources of public information about future prices and the associated levels of risk. At the present time, however, there are no established sources of price discovery for electricity equivalent to the futures market for natural gas at Henry Hub operated by the New

York Mercantile Exchange (NYMEX). A fundamental complication for electricity is that congestion on the transmission system makes it infeasible to rely on a single market for one location as the primary source of price discovery for all locations. Consequently, trading some set of prices for different locations will be needed, but the number of locations must be small to ensure that there is enough liquidity in the market for reliable price discovery. There are three existing types of forward market in New York State, and each one has different strengths and weaknesses. The objective of this research is to develop an analytical framework for evaluating their ability to meet the financial needs of potential investors.

A model of spot price behavior that allows for stochastic regime switching from a low-price to a high-price regime was developed. This is an essential feature of an analytical framework for evaluating investment decisions. Another important feature of this model allows factors such as the system load to affect the frequency of price spikes in the market, and as a result, the type of financial risk faced by participants in the market can be interpreted and evaluated. In addition, the potential effectiveness of using weather derivatives as a way to hedge price and volume risk in spot markets has been demonstrated.

An analysis of the relationship between spot prices and forward prices in California during the energy crisis was completed to evaluate how the market price of risk changes when financial risks and price volatility increase. Conventional models of spot to forward price linkages do not capture salient features of wholesale markets for electricity because the market price of risk is not constant and electricity is not storable. The new analytical framework uses a utility function approach to model risk-averse behavior, particularly to financial losses, and compare different types of forward contract in a consistent way.

10.2. Future Work

Future research topics include applying the developed analytical framework for estimation of justifiable premiums paid above standard electricity forward prices to bring new generating capacity into the market, identification of price distortion, coordination of generation and transmission investments, and strategic interactions between transmission investors.

In addition, research on reduced-form hub-and-spoke representation of a complex system for improving trading liquidity and the adequacy of market incentives are planned for further investigation in a follow-up project. Another research direction is to investigate alternative forms of property rights (for example, reservation capacity rights) as additional mechanisms for rewarding transmission investment. Transmission investments that relieve generation capacity reserve requirements convey a benefit that is not currently valued by the market. Usually, load serving entities (LSEs) are required to set up or buy generation capacity reserve for their service area. The marginal cost of such capacity reserve differs at different locations, and it changes as the available transmission capacity changes. For example, a spread up to $70/kW of installed capacity per capability year is known to exist between the marginal cost of generation capacity in New York City and that in the rest of the state. Therefore, Capacity Reserve Payment Rights could be introduced and awarded to a merchant transmission project that would lower this capacity reserve requirement and the associated costs. The potential payment could be up to the magnitude of the reduction in capacity times the spread between the prices with and without the transmission project.

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Appendix A: Effects of Random Outages

The market signals are affected by random events such as random tripping of transmission lines, random outages of generating units, etc. This appendix presents the models utilized for incorporating these effects.

Each component of the system is represented with a two-state Markov model i.e., the component is either working (up) or failed (down) as shown in Figure A.1. Based on the two-state Markov model of each component, a Markov state of a power system is defined by a particular condition where every component is in a given operating state of its own. All the possible states of a system make up the state space (Endrenyi, 1978).

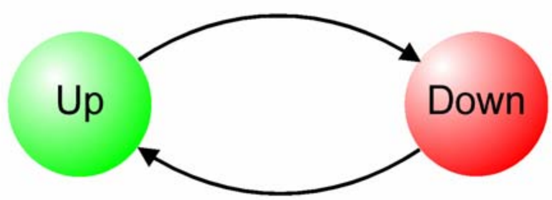

Figure A.1 A two-state Markov model

The electric load is modeled as a nonconforming load model. This model relates the bus loads to a small set of independent random variables. Discretization of the independent random variables provides discrete load states that are described with an equivalent Markov model where each load level is characterized with a probability and transition rates to any other load levels. In addition, each bus load is separated into interruptible, firm and critical components and associated with a voltage dependency assumed as follows: for the normal range of the bus voltage, the load is constant; for values below the normal voltage range, the load is dependent upon the voltage with a linear relationship.

A.1. State Enumeration

The state enumeration involves: (a) enumeration of contingencies, including both circuit outages and unit outages, and (b) enumeration of electric load levels according to a specified electric load model.

A.1.1. Contingency Enumeration

The objective of contingency enumeration is to identify the contingencies which may lead to unreliability. The enumeration of contingencies is based on the use of multiple contingency ranking schemes. Additional truncation of contingencies is obtained by truncating the depth level of contingencies and by neglecting contingencies with very small probabilities. The depth level is defined with three parameters: (a) Maximum allowable number of simultaneous outages (units or circuits), (b) Maximum allowable number of simultaneous circuit outages and (c) Maximum allowable number of simultaneous circuit outages.

The reasons for the use of multiple contingency ranking schemes are: First, complete and thorough evaluation of all contingencies is impractical. Thus, it is necessary to avoid the evaluation of contingencies that are not likely to affect system reliability. This task is achieved with contingency ranking methods. Second, present state of the art contingency ranking methods do not possess the desired speed and accuracy for reliability analysis.

Generally, contingency-ranking methods may be classified into two categories: (a) Performance Index (PI) methods, and (b) screening methods.

PI methods use the derivative of a performance index (or first order approximation) with respect to an outage to determine the severity of a contingency. In this work the single-phase quadratized power flow (SFQPF) model has been applied towards the development of a contingency selection method using several metrics as performance indices. It is well known that performance index approaches lead to mis-rankings because of the nonlinearities of the model involved. The quadratized power flow model has milder nonlinearities (by construction) and therefore performs better. The quadratized power flow model will be described later.

Screening methods use approximate network solutions to identify cases causing limit violations. In this approach, contingencies are first analyzed with an approximate model. If the approximate model indicates that the contingency may have severe effects on the system, then the contingency is analyzed to determine its effects on the system. The disadvantage of these methods is the fact that the approximate analysis has to be performed on each contingency. Because of the large number of contingencies, the method is inefficient.

PI methods are typically much faster than screening methods. To take advantage of the best properties of the two approaches, the critical contingencies are selected with a hybrid scheme that separates contingencies into two groups: (a) contingencies with mild nonlinearities and (b) contingencies with potential nonlinearities. The separation is performed with a very simple rule. The first set of contingencies represents the majority and is ranked with PI based methods with multiple PIs. The second set of contingencies is ranked with screening methods. Computational savings are achieved by applying the screening methods only to a small set of contingencies. The details for contingency selection technique can be found in Section 5.

The Wind-Chime enumeration scheme, as shown in Figure A.2, illustrates the contingency enumeration procedure using the ranking order obtained by the hybrid ranking method. The procedure starts with base case. All the first level contingencies are enumerated and ranked in the decreasing severity order. The second outage level contingencies are obtained from each contingency in the first outage level by having one more component on outage and ranked in the same way. The new outage component should be selected according to certain rule to make sure the obtained contingencies are distinct. This procedure continues until it reaches the predefined depth level or probability criteria of contingencies. In each outage level, contingencies are evaluated in the decreasing severity ranking order. The most severe contingencies are evaluated first. If there are several successive contingencies that are evaluated but have zero contribution to system unreliability, then it is reasonable that the rest contingencies which have lower severity indices need not to be investigated.

A.1.2. Electric Load Enumeration

Electric load levels are modeled with a multi-state Markov model. The enumeration of electric load is based on the predefined load levels. That is, if the load levels change, then the system enters another state.

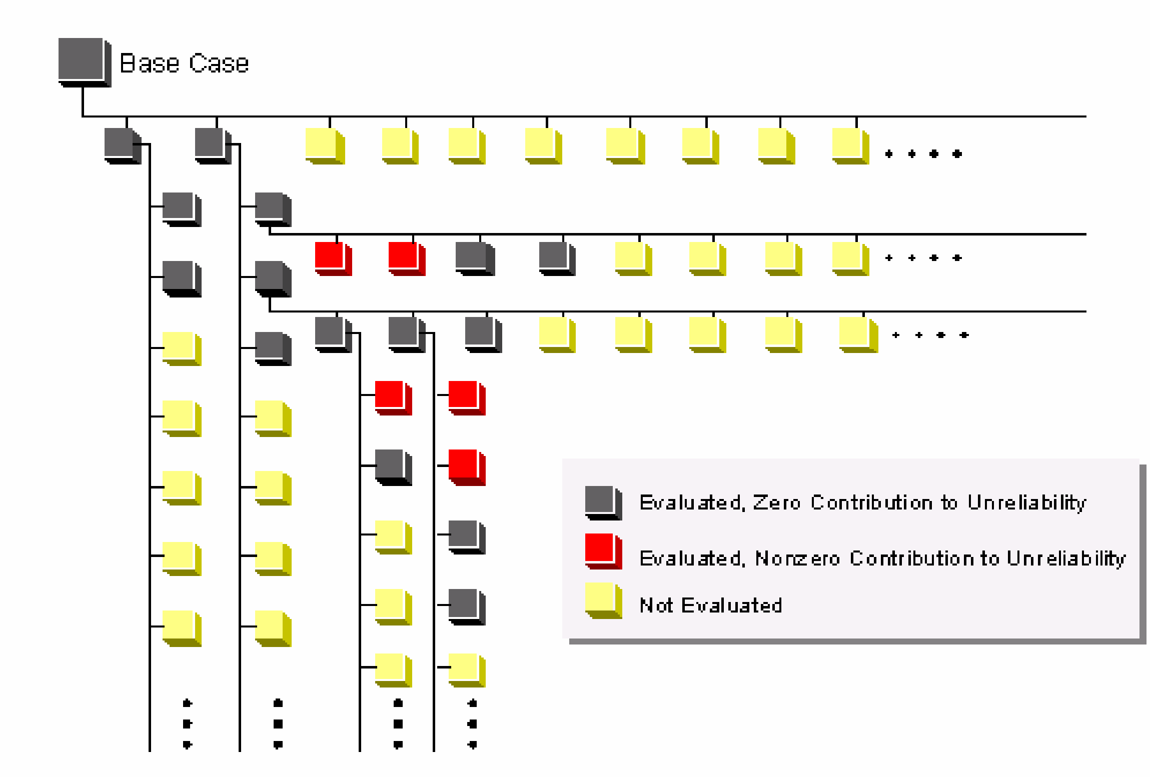

Figure A.2 Wind-chime enumeration scheme

A.2. Effects Analysis

Each combination of selected contingency and load level is analyzed to determine the effects on system performance. System performance is measured with a set of pre-specified criteria using the quadratized power flow and remedial actions if necessary. Failure criteria include: (a) circuit overloads, (b) bus under-voltage and over-voltage, (c) curtailment of interruptible load, (d) curtailment of firm load, (e) curtailment of critical load, etc.

In the effects analysis process, two approaches are available: (a) adequacy and (b) security. In adequacy approach the objective is to determine whether the system is capable of supplying the electric load under the specified contingency without operating constraint violations. For this purpose, the quadratized power flow and the remedial actions module are utilized to determine whether the system is adequate. A concise description of these tools follows.

A.2.1. Quadratized Power Flow Model

Quadratized power flow model is set up by applying the Kirchhoff's current law at each bus. The states variables are expressed in Cartesian coordinates. Subsequently, the power flow equations are quadratized, i.e., they are expressed as a set of equations that are linear or quadratic. This formulation is void of trigonometric terms, which makes the power flow equations less complex. The formulation of quadratic power flow provides superior performance in two aspects: (a) faster convergence, (b) ability to model complex load characteristics, and classes of loads such as interruptible load, firm load, critical load, and etc. More details about the quadratized power flow will be described in Section 4.

A.2.2. Remedial Actions

Remedial actions greatly affect reliability of the power system operation by providing the means of correcting the abnormal conditions, such as alleviating circuit overloads, abnormal voltages, etc. In the adequacy approach, whenever the inadequacy occurs after certain contingency, the remedial actions without load shedding capability will be applied first. If the operating constraint violations still exist, the remedial actions with load shedding capability are then applied to determine where and how much load shedding will be needed to alleviate emergencies, which is recorded as a system failure. The results of the contingency evaluations are stored and subsequently used by the reliability calculation model to calculate the reliability indices.

Appendix B: Contingency Selection and Ranking

Security assessment is defined as the real time analysis procedures by which the security of the system is measured (assessed). Security assessment procedures are classified into steady state and dynamic depending on whether the transients following the disturbance are neglected or not. Most of transmission line and transformer outages cause a rather fast rerouting of power flow in such a way that the transients following the disturbance are not of great consequence. The same is true for generating unit outages when the unit is small compared to the system or operating at low power points prior to the event. These cases represent the majority of outage events. Cases of major generation unit outages or major tie lines may cause transients with major effects on security. In this case, the transients must be studied and their effect on security must be assessed. This process is called dynamic security assessment.

In general, considering the power system as a nonlinear dynamic system, we can say that the steady state security assessment should evaluate if after a contingency (or a number of contingencies) occurs there will be a new equilibrium state for the post-contingency system and how secure this state is. The dynamic security assessment will, in addition to that, also show if there will in fact be a transient trajectory in the state space from the original pre-contingency equilibrium point to the post-contingency equilibrium point (thus, if the system will actually reach that equilibrium point) and what will be the security level of the system during this transition. It is therefore possible, for some severe disturbances, that even if a post-contingency equilibrium point exists the system may not be able to reach it, because there is no transient path from the one equilibrium to the other one. Or the final equilibrium state may be reached and may be a secure state, however, some of the transient states the system went through during the transition may have not be acceptably secure. This can only be investigated using transient analysis. However, in this report we are interested only in steady state or static security assessment. The purpose of this part of the project is simply to use security assessment techniques for contingency screening and ranking (not analysis) in order to reduce the size of the space of system states, to the few ones that worth to be further analyzed from the system reliability point of view. Dynamic security assessment is therefore beyond the scope of this report.

Steady state security assessment, i.e., assessment of the effects of equipment outages on system security, requires the analysis of the post-contingency steady state conditions. In other words, steady state security assessment involves the analysis of the steady state post-contingency conditions for any foreseeable and probable outage. Since the number of such contingencies may be extremely large for practical systems, the basic problems in static security assessment are: (a) identification of contingencies which may cause system problems or adversely affect security (contingency selection) and (b) techniques for contingency simulation to assess the effects of the contingency. These problems will be discussed next.

B.1. Contingency Ranking/Selection

Contingency analysis is necessary to determine the level of security and/or reliability of a given system following a disturbance (contingency). Because of the large number of possible contingencies, this analysis can be extremely costly from the computational point of view.

Fortunately for practical power systems, only a small number of contingencies are potentially critical to system security and/or reliability. If these contingencies can be identified, then only these contingencies should be analyzed to determine their effect. The problem of identifying the critical contingencies is known as contingency ranking. That is, contingencies are ranked in terms of their severity

Contingency ranking methods can be divided into two categories: Performance index (PI) methods and screening methods based on approximate power flow solutions. In the first case, the contingency ranking is facilitated by the use of performance indices which provide a measure of system "normality". These methods are computationally simple and efficient, however, they are prone to mis-ranking. On the other hand the methods based on approximate power flow solutions are in generally less efficient and require more computation; their accuracy depends on the level of approximation used. In this study we are interested only in PI methods and we use them to evaluate the system state after certain disturbances, therefore, estimate the severity of each disturbance. The more sever disturbances are to be further analyzed using reliability analysis methods.

Several different performance indices can be defined and used, depending on then network quantities that are considered more important for the specific study. Some of the most commonly used indices are listed below:

1. Current Based Loading Index

$$J_C = \sum_j w_j \left(\frac{I_j}{I_{N,j}} \right)^{2n} \tag{B.1}$$

where I_j current magnitude in circuit j

$I_{N,j}$ current rating of circuit j

w_j appropriate circuit weight, $0 < w_j \le 1$

n integer parameter defining the exponent

2. Apparent Power Flow Based Loading Index

$$J_T = \sum_j w_j \left(\frac{T_j}{T_{N,j}} \right)^{2n} \tag{B.2}$$

where T_j apparent power flow in circuit j

$T_{N,j}$ apparent power flow rating of circuit j

w_j appropriate circuit weight, $0 < w_j \le 1$

n integer parameter defining the exponent

3. Active Power Flow Based Loading Index

$$J_P = \sum_j w_j \left(\frac{P_j}{P_{N,j}} \right)^{2n} \tag{B.3}$$

where P_j active power flow in circuit j

$P_{N,j}$ current rating of circuit j

w_j appropriate circuit weight, $0 < w_j \leq 1$

n integer parameter defining the exponent

4. Voltage Index

$$J_V = \sum_k w_k \left(\frac{V_k - V_{k,mean}}{V_{k,step}} \right)^{2n} \tag{B.4}$$

where V_k voltage magnitude at bus k

$V_{k,mean}$ nominal voltage value (typically 1.0 p.u.). It is in general the mean value in the desired range, i.e., $\frac{1}{2}\left(V_k^{\max} + V_k^{\min}\right)$

$V_{k,step}$ voltage deviation tolerance (i.e., $\frac{1}{2}\left(V_k^{\max} - V_k^{\min}\right)$)

w_k appropriate bus weight $0 < w_k \leq 1$

n integer parameter defining the exponent

5. Generation Reactive Power Index

$$J_Q = \sum_{j=1}^{L} w_j \left(\frac{Q_j - Q_{j,mean}}{Q_{j,step}} \right)^{2n} \tag{B.5}$$

where w_j generator weight $0 < w_j \leq 1$

$Q_{j,mean}$ the expected generated reactive power value. This is the mean value is the allowable range for each generator, i.e., $\frac{1}{2}\left(Q_j^{\max} + Q_j^{\min}\right)$

$Q_{j,step}$ reactive power deviation tolerance. This is half of the allowable range, i.e., $\frac{1}{2}\left(Q_j^{\max} - Q_j^{\min}\right)$

Q_j reactive power generated by unit j

n integer parameter defining the exponent

Note that the quantities inside the parenthesis express normalized circuit power flow, circuit current, voltage magnitude and generator reactive power respectively. The normalization is with respect to equipment capability or allowable limits. Thus, values of the quantities in the parenthesis in the range (-1.0 to -1.0) indicate normal operation while values outside this range indicate abnormal operation. When these quantities are raised to the $2n$ power, they will produce a large number for abnormal conditions and a very small number for normal conditions. Specifically, large values of the performance indices J_C, J_T, J_P indicate that one or more circuits are overloaded. Similarly, large values of the performance index J_V indicate that one or more voltage magnitudes are outside the permissible range for voltage magnitude. Large values of the performance index J_Q indicate that one or more generating unit produces reactive power outside its limits. A contingency will cause a change in system operating conditions which will be accompanied by a change in the performance indices J_C, J_T, J_P or J_Q.

The security indices provide a quantitative way to access the security of the system. Contingencies that may impact system security can be recognized by the change of the performance indices. Thus in order to rank contingencies on the basis of their impact on security, we can use the changes in the performance indices due to the contingency. In general, the exact change of the performance indices J_C, J_T, J_P or J_Q due to a contingency can be computed by first obtaining the system post contingency solution (power flow solution) and then computing the performance index by direct substitution. This procedure is computationally demanding and negates the objectives of a contingency ranking algorithm. Specifically, the objective of contingency ranking is to compute the approximate change of the security indices due to a set of postulated contingencies with a highly efficient computational method. Such methods were introduced in the late 70's.

In this work the Quadratized Power Flow (QPF) model has been applied towards the development of a contingency selection method using as metric performance indices. It is well known that performance index approaches lead to mis-rankings because of the nonlinearities of the model involved. The idea here is to use the quadratized power flow model that is expected to have milder nonlinearities and therefore should performed better. This is indeed the case. In addition, the quadratized power flow model is better suited to use current based ratings of circuits as opposed to power based ratings of circuits. It is pointed out that most capacity limitations of circuits are thermal limitations, i.e., electric current limitations. Thus using current limits, results in a more realistic approach.

The described approach has been applied to contingency selection using a variety of performance indices, circuit current index, voltage index, reactive power index, etc. In this report we present the methodology of the new method for some of these performance indices.

The contingency selection is based on the computation of the performance index change due to a contingency and subsequent ranking of the contingencies on the basis of the change. Mathematically one can view the outage of a circuit as a reduction of the admittance of the circuit to zero. We introduce a new control variable, the outage control variable, u_c, as illustrated in Figure B.1. Note that the contingency control variable, u_c, has the following property:

$$u_c = \begin{cases} 1.0, & \text{if the component is in operation} \\ 0.0, & \text{if the component is outaged} \end{cases} \tag{B.6}$$

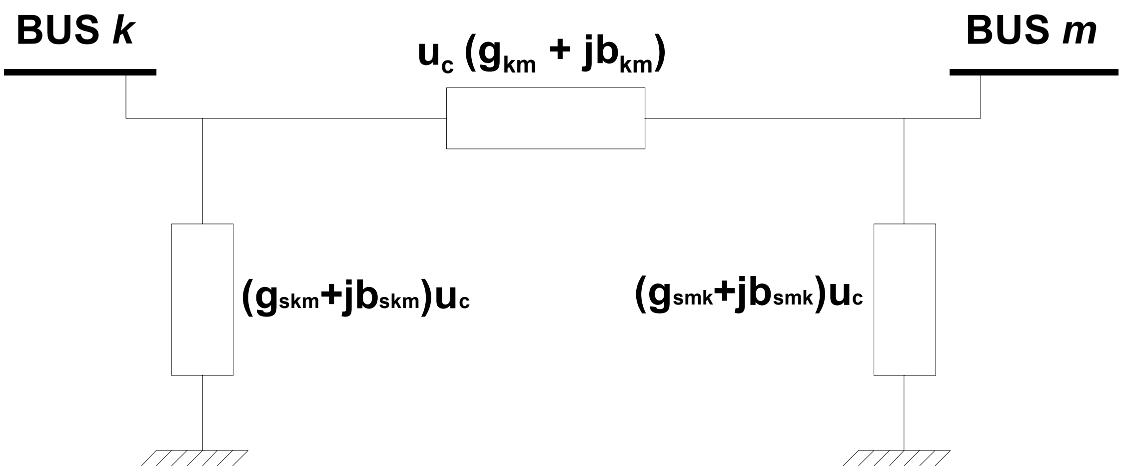

Figure B.1 Definition of the contingency control variable u_c

The current flow in the circuit km is now a function of the contingency control variable, u_c.

$$I_{kmr} = \left[(g_{km} + g_{skm})V_{kr} - (b_{km} + b_{skm})V_{ki} - g_{km}V_{mr} + b_{km}V_{mi}\right]\cdot u_c = I^0_{kmr}\cdot u_c \tag{B.7}$$

$$I_{kmi} = \left[(b_{km} + b_{skm})V_{kr} + (g_{km} + g_{skm})V_{ki} - b_{km}V_{mr} - g_{km}V_{mi}\right]\cdot u_c = I^0_{kmi}\cdot u_c$$

where V_{kr} the real part of the voltage at bus k

V_{ki} the imaginary part of the voltage at bus k

V_{mr} the real part of the voltage at bus m

V_{mi} the imaginary part of the voltage at bus m

I^0_{kmr} the real part of the base case current value from bus k to bus m

I^0_{kmi} the imaginary part of the base case current value from bus k to bus m

Similarly, consider the outage of a generating unit. Following the outage, the system will experience a generation deficiency which will result in frequency decrease. The outage will be also followed by transient. At the same time, the output of other generators will increase accordingly to their inertia initially. The net interchange (power import export) will also change. In the post contingency steady state the output of the remaining units will be increased by the action of the AGC and the net interchange will return to its scheduled value. The change of the remaining generating unit outputs at the steady state is determined by economic factors. In other words, the lost generation will be made up by increasing the output of the remaining generators according to their economic participation factors. This is shown in Figure B.2. Specifically, considering the outage of unit i, we introduce again a contingency control variable u_c which is defined as follows:

$$P_{gi} = u_c P_{gi}^0 \tag{B.8}$$

where P_{gi}^0 the precontingency output of the generating unit i

P_{gi} the generating unit i output

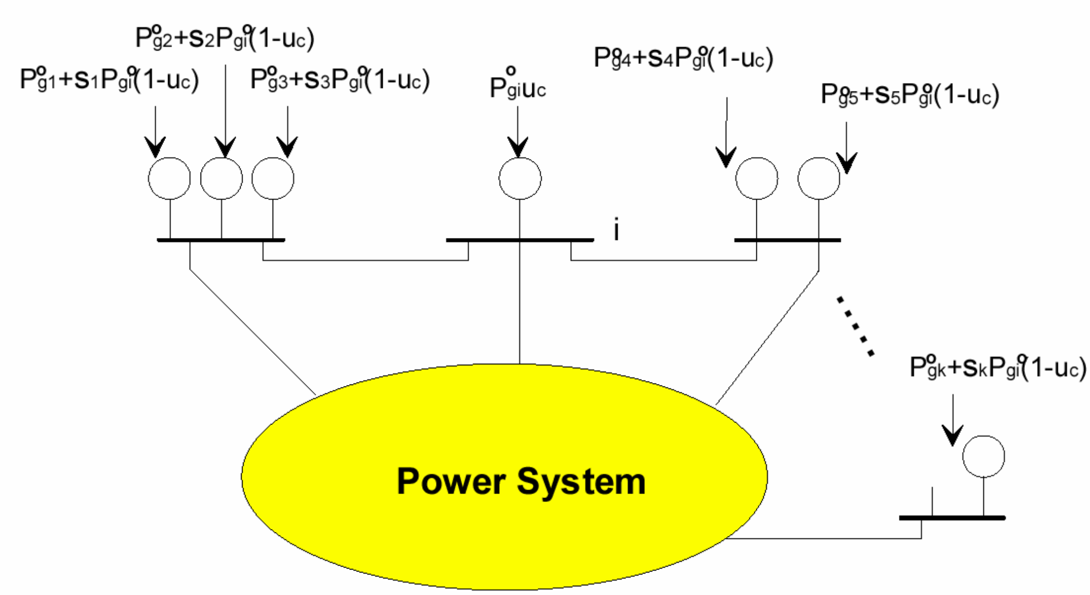

Figure B.2 Illustration of a unit outage model with the contingency control variable u_c

Note again that

$$u_c = \begin{cases} 1.0, & \text{if the unit is in operation} \\ 0.0, & \text{if the unit is outaged} \end{cases} \tag{B.9}$$

The generation deficiency P_{gi}^0 caused by the outage of this unit is absorbed by the other units. Consider the generating unit j. The output of this unit will be controlled by the automatic generation control loop to the value:

$$P_{gj} = P_{gj}^0 + (1 - u_c)\sigma_j P_{gi}^0 \tag{B.10}$$

where σ_j is the unit economic participation factor. Note again that the generating unit outputs are expressed as a function of the contingency control variable. The reactive power deficiency will also be allocated the same way.

It should be noted that the use of the contingency control variable also provides a very simple and efficient way of modeling common mode contingencies (outages). Common mode contingencies are defined as contingencies that take place together. In the general case this may be a very low probability event, however in certain specific cases this is not necessarily true. In the case of a double transmission line for example (parallel lines on the same pole), an event (e.g. a tree fall, or a lighting strike) can cause the outage of both lines at the same time instead of just one. This is a common mode outage and can be modeled with one outage control variables as illustrated in Figure B.3.

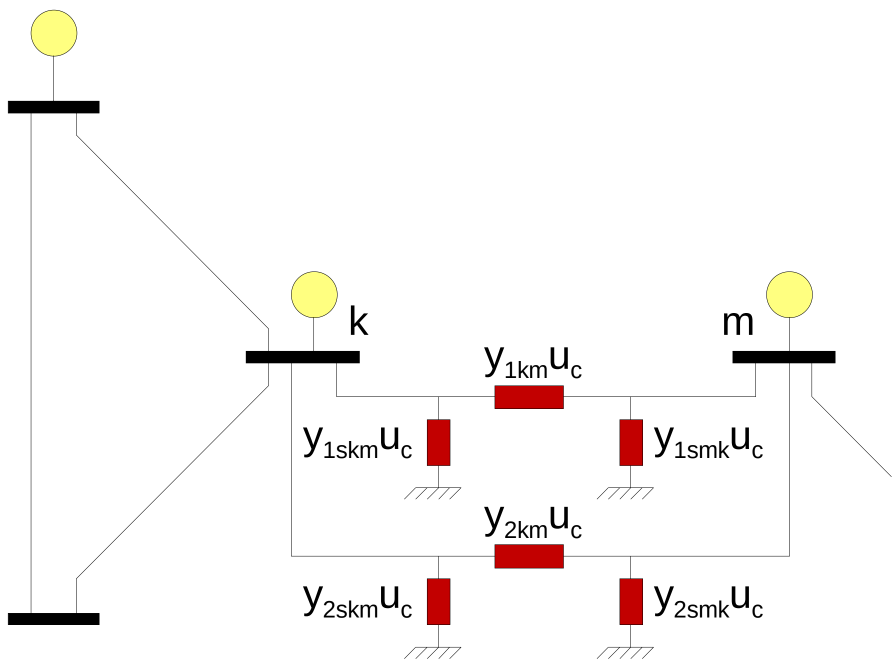

Figure B.3 Common mode line outage model with the contingency control variable u_c

In summary, any circuit or generating unit outage can be modeled with a control variable, the contingency control variable. Using these control variables, the power flow equations can be written as a function of the control variables. Specifically, the quadratic power flow equations are written in the usual compact form:

$$G(x,u) = 0.0 \tag{B.11}$$

where u is a vector of all contingency control variables. The contingency control variable, u_c, completely defines a contingency. $u_c = 1$ defines the precontingency system and $u_c = 0$ defines the post-contingency system. The security indices are in general complicated functions of the contingency control variables. Let J be anyone of the performance indices discussed earlier. Linearization of the performance index around the precontingency condition ($u_c = 1$) yields:

$$J(u_c) \cong J(u_c = 1) + \frac{dJ}{dt}(u_c - 1.0). \tag{B.12}$$

The first order change of the security index ΔJ due to a contingency is given by:

$$\Delta J = J(u_c = 0) - J(u_c = 1) = -\frac{dJ}{du_c}. \tag{B.13}$$

The above equation provides the basis of contingency ranking algorithms: The first order approximation of the effect of a contingency on security indices is determined by the derivative of the security index with respect to the contingency control variable.

Thus, the central computational problem in contingency ranking is the computation of the sensitivities $\frac{dJ}{du_c}$. For this purpose, observe that, in general, the performance index is a function of the system state, x, and the contingency control variables u.

$$J = f(x,u). \tag{B.14}$$

On the other hand, the state of the system must obey the power flow equations:

$$G(x,u) = 0. \tag{B.15}$$

The co-state method (previously developed by the authors) is applied to perform sensitivity analysis of the system state with respect to the control variable:

$$\frac{dJ}{du_c} = \frac{df}{du_c} = \frac{\partial J}{\partial u_c} - \hat{x}^T \left[\frac{\partial G(x,u)}{\partial u_c} \right] \tag{B.16}$$

where $\hat{x}^T = -\left[\frac{\partial J(x,u)}{\partial x} \right] \left[\frac{\partial G(x,u)}{\partial x} \right]^{-1}$ is the co-state vector.

Note that the co-state is pre-computed at the present operating condition and remains invariant for all contingencies. Thus for each contingency we have to only compute the partial derivatives of the power flow equation $G(x,u)$ with respect to the contingency control variable. This vector has only few nonzero entries and therefore the computations are extremely fast.

B.2. Improvements in Performance Index Contingency Ranking

Performance index contingency ranking methods are very efficient and fast, however, they are susceptible to mis-rankings, mainly due to the highly nonlinear nature of the power flow equations. In this report, besides from transforming the power flow problem using the QPF formulation, several techniques are investigated to achieve less mis-ranking.

In order to reduce the error introduced by the approximation in PI method, one approach is to include higher order terms to reduce the error. Another method is to do the proper control variable transformation such that the resulting $J-u$ curve has less nonlinearity. Both methods based on the quadratic power flow model are described below:

B.2.1. QPF Sensitivity Method

The described approach has been applied to contingency selection using a variety of performance indices, circuit current index, voltage index, reactive power index, etc. In this report we present the methodology and comparison of the new method for one of these performance indices.

In this method, instead of linearizing the performance indices directly, the system states of the QPF model are linearized with respect to the control variable, the performance index J is then calculated as following:

$$J = J(x^0 + \frac{dx}{du}(u-1), u) \tag{B.17}$$

where x^0 present operating condition

x system state of the QPF problem

u control variable

The utilization of the linearized system states in calculating the system performance index provides the higher order terms in Taylor's series. The unique potential of this method has been proven in the simulation of an example power system. Three indices, the quasi-linearized indices by the QPF sensitivity method, the linearized indices based on TPF, and the original index, have been computed and compared. The QPF sensitivity method provides the traces of indices with curvature, which can follow the highly nonlinear variations of the original indices to some extent. While the TPF method provides only the straight line. Therefore, the QPF higher order sensitivity method is superior to the PI method based on TPF.

The contingency selection is based on the computation of the performance index change due to a contingency and subsequent ranking of the contingencies on the basis of the change. Mathematically one can view the outage of a circuit as a reduction of the admittance of the circuit to zero. We use again the outage control variable, u_c, as illustrated in Figures B.1 and B.2.

Consider the performance index J. The change of J due to the contingency is:

$$\Delta J = J\left(x^o + \frac{dx}{du_c}(u_c - 1), u_c\right) - J\left(x^o, u_c = 1.0\right) \tag{B.18}$$

where x^o is the present operating condition. The sensitivity of the state with respect to the control variable can be easily computed as:

$$\frac{dx}{du_c} = -\left[\frac{\partial G(x,u)}{\partial x}\right]^{-1}\left[\frac{\partial G(x,u)}{\partial u_c}\right] \tag{B.19}$$

Note that $\frac{\partial G(x,u)}{\partial x}$ is the Jacobian of the system and therefore it is precomputed at the present operating condition and remains invariant for all contingencies. Thus for each contingency we have to only compute the partial derivatives of the power flow equation G(x,u) with respect to the contingency control variable. This vector has only few nonzero entries and therefore the computations are extremely fast. It should also be noted that $\frac{dx}{du_c}$ is a vector of the same size as the state vector each element of which is the derivative of the corresponding state with respect to the control variable. Once the new state is computed via this linear approximation, the calculation of the new value of the performance index is a straightforward operation.

The concept of the approach is presented graphically in Figures B.4 and B.5 based on results obtained from the application of the method to a test system. The first order analysis curve represents the classical linear curve after performing the linearization of the index with respect to the contingency control variable. The higher order analysis curve is the state linearization curve with respect to the contingency control variable.

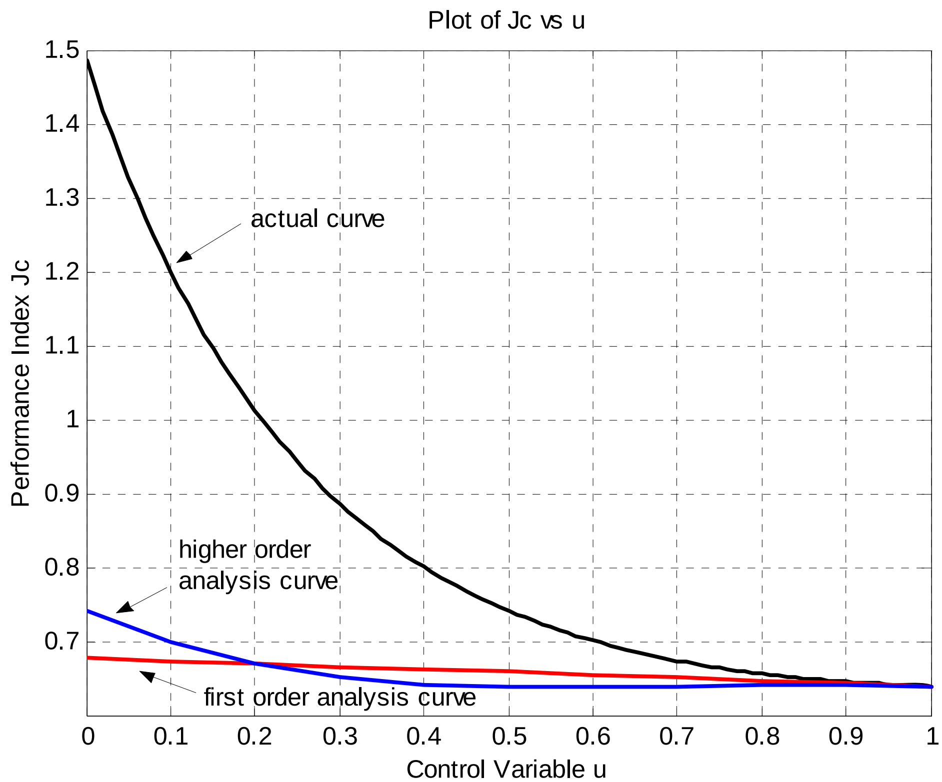

Figure B.4 Plots of circuit-loading index vs. the contingency control variable u_c

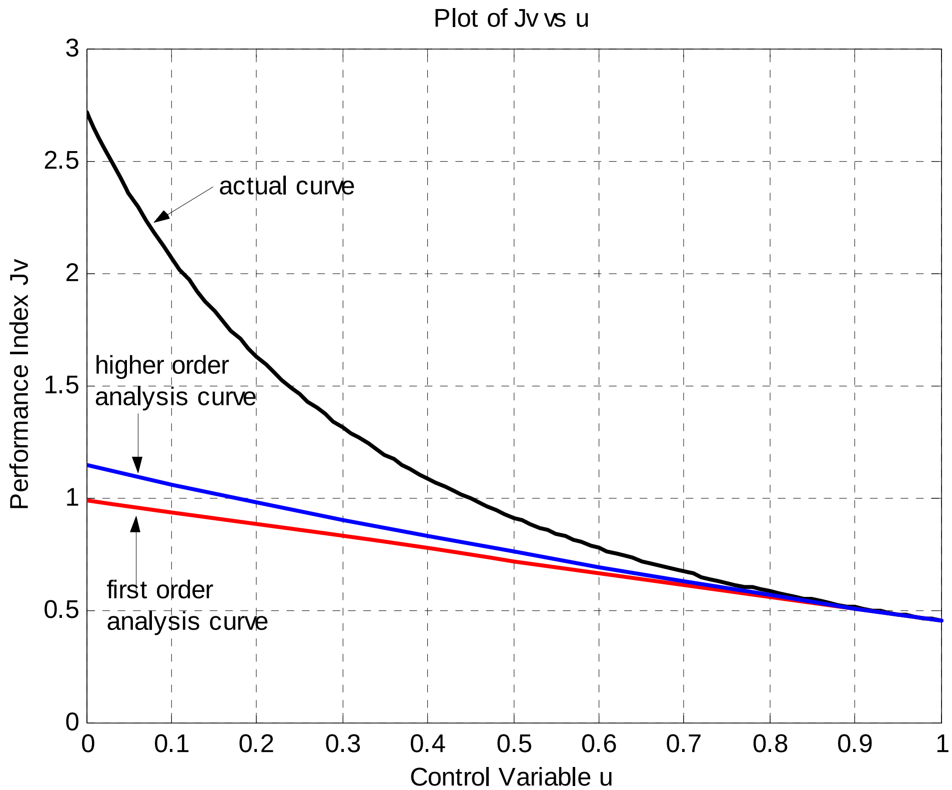

Figure B.5 Plots of voltage index vs. the contingency control variable u_c

The method has been applied to a small power system and compared to the traditional contingency selection algorithms (based on the traditional power flow formulation). The results for both methods are shown in Tables B.1 and B.2. Note that the proposed method predicts much better the changes of the performance index due to the outage (Table B.1). Note also that the proposed method provides the correct ranking of the outages, as compared to the traditional method which results in severe misrankings for this system (Table B.2).

Table B.1 Performance index change computed directly with the traditional method and with the proposed method

Contingency	Before Contingency	After Contingency					
	Original Index	Original Index		Linearized Index (TPF)		Linearized Index (QPF)	
		Value	Change	Value	Change	Value	Change
u_{c12}	0.30392	0.30395	0.00003	0.30394	0.00002	0.30394	0.00002
u_{c13}	0.3039	5.6357	5.3318	0.1917	-0.1122	0.5403	0.2364
u_{c14}	0.3039	4.9665	4.6626	0.4910	0.1871	0.9684	0.6645
u_{c24}	0.3039	2.7788	2.4749	0.3046	0.0007	0.3284	0.0245
u_{c34}	0.3039	0.2921	-0.0118	0.2977	-0.0062	0.2994	-0.0045

Table B.2 Ranking results

Contingency	Ranking				
	u_{c12}	u_{c13}	u_{c14}	u_{c24}	u_{c34}
Original Index	4	1	2	3	Improved
Linearized Index (Pbase)	2	improved	1	Improved	Improved
Linearized Index (TPF)	3	improved	1	2	Improved
Linearized Index (QPF)	4	2	1	3	Improved

Some additional results from the small test system illustrated in Figure B.6 are presented in Tables B.3 and B.4.

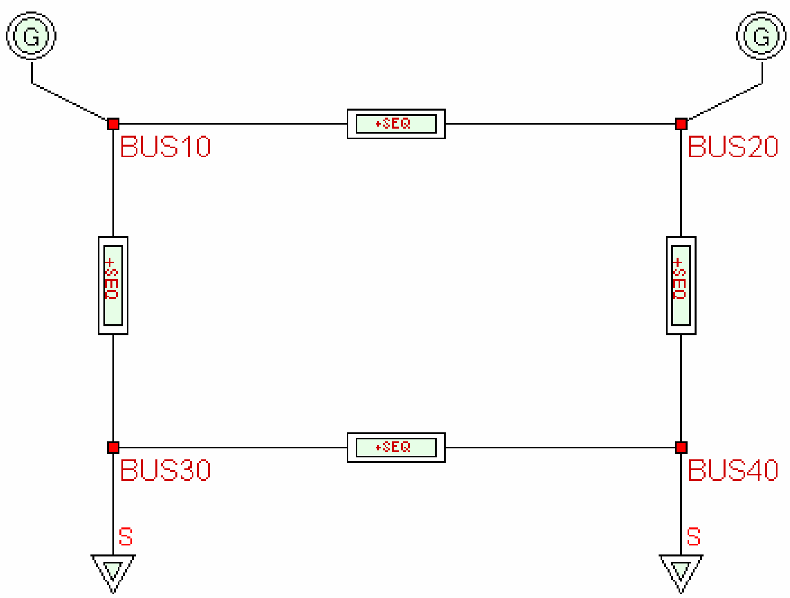

Figure B.6 Test system used for contingency ranking evaluation

Table B.3 Performance index change and ranking results for the circuit loading index.

Outaged Line	J(u=1)	J(u=0)	Actual ΔJ	Nonlinear Approach Ranking	ΔJ = -dJ/du	Proposed Index Linearization Ranking	State Linearization Analysis ΔJ	Proposed State Linearization Ranking
10_30	8.84401			1	24.87533	1	51.93819	1
20_40	8.84401	18800.67	18791.83	2	19.98223	2	41.22497	2
30_40	8.84401	12.28402	3.44001	3	-0.0082	4	0.01342	3
10_20	8.84401	8.99846	0.15445	4	-0.00059	3	-0.00316	4

Table B.4 Performance index change and ranking results for the voltage index

Outaged Line	J(u=1)	J(u=0)	Actual ΔJ	Nonlinear Approach Ranking	ΔJ = -dJ/du	Proposed Index Linearization Ranking	State Linearization Analysis ΔJ	Proposed State Linearization Ranking
10_30	0.27091			1	-0.06029	4	1.92924	1
20_40	0.27091	22.24559	21.97468	2	0.1814	1	0.97924	2
10_20	0.27091	0.31572	0.04481	3	0.0029	2	0.00311	3
30_40	0.27091	0.25285	-0.01806	4	-0.00861	3	-0.00737	4

Finally some preliminary results from the IEEE 24-Bus Reliability Test System are presented in Table B.5.

Table B.5 Performance index change and ranking results for the voltage index for the IEEE 24-bus reliability test system

Outaged Branch	J(u=1)	J(u=0)	Actual ΔJ	Nonlinear Approach Ranking	ΔJ = -dJ/du	Proposed Index Linearization Ranking	State Linearization Analysis ΔJ	Proposed State Linearization Ranking
60_100 C	25.41	3306.22	3280.81	1	-243.87	39	120.99	1
20_60	25.41	133.82	108.41	2	30.72	1	49.99	2
100_110 T	25.41	63.10	37.69	3	16.73	2	24.95	3
150_240	25.41	58.58	33.17	4	0.00	19	1.65	8
50_100	25.41	55.57	30.16	5	7.48	5	8.68	6
100_120 T	25.41	50.63	25.22	6	12.98	3	19.67	4
80_100	25.41	48.74	23.33	7	10.20	4	12.24	5
10_50	25.41	39.40	13.98	8	4.12	6	4.55	7
240_30 T	25.41	37.04	11.63	9	-1.33	31	-0.90	32
110_140	25.41	30.62	5.21	10	1.08	7	1.18	9
30_90	25.41	28.41	3.00	11	0.88	8	1.10	10

B.2.2. Reducing the nonlinearity of the variations of performance indices

In the formulation of QPF model, the control variable transformation is introduced to reduce the nonlinearity of the changes of performance indices. As shown in Figure B.7, the curve, which represents the relation between a performance index and a control variable, is generally nonlinear due to the inherent nonlinearity of power systems.

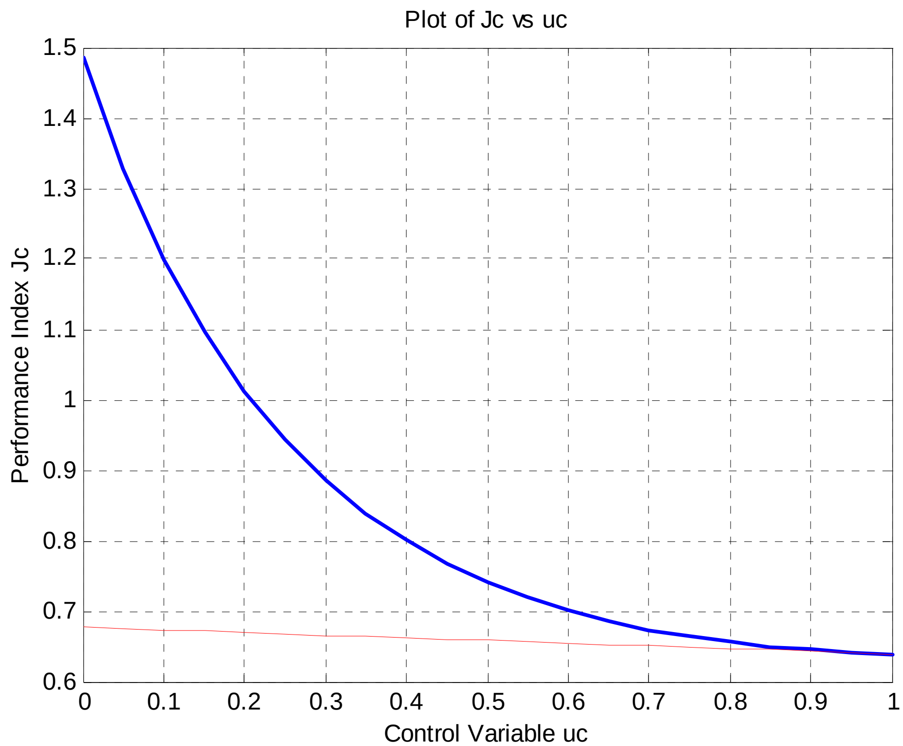

Figure B.7 Nonlinear curve of current based loading performance index with respect to a circuit outage control variable

If proper control variable transformation is applied, such that the curve of the performance index via the new control variable is more close to a straight line, then the prediction of post-contingency performance index based on the new curve can provide more accurate information by the linearized model. A basic restriction is that the values of the original and transformed control variables (and therefore the performance index values) at the end points should be the same, i.e., zero and one. The proper control variable transformation is still being investigated.

The general concept of the approach is graphically presented in Figures B.8 and B.9.

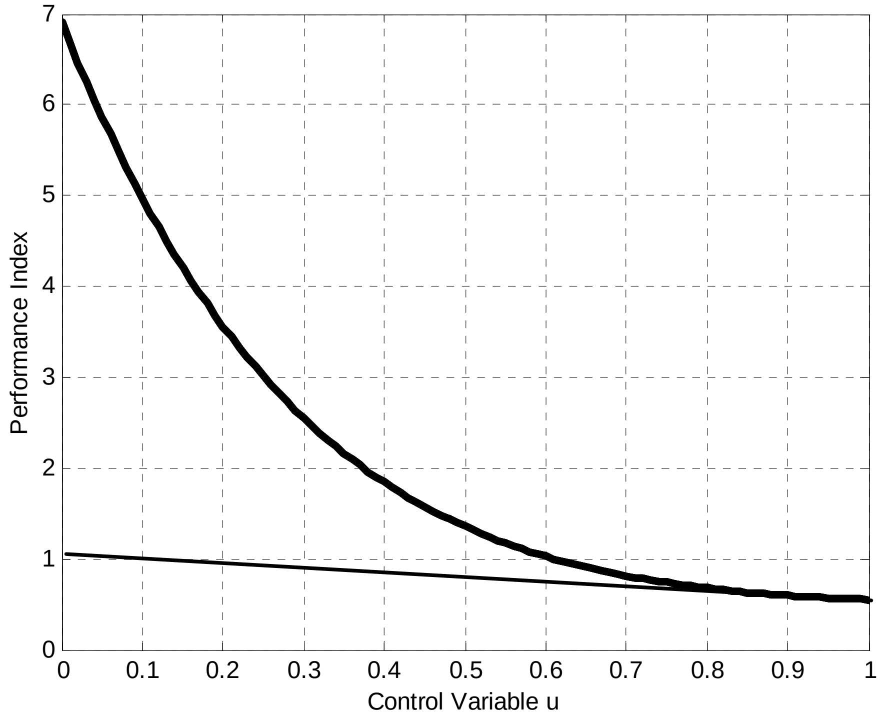

Figure B.8 Nonlinear curve of original performance index with respect to a circuit outage control variable and first order approach line

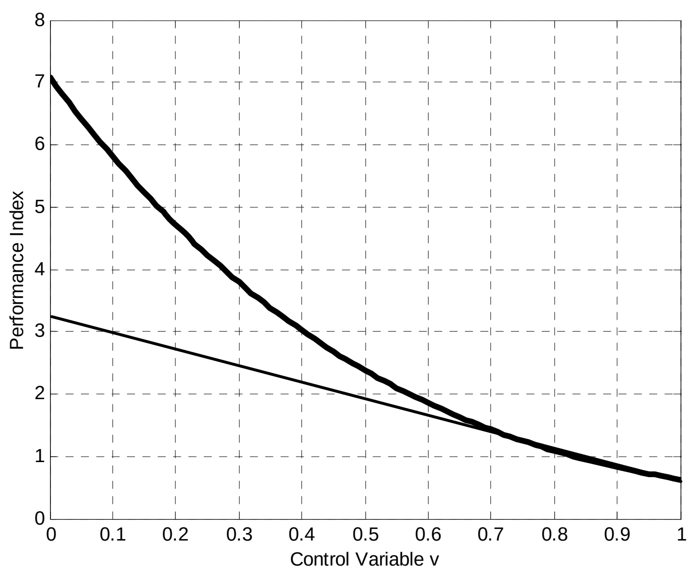

Figure B.9 Nonlinear curve of transformed performance index with respect to a transformed circuit outage control variable and first order approach line