Discrete Event Dynamic Systems: Theory and Applications, 9, 351–388 (1999)

Dynamics of Transmission Provision in a Competitive Power Industry

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Abstract. The main objective of this paper is to revisit the operations and planning of an electric power system, and, more specifically, of its transmission system. The intent is to formulate the underlying problems as decision-making problems with specific performance objectives. Once this is done, it becomes possible to identify open research questions on this subject, including their dependence on the overall industry structure.

Keywords: electric power systems, transmission, competition, optimal stochastic control, dynamic programming, discrete event dynamic systems

1. Introduction

Transmission provision for the electric power industry under restructuring has become one of today's hottest topics. System users are concerned with grid availability as they establish power trades in the electricity markets. System providers, on the other hand, are concerned with transmission system reliability. A transmission provider is asked to provide short-term access to the power spot market participants at the rate at which these markets evolve, typically only one day ahead. In addition, new power plants often request longer-term use of a transmission network. The problem of transmission system expansion necessary to serve probable market requests which evolve at different rates is a very difficult theoretical and practical problem. At the same time, the main responsibility of a transmission provider remains keeping the system intact continuously.

This need to simultaneously serve short-term market requests and to make commitments to new entrants for future system use is hard to meet with presently available computer methods. At present, industry tools for transmission system planning do not allow a view of the problem as one of dynamic optimization under uncertainties with well-posed long-term performance objectives. Most of the methods are either useful only for short-term optimal use of the network, like deterministic optimal load flow, or are long-term planning methods not capable of optimal scheduling in short-term operations.

This paper concerns several fundamental problems related to transmission system operations and planning in a competitive power industry. The network plays a basic coordinating role in this otherwise decentralized industry. Coordinating signals could be implemented as technical- and/or price-feedback over various time horizons from short-term operations to time horizons over which physical, financial and planning processes are interwined.

In the first part of this paper, we pose the composite problem of operations and planning for the regulated electric power network as a single stochastic optimal control problem.[1] The decomposition of this complex problem into more manageable subproblems is introduced next. Transmission architectures which enable partial coupling of these subproblems lead to near-optimal long-term transmission system provision.

In the second part of this paper, we pose the problem of transmission provision in the competitive industry and review the objectives of a transmission provider. We introduce a transmission provision and pricing scheme which relaxes commonly made assumptions of short-term perfect market conditions and grants a coordinating role to an independent grid operator. The operator allocates non-firm transmission capacity on a long-term basis and manages short-term use of the grid, based on the operator's estimation of the arrival process of requests for transmission capacity. In this dynamic allocation of non-firm transmission capacity, a provider uses knowledge of existing transmission contracts to optimally invest in transmission capacity.

Finally, the paper re-visits the composite operations/planning problem in light of possible algorithmic approaches to transmission provision under open access. In particular, a method for predicting long-term system conditions using a probabilistic optimal power flow-based approach is introduced as an essential tool for long-term decision-making. Next, we show how this method could be used by a system provider to design menus for selling priority service of different firmness for next season use. Once the menus are in place, it becomes necessary to make short-term decisions concerning the tradeoff between denying new short-term requests for using the system or paying back the owners of priority service for not being served. This problem is posed as a dynamic programming problem that needs to be solved, keeping in mind the cumulative effects of short-term decisions over the entire season.

2. Transmission System Operations and Planning as a Single Stochastic Control Problem

As the industry restructures, it has become necessary to start by formulating the coupled operations and planning problem. While it may appear that it is sufficient for a system operator to manage only short-term transactions optimally and not have any systematic decision-making approach to expanding a transmission system, we argue in this paper that the ultimate longer-term benefits of electricity users will be hard to ensure in the new industry without an approach which links short-term transmission operations and investment decisions. In this section, we consider the problem of optimal transmission provision as a single stochastic control problem comprising short-term decision-making and planning.

As a rule, any real-life transmission network is likely to be congested for some load patterns and certain equipment outages. A theoretical formulation of transmission system operations and planning as a single decision-making problem capable of quantifying the cost tradeoffs between using more expensive generation to supply load demand under the transmission constraints or enhancing the system design is not available at present.

In this section, we propose one possible formulation of the composite operations and planning problem for the regulated electric power industry. The problem is posed as a stochastic optimization problem with the system-wide objective of minimizing the total expected operating and investment cost of meeting the uncertain demand.

Notation:

$K_l^T(t)$ is the amount of installed transmission capacity for line l.

$K_i^G(t)$ is the amount of installed generation capacity at node i.

$I_l^T(t)$ is the rate of investment in transmission capacity for line l.

$I_i^G(t)$ is the rate of investment in generation capacity at node i.

$C_l^T(K_l^T, I_l^T, t)$ is the cost of investment in line l.

$C_i^G(K_i^G, I_i^G, t)$ is the cost of investment at node i.

$P_i(t)$ is the production at node i, at time t; $P_G(t) = [P_1(t) \cdots P_n(t)]$.

$c_i(t)$ is the cost of this production, excluding capacity costs.

$P_{L_j}(t)$ is the uncertain (uncontrolled) load at node j at time t; $P_L(t) = [P_{L1}(t) \cdots P_{L_{nd}}(t)]$.

$F_l(P_G(t), P_L(t))$ represents the flow on line l as a function of generation and demand system inputs.

$\lambda(t)$ is the spot electricity market price at time t.

ρ is a discount rate.

2.1. *Problem Formulation*

Consider an electric power system with n nodes whose net generation/demand is controllable and the remaining nd nodes whose power injections are uncertain load demands.

Historically, utilities have viewed load demand as uncertain system input; various forecasting methods have been developed for forecasting hourly, daily, weekly, seasonal and, to a lesser extent, annual cycles in load demand changes. Power system operations and planning were carried out with the main objective of supplying this forecasted demand. Without loss of generality, we formulate the control problem by representing the uncontrolled portion of the load as an uncertain disturbance $P_L(t)$, and the controllable portion of the load demand (including its responsiveness to change in the price of electricity) as a negative, controllable, generation.[2] The representative load demand characterization and its periodicities are shown in Figure 1 (FERC, 1999). The corresponding cumulative probability (load duration curve) is shown in Figure 2. Based on these figures, one can observe at least three periodicities relevant for our problem formulation. Depending on the optimization period T of interest, one can model demand as a diffusion-type process characterized with different load duration curves (probability distribution curves).

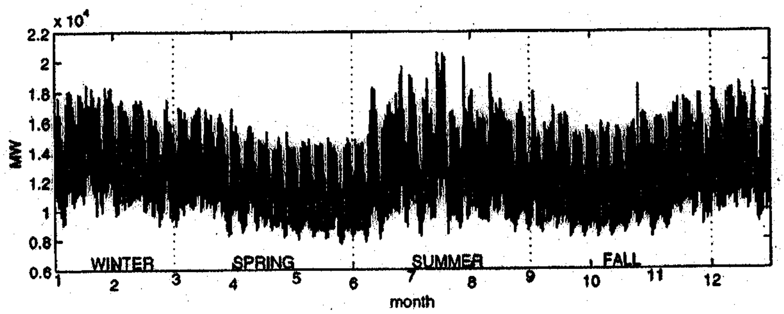

Figure 1. Total electricity demand for 1997 in the NEPOOL area.

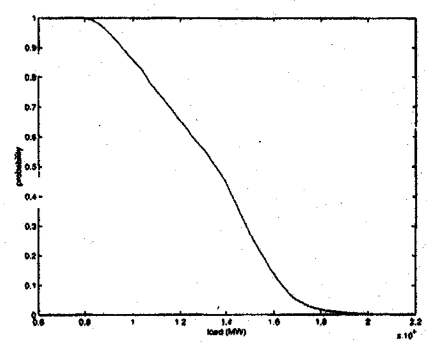

Figure 2. The load duration curve constructed from NEPOOL data of 1997.

For instance, if one is interested in the short run demand, e.q., hourly load fluctuation P_L^{hour}, the load demand model could be represented as a diffusion process of the form (Delebecque et al., 1978; Delebecque et al., 1981):

$$dP_L^{hour} = \beta(\tau, P_L^{hour})d\tau + \sqrt{\sigma}\, dW_\tau \tag{1}$$

Similarly, the diffusion model for seasonal demand could be modeled as:

$$dP_L^{season} = \frac{1}{\varepsilon}\beta\left(\frac{\tau}{\varepsilon}, P_L^{season}\right) d\tau + \sqrt{\frac{1}{\varepsilon}\sigma}\, dW_\tau \tag{2}$$

where $\varepsilon = \frac{1}{2160}$.

The coordinated operations and planning problem is a combined problem of short-term generation scheduling and investment in new generation and transmission to balance load demand deviations ranging from hourly through seasonal and long-term, and do this at the lowest cost. A possible mathematical formulation is as follows:

$$\min_{I_l^T, I_i^G, P_i} \mathcal{E}\left\{ \sum_i \int_{t_0}^{T} e^{-\rho t} \left(c_i(t, P_i(t)) + C_i^G \left(K_i^G(t), I_i^G(t), t\right)\right) dt + \sum_l \int_{t_0}^{T} e^{-\rho t} \left(C_l^T (K_l^T(t), I_l^T(t), t)\right) dt \right\} \tag{3}$$

subject to:

$$\begin{aligned} \frac{dK_l^T}{dt} &= I_l^T(t) \\ \frac{dK_i^G}{dt} &= I_i^G(t) \\ I_l^T(t) &\geq 0 \\ I_i^G &\geq 0 \\ F_l(P_G(t), P_L(t)) &\leq K_l^T : \mu_l(t) \\ P_i(t) &\leq K_i^G : \sigma_i(t) \end{aligned} \tag{4}$$

$$c_{spot}\left(\sum_{i=1}^{n} P_i(t) - \sum_{j=1}^{nd} P_{L_j}(t)\right) = \frac{d\lambda(t)}{dt}, \qquad \lambda(t_0) = \lambda_0 \tag{5}$$

The optimization period, T, corresponds to the longer of two time intervals over which the generation or transmission investments are valued. $\lambda(t)$, $K_i^G(t)$ and $K_l^T(t)$ are state variables. The control variables are the rate of investment in transmission capacity $I_l^T(t)$, the rate of investment in generation capacities $I_G^T(t)$, and the injection of power at each node $P_G(t)$. The uncertain portion of the load at nodes j is disturbance inputs $P_L(t) = [P_{L_1}(t) \cdots P_{L_{nd}}(t)]$. The control is bounded by the set of constraints described above. A set of Lagrange multipliers is associated with each set of constraints.

Note: In this formulation, the process of balancing total generation and demand is represented with consideration of evolving electricity spot markets, and it assumes that the market clears at the (economic) equilibrium. In this sense, (5) represents a sequence of daily spot market equilibria. This highly simplified formulation is used to stress the fact that even the daily market-clearing process should be viewed as a dynamic process in composite operations and planning decision-making, see (Visudhiphan et al., 1999). The effect of longer-term bilateral transactions taking place outside daily spot markets is modeled as a more slowly evolving process, as described in the later part of this paper devoted to the more complex industry forms under restructuring.

This problem formulation, in spite of its apparent complexity, captures many well-known trade-offs relevant for the efficiency of the power industry. First, the discount rate reflects the time value of money. Everything being equal, it is better to spend money now than later.

Thus, the investment timing balances the trade-off between the costs and benefits over time. Second, this formulation shows that different technologies at different locations can be used to produce power. Thus, for a given load duration curve, the ratio between variable costs and capacity costs for each of these generation resources determines the optimal pattern and mix of generation. Third, generation capacity can be substituted for transmission capacity. The main trade-off, of interest in this paper, between saving on generation costs and investing in transmission capacity is also encapsulated in the problem. The level of transmission capacity is not based on the maximum yearly flow. A trade-off between the costs of congestion and the costs of transmission capacity must be considered. Finally, the problem stated above is an uncertain problem. The stochastic formulation reflects the value of flexible investment under uncertainties.

2.2. *Temporal Decomposition of the Problem*

Possibly one of the most difficult tasks in developing effective software tools for transmission provision in the future is thinking about the problem as a stochastic dynamic problem evolving at vastly different rates. The very question of conditions under which the single problem can be decomposed into simpler subproblems when the objective is the long-term optimization under uncertainties subject to short-term operating constraints makes this problem a singularly perturbed stochastic control problem (Bensoussan, 1981; Khalil et al., 1984). Establishing this formulation is potentially helpful to define these conditions.

The relevance of particular subproblems of interest could be understood by addressing questions discussed by the industry and the regulators. The anticipated load pattern is met differently depending on which industry structure is in place. For example, in an industry which allows long-term bilateral contracts between load and power suppliers, real-time operations concern only adjustments of power produced and consumed around these patterns, so that short-term load variations are compensated; this is done without violating transmission system constraints.[3] On the other hand, in a power market in which all power supplied and consumed must be traded on daily basis, short-term operations concern generation scheduling to meet the entire demand, including its longer-term trends and short-term deviations simultaneously.

In this paper, we discuss transmission provision problems under the assumption that a portion of the load is supplied through longer-term, pre-committed bilateral contracts (since at present there are no mature long-term markets for trading electricity; they are being formed), while faster variations are managed through daily electricity spot markets. In this case, the long-term bilateral system users often require an ex ante guarantee (a transmission "right") that they will be able to use the system in the future according to pre-specified conditions and independent from actual system conditions.

The coupled operations and planning formulation is obviously complex because it poses operations and planning as a single optimization problem evolving at the same time t. In reality, however, the process of scheduling supply to meet demand in operations typically happens much faster than the rate at which investment decisions are made.

This observation is the basis for solving the two subproblems as if they were decoupled. To formally introduce these two subproblems, assume without loss of generality that the short-term (daily or hourly) decisions are made each hour $[kT_H]$, and investment decisions are made each season $[nT_S]$, and $k, n = 0, 1, \ldots$, where $T_H = \frac{T_S}{2160}$. The problem defined in (3)–(5) can then be re-stated as an optimization problem subject to multi-rate discrete-time processes using techniques introduced in (Haddad et al., 1977). The objective function (3) takes on the form

$$\min_{I_l^T[nT_S], I_i^g[nT_S], P_i[kT_H]} \mathcal{E}\left\{ \sum_i \sum_{k=0}^{\frac{T}{T_H}} e^{-\rho[kT_S]}(c_i(kT_H, P_i[kT_H], [kT_H]) + \sum_i \sum_{n=0}^{\frac{T}{T_S}} e^{-\rho[nT_S]} C_i^G(K_i^G[nT_S], I_i^G[nT_S], [nT_S]) + \sum_l \sum_{n=0}^{\frac{T}{T_S}} e^{-\rho[nT_s]} C_l^T(K_l^T[nT_S], I_l^T[nT_S], [nT_S]) \right\} \tag{6}$$

subject to:

$$\begin{aligned} K_l^T[(n+1)T_S] &= K_l^T[nT_S] + I_l^T[nT_S]T_S \\ K_i^G[(n+1)T_S] &= K_i^G[nT_S] + I_i^G[nT_S]T_S \end{aligned}$$

$$\begin{aligned} I_l^T[nT_S] &\geq 0 \\ I_i^G &\geq 0 \end{aligned}$$

$$\begin{aligned} F_l(P_i[kT_H], P_{L_j}[kT_H]) &\leq K_l^T[nT_S] : \mu_l[kT_H] \\ P_i[kT_H] &\leq K_i^G[nT_S] : \sigma_i[kT_H] \end{aligned} \tag{7}$$

$$\lambda[(k+1)T_H] = \lambda[kT_H] + c_{spot}\left(\sum_{i=1}^{n} P_i[kT_H] - \sum_{j=1}^{nd} P_{L_j}[kT_H]\right) , \tag{8}$$

This problem can be interpreted as a stochastic optimal control problem for a dynamic model in a standard discrete-time singularly perturbed form (Haddad et al., 1977)

$$\min_{u_f, u_s} J_T(u_f, u_s, w) \tag{9}$$

subject to

$$\begin{aligned} dx &= g_1(x, u_s, w)\,dt \\ dz &= g_2(u_f, w)\,dt \end{aligned} \tag{10}$$

and

$$h(u_f, x, w) \leq 0 \tag{11}$$

where $x = [K_l^T \; K_i^G]$, $z = \lambda$, $u_f = [P_G]$, $u_s = [I_l^T \; I_i^G]$ and $\sqrt{\sigma}\,dw = dP_L - \beta(t, P_L)\,dt$.

Observe that the slow and fast variables are coupled primarily through load demand (disturbance) dynamics. The multiple periodicity of the load demand sets the basis for separation of planning and operations objectives in the regulated industry. Planning is the process of controlling the rate of investments in transmission and generation, I_l^T and I_l^G respectively, so that load demand evolving over longer-term horizons (seasons and longer) is served at the lowest possible cost. (This is done assuming that generation/demand scheduling in operations will be a stable process.) Similarly, controlling use of available generation P_G in real time operations (hourly and shorter) is done to meet anticipated hourly demand at the lowest possible cost. The ultimate objective is to minimize the cost of both investments and operations while meeting the uncertain system load demand $P_L(t)$. The theoretical conditions under which the two subproblems are separable and the implications on suboptimality of J_T have never been studied.

In what follows, we first describe the zero-th order (decoupled) short-term and long-term stochastic control subproblems for the regulated industry. Next, in section 2.3 we show that much-debated nodal pricing as a proposed means of short-term congestion pricing is a result of solving the fast control subproblem in the near-optimal composite control of the coupled operations/planning problem.

A computationally simpler version of deciding periodically (once a season, or once a year) about pricing for transmission for the next season so that at the end of the period a long-term optimal investment is made is posed in section 2.4 as solving the slow control subproblem of the fully coupled operations/planning problem. We point out that a stochastic peak load pricing for transmission approach is equivalent to solving this slow control subproblem (Leotard, 1999).

Much the same way as in any other composite control design for singularly perturbed systems, one could study the conditions under which solving two subproblems makes sense. Moreover, inherent in solving the slow control problem is the optimal solution of the expected fast control problem over the entire time horizon.[4] The point is made that, by viewing the composite operations/planning problem as one and decomposing it into simpler dynamic decision subproblems under relatively unrestrictive conditions, a near-optimal transmission may be possible.

2.3. Short-Term Coordination: Fast Control Subproblem

The composite operations/planning problem formulation is used next to pose the objectives of short-term transmission operations and planning as two decoupled near-optimal subproblems evolving at significantly different rates.

Assuming that network and generation are given over the entire T, a zero-th order fast control subproblem becomes a decision-making process about which units to turn on and off and how to adjust the power generated in short-term operations.

In this section, we focus on the short-term operations of the daily spot power market. This sub-problem formulation directly follows from the composite optimization problem under the assumption that $\frac{T_\mu}{T_s} \ll 1$. The network topology and parameters, $K_l^T[nT_S]$, as well as generation plants, $K_i^G[nT_S]$, are given. Assuming furthermore that the daily power market is at its moving equilibrium (each day there is enough generation to meet load demand and power is sold at the optimum clearing price $\lambda(t)$), a short-term operating optimization problem is the problem to:

$$\min_{P_i[kT_H]} \mathcal{E} \sum_{k=0}^{k=\frac{T}{T_H}} \sum_{i=1}^{n} c_i(P_i[kT_H], P_L[kT_H]) \tag{12}$$

subject to the constraints:

$$\begin{aligned} \sum_{i=1}^{n+nd} H_{li}(P_i[kT_H] - P_{L_i}[kT_H]) &\leq K_l^T[nT_S] : \mu_l[kT_H] \\ P_i[kT_H] &\leq K_i^G[nT_S] : \sigma_i[kT_H] \end{aligned} \tag{13}$$

$$\lambda[(k+1)T_H] = \lambda[kT_H] + c_{spot}\left(\sum_{i=1}^{n} P_i[kT_H] - \sum_{j=1}^{nd} P_{L_j}[kT_H]\right). \tag{14}$$

Here, a simplified DC load flow approximation is used to express line flow constraints. H is the matrix of distribution factors (Kirchmayer, 1985) and transmission losses are neglected.

This problem is also a stochastic control problem; a fast control (decision) variable is the controllable power injected into individual network nodes in response to very fast random fluctuations in load demand given in equation (1). This problem is a dynamic control problem which could be solved using various computing methods (Bertsekas, 1995; Bertsekas et al., 1996).

Presently used tools for short-term operations are deterministic approximations which are static tools. This problem is typically solved as a static optimization problem each $[kT_H]$ assuming $P_L[(k+1)T_H]$ given for the next hour and optimizing generation, $P_G[(k+l)T_H]$, to meet it at the lowest possible cost. This problem is known as the optimal power flow (OPF) problem. The result of solving the OPF problem is given as:

$$p_i(t) = \frac{dc_i(t)}{dP_i(t)} = \lambda(t) - \sum_{l=1}^{L} H_{li}\mu_l(t) \tag{15}$$

The symbol λ represents the price of power at the chosen arbitrary (slack) node. The term $\sum_{l=1}^{L} H_{li}\mu_l$, where L is the total number of transmission lines, reflects locational differences in optimal prices. Even though μ_l is always positive by definition, the term $\sum H_{li}\mu_l$ can be positive or negative. The value of λ and the distribution factors matrix depend on the choice of the arbitrary slack bus. However, the value of nodal prices p_i and of μ_l are independent from this choice. The term μ_l represents the marginal value of the existing transmission capacity of line l. In other words, it represents the increment in total cost that would result from a unit transmission capacity upgrade. This value is equal to zero, as long as the line is not congested, and becomes strictly positive when the flow on line l is equal to the capacity K_l. These formulae provide the basis for the so-called nodal or locational based marginal cost (LBMC) transmission pricing (Schweppe et al., 1988).

2.4. *Long-Term Coordination Subproblem: Optimal Investment*

Assuming that real-time optimization can be decoupled from the investment problem, consider the more complex, less studied, issue of optimal investments. Generally speaking, the notion of investment is inherently inter-temporal (Caramanis, 1981). By investing a fixed amount of money today, the centralized utility reduces its costs over time. For this reason, uncertainty issues are at the heart of investment theories. The basic existence of risk is taken into account through the choice of the discount rate ρ: the more uncertain future pay-offs are, the higher the discount rate and the lower the optimal investments.

To pose the investment problem as an active risk management problem, we view it here as a slow optimal control subproblem of the coupled operations/planning problem given in equations (3)–(5) as follows:

$$\min_{I_l^T[kT_S],I_l^G[kT_S]} \mathcal{E}\left\{ \sum_l \sum_{k=0}^{\frac{T}{T_H}} e^{-\rho[kT_S]}(c_l[kT_H], P_l[kT_H]) \right.$$
$$+ \sum_l \sum_{n=0}^{\frac{T}{T_S}} e^{-\rho[nT_S]} C_l^G(K_l^G[nT_S], I_l^G[nT_S], [nT_S])$$
$$\left. + \sum_l \sum_{n=0}^{\frac{T}{T_S}} e^{-\rho[nT_S]} C_l^T(K_l^T[nT_S], I_l^T[nT_S], [nT_S]) \right\} \tag{16}$$

subject to:

$$K_l^T[(n+1)T_S] = K_l^T[nT_S] + I_l^T[nT_S]T_S$$
$$K_l^G[(n+1)T_S] = K_l^G[nT_S] + I_l^G[nT_S]T_S$$

$$I_l^T[nT_S] \geq 0$$
$$I_l^G[nT_S] \geq 0 \tag{17}$$

2.4.1. *Relation to Stochastic Peak-Load Pricing for Transmission*

Drawing from the work of Kleindorfer and Crew (Crew et al., 1979), a definition of an optimal grid in a static and deterministic set-up was introduced in (Lecinq, 1996; Lecinq et al., 1997). Knowing the cost functions of generators and demand function in the future, it is possible to define the cost functions $c_l(t, P_l)$, as well as the total cost function, as time dependent functions.

At $t = 0$, investments in transmission capacity are made to minimize both the discounted costs of generation over the planning horizon and the initial cost of investments. If T is a planning horizon and ρ the appropriate discount rate, then the optimal transmission investments K_l^T result from solving the following optimization problem:[5]

$$\min_{K_1^T,\ldots,K_L^T} \mathcal{E}\left\{\int_0^T e^{-\rho t} TC(t, K_1^T, \ldots, K_L^T)\, dt + \sum_{l=1}^{L} C_l^T(K_l^T)\right\} \tag{18}$$

subject to $K_l \geq 0$ where the total cost function is defined by:

$$TC(t, K_1^T, \ldots, K_L^T) = \min_{P_i} \sum_{i=1}^{n} c_i(t, P_i) \tag{19}$$

The novel aspect of transmission pricing as a feedback design problem for a dynamic system driven by uncertainties evolving at various rates can be interpreted in the context of this basic problem formulation. An ex ante probabilistic peak-load pricing for transmission introduced in (Leotard, 1999) as one possible way of evaluating the tradeoffs between using more expensive generation or expanding the transmission system has the same formulation as the long-term coordination problem described here. This formulation leads to a possible notion of an optimal transmission grid as a system in which the expected cost savings in long-term generation cost cannot be larger than the cost of investing in the transmission system upgrades (Lecinq et al., 1997).

It is important to notice that this definition is probabilistic even for normal operating conditions if the equipment status is as designed. It further depends on the initial conditions, that is on existing transmission at the time new investment is considered (Lerner et al., 1997). It is also a long-term notion because, for the expensive transmission equipment to pay off, the long term savings on the cost of generation must be analyzed. The longer time T over which the investment in transmission is assessed, the more expensive equipment can be justified. On the other hand, the prediction of load demand trends far into the future as well as the trends of the fuel costs become less accurate. In addition, the new generation investments are highly uncertain over prolonged future periods.

The investment problem is inherently a stochastic control problem. The evolution of the random variables is modeled through a stochastic process and the investment decisions are made based on the expected long-term costs. Contrary to the stochastic model referred to in the static optimal grid model, the investment planning problem is now characterized by inter-temporal considerations. In particular, the tradeoff between reduction of costs and flexibility of investment is at the center of the following model. This model draws on the ideas in (Dixit et al., 1994).

3. Unbundling the Power Industry into Transmission Service and Its Users

In the remainder of this paper transmission provision for the newly evolving industry structures is studied. In a deregulated industry the objectives of newly evolving generation, transmission and distribution businesses are generally different and often conflicting; this is in sharp contrast with the principles of transmission provision in a regulated industry, which have been established to serve system-wide generation/demand patterns, and not individual users. This requires decomposing the single optimization problem of a regulated industry into subproblems with decentralized objectives. The main objectives of power producers are introduced in (Guan et al., 1999). This paper stresses the role of transmission. For this reason, a basic novel formulation of a transmission provider's objective and the relation of this objective to the system-wide optimal performance is introduced in this section. The sub-optimality issues and the minimal coordination of these separate objectives necessary for near-optimal system-wide performance need further studies in view of the proposed industry structures.

The basis for creating a power market is that market participants (generators, loads), by maximizing their individual expected profit or utility, will optimize total cost (social welfare) in the same way as integrated utilities did. The main question to address in this section is whether the same concept can be developed when transmission capacity constraints are accounted for.

To answer this, consider the certainty equivalent problem to the integrated utility problem (3)–(5). Uncertain parameters are replaced by their expected values first. The solution to this problem can be formulated by introducing the following Lagrangian:

$$\begin{aligned}\sum_i \int_{t_0}^{T} & e^{-rt}[c_i(t)P_i(t) + C_i^G(K_i^G(t), I_i^G(t), t)]\,dt \\ &+ \sum_l \int_{t_0}^{T} e^{-rt}[C_l^T(K_l^T(t), I_l^T(t), t)]\,dt \\ &+ \int_{t_0}^{T} \Bigg\{ \sum_i \sigma_i(t)(K_i^G - P_i(t)) + \lambda(t)\left(\sum_j P_{L_j}(t) - \sum_i P_i(t)\right) \\ &\qquad + \sum_l \mu_l(t)\Big(K_l^T - \sum_{i,a} H_{li}(P_i(t) - P_{L_i}(t))\Big) \Bigg\}\,dt \end{aligned} \tag{20}$$

The terms in this Lagrangian can be rearranged in order to decompose this single optimization problem into several simpler optimization sub-problems. If the values of $\mu_l(t)$ and $\lambda(t)$ (transmission and electricity prices) are given, the simpler optimization problem at node i:

$$\begin{aligned}\max_{I_i^G, P_i} \lambda(t)P_i(t) &+ \sum_l \mu_l(t)H_{li}P_i(t))\,dt \\ &- \int_{t_0}^{t} c_i(t)P_i(t) + C_i^G(K_i^G(t), I_i^G(t), t)\,dt \end{aligned} \tag{21}$$

subject to:

$$\frac{dK_i^G}{dt} = I_i^G(t) \tag{22}$$

$$I_i^G \geq 0 \tag{23}$$

$$P_i(t) \leq K_i^G : \sigma_i(t) \tag{24}$$

The task of a coordinator is to set the trajectories of the investment rate and the dual variables $\mu_l(t)$ and $\lambda(t)$ and to ensure that those values are consistent with the thermal line constraint (4) and the balance equation constraint (5).

This minimization subproblem can be interpreted very simply. If $\lambda(t)$ is the price of energy and $\mu_l(t)$ is the price of transmission service line by line, then the objective function in this optimization subproblem is the difference between revenue and costs: profits. Thus, by imposing the proper prices for energy and transmission services and ensuring that the investment policy in transmission will be adequate to accommodate the pattern of flows, the grid operator can control the entire problem and induce the profit maximizing entities to choose the optimal amount of net injection.

The variables $\lambda(t)$ and $\mu_l(t)$ act as coordinating variables for the dispatch of power.

At this stage, we are one step away from a true competitive market for generation since the price of energy $\lambda(t)$ in the above framework is still imposed by the coordinator. We will assume that this price will result naturally from information exchanges between generators and consumers and that it will obey the law of supply and demand. The entire optimal control problem (3)–(5) then reduces to the choice of transmission prices $\mu_l(t)$ and capacities $K_l^T(t)$. It is important at this stage to consider these two decisions as mutually dependent. Thus, a transmission pricing scheme cannot ignore the investment policy and the investment policy should be dependent on the amount of congestion on the grid.

The main issue in this formulation of transmission pricing as a coordinating activity resides in the information structure of the problem. Not only is a transmission provider unable to predict with perfect certainty the future values of demand, but he does not know the cost structure of generators. The transmission industry should thus be structured in a way that enables the incorporation of this information in the appropriate time frame.

In the short-run, the prices of transmission services must be set in accordance with existing transmission capacities, whereas in the long-run, capacities are adjusted in order to accommodate the long-trend dynamics of the system at a minimum cost.

The above decomposition of objectives assumes generation capacity issues are handled in a decentralized way by profit-maximizing generators. However, transmission constraints are hard to handle in a decentralized way since they appear in the objective function along with the matrix H (equation (4)). The optimization function is no longer separable. This explains why these constraints have to be handled through a coordinating mechanism similar to the power price mechanism. Nevertheless, near-optimal transmission provision could be posed (McGuire, 1999), and further work is needed toward such solutions.

4. Static Congestion Pricing as a Means of Short-Term Coordination

In the new competitive market for power, each market participant tries to maximize its profit. The existence of a single price for power, $\lambda(t)$, seen as a coordinating variable, ensures that during each period, the forecasted generation output balances the expected load. This market mechanism performs the minimization of generation costs in a decentralized way. However, the optimal power flow program performed daily by integrated utilities not only includes the power balance constraint but also accounts for the transmission capacity constraints. These additional constraints cannot be handled individually by each market participant and create the need for new forms of network coordination: i.e., congestion management.

If market participants are ultimately to be responsible for the choice of their generation output or consumption, short-run prices of transmission services, $\mu_e(t)$, are the only control variables left to ensure that the system operates within the constraints at the minimum cost. Ideally, transmission services should be priced in the short-run at their marginal value in order to achieve this objective. This pricing can be made explicit by charging exogenously for each transaction on a locational and temporal basis (Hogan, 1992), or it can result from the interaction of demand and supply for transmission capacity in a competitive way by auctioning transmission rights (Chao et al., 1997), or it can be interpreted as an opportunity value when firm transmission rights are pre-allocated to market participants.

4.1. The Pool-Co Model

The Pool-co pricing scheme was introduced by Hogan (Hogan, 1992). The existing mandatory power pool implemented in England and Wales is directly based on this concept.

Market participants bid their supply curves and the market maker simultaneously dispatches power and allocates transmission capacity using the same OPF used in a vertically integrated structure. The one exception is that the costs functions are replaced by market bid functions. In this way, power and transmission capacity remain bundled. Competition among generators gives them the incentive to bid their marginal cost curve. Likewise, under the assumption of elastic demand, loads bid their marginal value curve.

4.2. Tradable Transmission Rights

The concept of tradable transmission rights was introduced by Chao and Peck (Chao et al., 1997). According to this scheme, the ownership of a line is split into transmission rights. Those rights can be traded freely by their owners. The link between the market for transmission rights and the market for power at one arbitrarily chosen node is established by forcing market participants to buy the quantity of transmission rights that corresponds to the amount of flow each of their transactions is causing. These trading rules for congestion management enable the incorporation of the externalities associated with the use of congested transmission lines. Counterflows create new transmission rights, eligible for trade.

The price of power and the prices of transmission rights evolve in accordance with the law of supply and demand: the price increases whenever the residual demand is positive and decreases otherwise. By making the strong assumptions about the shape of the cost functions, the pricing process can be shown to converge toward a unique equilibrium (Wellman et al., 1998).

In this scheme, the role of the grid operator is limited to making sure that all transactions comply with the trading rules. He does not play any role in the trading process.

As argued in (Oren, 1997), the active role of the transmission owner could bring the price of the transmission rights closer to its value and thus mitigate the incentive for market participants to appropriate the rent.

For interpretation of tradable transmission rights and power as the only components of a multi-product economy and general equilibrium dynamics conditions under perfect market assumptions, see (Chao et al., 1997; Leotard, 1999).

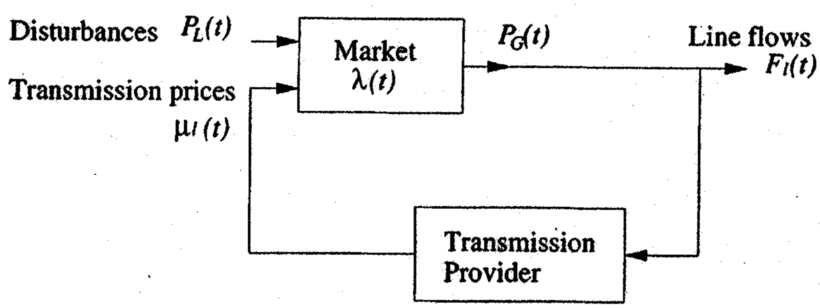

Figure 3. Real-time transmission pricing.

5. Possible New Dynamic Pricing Schemes for Transmission

In this section, we consider some new models for transmission pricing, recognizing that perfect market conditions do not always prevail.

5.1. *Real-Time Transmission Pricing*

This congestion management scheme rests on the interpretation of transmission prices $\mu_l(t)$ as control variables and recognizes the existence of dynamics in the market reaction to price changes. Market participants do not always react immediately to price changes. There exist some information delays.

Through the setting of transmission prices $\mu_l(t)$, a transmission provider controls line flows, $F_l(t)$, and ensures that they remain below the maximum allowable limits. Thus, transmission prices are changed in real time in order to influence the energy trading process. However, as emphasized in the previous sections, parameters for demand functions are not known to a transmission provider, making the optimal control even more difficult than when solving the coupled stochastic control problem in a coordinated industry.

The Objective Function

The objective function of a transmission provider is to minimize the value of unused transmission capacity, while leaving transmission flows below the maximum transmission capacity value:

$$\min_{\mu_l(t)} \mathcal{E}\left\{\int_0^T \mu_l(t)\left(K_l^T(t) - F_l(t)\right) dt\right\} \tag{25}$$

This term is always positive and it can be made equal to zero by either setting a price equal to zero or adjusting it so that $F_l(t) = K_l^T(t)$. These conditions correspond to the optimal pricing conditions.

The price-setting problem can then be stated as a stochastic optimal control problem. Some parameters of the problem, in particular the market dynamic parameters, are unknown but can be learned by a transmission provider.

Because of the dynamics in market participants reactions, the optimal prices will not result in transmission flows equal to transmission capacity when prices are strictly positive. Instead, transmission flows will remain below maximum transmission capacity.

5.2. *Dynamic Allocation of Non-Firm Transmission Capacity*

We introduce here a new scheme for the dynamic allocation of transmission capacity. Market participants have expressed the need for the possibility to secure early transmission rights. Such concern is taken into account in the concept of tradable transmission rights (Chao et al., 1997). In contrast with tradable transmission rights, a transmission provider plays a central role in the scheme we introduce here. He has the responsibility of allocating and pricing ex-ante transmission rights for each period in the future. These transmission rights are not tradable on a secondary market.[6]

We assume that a transmission provider at each period posts prices for the use of the transmission grid in the future. However, in order to achieve ex-post optimality and to cope with short-term uncertainties, these transmission rights are not firm. Several classes of transmission rights co-exist and have to be priced consistently.

Through prices, a transmission provider controls the rate of arrival of transactions on the system. In real time, the transmission provider controls the use of the system and effects which transactions have to be modified.

In essence, this transmission scheme proposal builds on both the real-time pricing and priority service (Chao et al., 1987). The spot price for transmission lines is thus set in real-time by a transmission provider as a function of real-time requests for the use of the system and curtailment of non-firm transactions.

This arrival process is represented in Figure 4. At time t several transactions request the use of the system in the immediate or remote future at different levels of priority firmness.

At time t, a transmission provider posts the price for point-to-point service for different dates T in the future. This price also depends on the level of priority firmness. This level is represented by the amount of money a transmission provider will reimburse the transaction in case of non-implementation. The higher this amount, the higher is the probability of implementation. Let us denote by $P_{ij}(t, T, \mu_{ij})$ this price. The price for multi-period contracts such as these represented in Figure 4 is the sum $\int_t^{T_1} P_{ij}(t, T, \mu_{ij})\, dT$. For each period (t, T) and each class of priority μ_{ij}, there is an associated probability r_{ij} of implementation. Even though a transmission provider does not commit to this probability, it can be advertised so that transactions can make their choice.

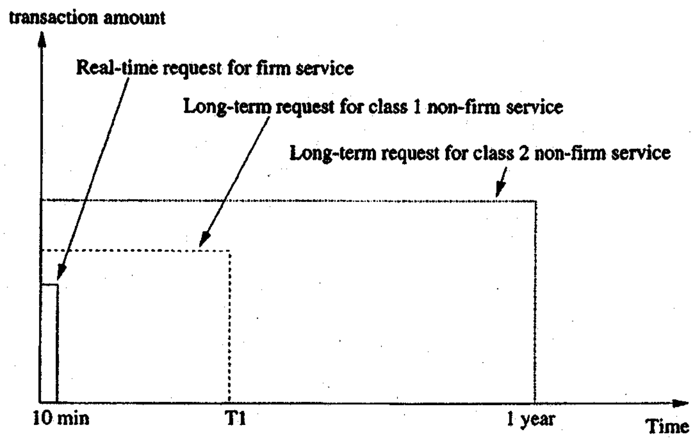

Figure 4. Typical dynamics of requests for transmission use.

5.2.1. *Self-Selection*

Similarly to priority service (Chao et al., 1987), a transaction of value v will expect to make a profit equal to $vr_{ij} + \mu_{ij}(1 - r_{ij}) - P_{ij}$. The optimal choice of the transaction is thus characterized by:

$$v = \frac{1}{\frac{dr_{ij}}{d\mu_{ij}}} \left(\frac{dP_{ij}}{d\mu_{ij}} + \mu_{ij} \frac{dr_{ij}}{d\mu_{ij}} + r_{ij} - 1 \right) \tag{26}$$

Thus, from the choice of μ_{ij}, a transmission provider can derive the value of the transaction v and use it in real-time implementation in order to maximize the values of transaction on the grid.

5.2.2. *The Arrival Process*

The previous self-selection property is valid under any price-reliability menu. However, this menu has to be designed in order to maximize the value of the transmission grid in real-time. This result was achieved in static priority service by imposing the condition $v = \mu_{ij}$ resulting from a static optimization. In this scheme, we do not impose such a condition but rather consider a dynamic optimization. Prices are considered control variables and therefore influence the arrival rate of transaction on the system. Let us denote by $S_{ij}(t, T, \mu_{ij})$ the total amount of allocated transmission capacity between i and j at time t for period T with priority μ_{ij}. We assume that between t and $(t + dt)$, this quantity increases by an uncertain amount:

$$dS_{ij}(t, T, \mu_{ij}) = f_{ij}(P_{ij}(t, T, \mu_{ij}), S_{ij}(t, T, \mu_{ij}))\, dt + \sigma\, dz \tag{27}$$

This increment is dependent on the price but also on the amount of allocated transmission capacity. This formula reflects the fact that for a given price, only a part of the total demand will be allocated during this period. Thus, through prices, a transmission provider can influence the rate of arrival of transactions on the system, and as a consequence, can modify his expectations about the total transmission demand for period T.

5.2.3. *Real-Time Operations*

In real time, a transmission provider sets the spot prices of transmission lines $\mu_l(T)$. This price represents:

- the price at which short-term bilateral transactions can get on the system. Since there is no uncertainty left in real time, short-term transactions from i to j have to pay the following price:

$$\sum_l (H_{li} - H_{lj})\mu_l(T) \tag{28}$$

- these prices also represent cut-off values for the curtailment of non-firm contracts. Whenever the value of a transaction v from i to j is less than the term $\sum_l (H_{li} H_{lj})\mu_l(T)$, the transaction is curtailed and the amount of money μ_{ij} is paid back to the transaction.

Note that this curtailment rule, along with condition (26), sets the structure of price-reliability menus. In real time valuable transactions will be curtailed as a last resort because they will pay a higher price. However, there are no explicit formulae for the expression of prices. They are instead the result of a stochastic optimal control problem.

5.2.4. *The Objective Function*

As in the real time problem, the objective of a transmission provider is to minimize in real-time the value of unused transmission capacity

$$\min_{\mu_l(T)} \sum_l \mu_l(T)(K_l^T - F_l) \tag{29}$$

while accepting all real-time requests and remaining below the maximum available transmission capacity.

5.2.5. *Similarities with Other Pricing Schemes*

Compared to the long-term version of priority service (Chao et al., 1987), the learning process by a transmission provider is explicitly taken into account. As transaction requests arrive to a transmission provider, they provide him with valuable information on future transmission demand. Moreover, this process can be influenced by the transmission provider through his pricing policy: this is an active learning process.

5.2.6. Coupling the Pricing-Investment Decisions

As a transmission provider allocates transmission capacity for future use, he also has to make investment decisions. These two problems can be coupled into a single problem in which pricing decisions depend on the possibility of investment and, inversely, investment decisions depend on information collected through long-term commitments. For instance, even though a transmission capacity still does not exist, it can be allocated on a non-firm basis. The mere possibility of investment has to be incorporated in the pricing decisions. Conversely, securing long-term transmission contracts will help reduce the information asymmetries between users of the transmission grid and a transmission provider. Thus, the additional uncertainties created for the transmission provider by the asymmetries of transmission and generation are greatly reduced through long-term commitments.

This pricing scheme effectively achieves a centralized form of the long-term coordination task described in section 2.4.

6. Computational Aspects of Transmission Provision under Competition

Based on the derivations in this paper, it is possible to identify at least three types of complex computing tools necessary for assisting a transmission provider in the newly evolving industry. These are:

1. Tools for projecting long-term (season, year) system conditions; this is essential for predicting locations and amounts of transmission constraints.
2. Tools for optimizing short-term decisions so that long-term performance is improved. For example, given that a transmission provider is obliged to sell transmission rights to system users ahead of time, once this is done, he needs to evaluate in short-term operations the tradeoff between denying short-term requests by the spot market participants and curtailing long-term system users, so that over the long period he is better off.
3. Tools for long-term optimal decisions, such as periodic optimal investment or pricing long-term users of the grid. These long-term projections are made assuming optimal short-term decision-making.

We illustrate possible methods for solving the first two problems. The first method is an efficient probabilistic optimal power flow and the second problem is an inherent dynamic programming problem which uses the results of the first problem as a cost function to go. The last problem is a direct generalization of the second problem.

6.1. A Tool for Predicting Long-Term Transmission System Conditions

The simplest input characterization is to think of load demand as an a priori defined load duration curve such as that shown in Figure 2 and, based on this, create a coarse pattern for its probability distribution as well as deviation characterization around each of the coarse patterns.

Over the past several decades, optimal power flow (OPF) analysis has been adopted as an efficient tool in power systems planning and operations. As the power industry is being deregulated, the importance of OPF has increased significantly because of its ability to determine static economic equilibrium and calculate locational-based marginal prices (LBMPs) under the perfect competitive market assumptions (Schweppe et al., 1988; Hogan, 1992).

Conventional OPF analysis is typically used on a snapshot of time basis, i.e., for obtaining optimal generation patterns for average or extreme loading conditions only, and it does not give any information about the degree of importance or likelihood of each violation. In actual operating practice, load always deviates away from these snapshot conditions in a random fashion. Several efforts have been made over the years to introduce a probabilistic load flow (Borkowska, 1974; Allan et al., 1974; Allan et al., 1981; Sauer, 1982).

In this section, we propose an efficient Monte Carlo-based method to solve probabilistic optimal power flow (POPF) which takes into account transmission line flow and generation capacity constraints (Descamps et al., 1995; Yu, 1999). Recall that the deterministic OPF is the short-term coordination problem that assumes load demand $P_L = [P_{L_1}, \ldots, P_{L_{nd}}]$ to be known, solves for the optimal dispatch of available generation resources $P_G^* = [P_{G_1}^*, \ldots, P_{G_n}^*]$:

$$P_G^* = \arg\min_{P_G} \sum_{i=1}^{N_G} c_i(P_{G_i}) \tag{30}$$

subject to load flow equality and inequality constraints on all transmission lines. After the optimal generation dispatch, P_G^*, is obtained, the corresponding transmission line flows, F_l, and nodal prices, p_i can also be obtained as byproducts of the OPF calculation.

Here, we develop a POPF-based method for projecting system conditions based on our knowledge of random load demand, $P_L = [P_{L_1}, \ldots, P_{L_{nd}}]$ with corresponding joint probability density functions, $f_{P_L}(P_{L_1}, \ldots, P_{L_{nd}})$, and generation cost functions estimated using public information.

Assume that $P_L = [P_{L_1}, \ldots, P_{L_{nd}}]$ is a random load demand vector having a joint probability density function, $f_{P_L}(P_{L_1}, \ldots, P_{L_{nd}})$.

Let us denote deterministic OPF as a set of nonlinear functions $\Psi(.)$, i.e., $[P_{G_1}^*, \ldots, P_{G_n}^*] = [\Psi_1(P_{L_1}, \ldots, P_{L_{nd}}), \ldots, \Psi_n(P_{L_1}, \ldots, P_{L_{nd}})]$. Then, the basic POPF problem is the problem of finding the probability density distribution of $P_{G_i}^*$, $f_{P_G^*}(P_{G_1}^*, \ldots, P_{G_n^*})$, via a nonlinear transformation between $f_{P_L}(.)$ and $f_{P_G^*}(.)$.

For instance, the probability density function of optimal generation $P_{G_i}^*$, $f_{P_{G_i}^*}(P_{G_i}^*)$, can be obtained by performing the following calculation:

$$f_{P_{G_i}^*}(P_{G_i}^*) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\cdots\int_{-\infty}^{\infty} f_{\{P_L\}}(P_{L_1}, \ldots, P_{L_{nd}}) \\ |J(P_{L_1}, \ldots, P_{L_{nd}})|^{-1}\, dP_{G_1}^* \cdots dP_{G_{i-1}}^*\, dP_{G_{i+1}}^* \cdots dP_{G_n}^* \tag{31}$$

where J is the determinant of the Jacobian matrix

$$J(P_{L_1},\ldots,P_{L_{nd}}) = \det \begin{bmatrix} \frac{\partial\Psi_1}{\partial P_{L_1}} & \frac{\partial\Psi_2}{\partial P_{L_1}} & \cdots & \frac{\partial\Psi_n}{\partial P_{L_1}} \\ \frac{\partial\Psi_1}{\partial P_{L_2}} & \frac{\partial\Psi_2}{\partial P_{L_2}} & \cdots & \frac{\partial\Psi_n}{\partial P_{L_2}} \\ \vdots & \vdots & & \vdots \\ \frac{\partial\Psi_1}{\partial P_{L_{nd}}} & \frac{\partial\Psi_2}{\partial P_{L_{nd}}} & \cdots & \frac{\partial\Psi_n}{\partial P_{L_{nd}}} \end{bmatrix} \tag{32}$$

However, it is not possible to carry out analytically the above integration exactly or even to numerically approximate it within a given accuracy because of the complexity of load flow equations and the large number of variables. Furthermore, functions $\Psi_1, \Psi_2, \ldots, \Psi_n$ usually do not have continuous partial derivatives everywhere because of the inequality constraints imposed; therefore, the above integration has to be carried out in a piecewise continuous manner. This makes the computation even more difficult.

6.1.1. *Monte Carlo Simulations*

One possibility is to approximate the solutions by means of simulation. For instance, one can generate a sample load vector $P_L^{(1)} = [P_{L_1}^{(1)}, \ldots, P_{L_{nd}}^{(1)}]$ and calculate the corresponding OPF solution $P_G^{*(1)}$. Next, one can generate another sample vector $P_L^{(2)}$ correlated to the first one in the way specified by its probability distribution and, again, compute corresponding OPF solution $P_G^{*(2)}$. This process repeats until an identically distributed random variable has been generated. Therefore, we can use the distribution of based on $(P_G^{*(n)}, n = 1, \ldots, N)$ as an estimate of the exact answer. By the strong law of large number, when the number of sample points is large enough, $N \to \infty$, the simulation results converge to the exact solutions. This approach is called the Monte Carlo simulation approach (Rubenstein, 1981; Ross, 1980).

Next, we give an example illustrating the use of a Monte Carlo simulation for solving a POPF problem. A simple 3-bus system shown in Figure 5 consists of two generators and one load. All transmission lines are lossless and have the same parameters. The marginal cost curves for G_1 and G_2 are $c_l(P_{G_1}) = 10+0.05P_{G_1}$ and $c_2(P_{G_2}) = 20+0.1P_{G_2}$ respectively. Thus, the real power generation of G_1 is less expensive than that of G_2.

Assume that demand at bus L exhibits a probability distribution following a normal distribution with a 1000 MW mean and a 200 MW variance. The load duration curve, i.e., the cumulative distribution function of P_L, of this distribution is shown in Figure 5. Note that, for the purpose of graphical illustration, we plot the complement of the cumulative distribution function, $G_{P_L}(P_L)$, i.e.,

$$\begin{aligned} \overline{G}_{P_L}(P_L) &= \int_{P_L}^{\infty} f_{P_L}(x)\,dx \\ &= 1 - G_{P_L}(P_L) \end{aligned} \tag{33}$$

For example, the values read from the Y-axis of Figure 5 indicate the probability of demand at L exceeding corresponding X-axis value., e.q., 50% probability of load exceeding 1000 MW.

In the first case, the system is assumed without any transmission line constraints. In this study, we generate 1000 sample load points and solve the OPF result for each point.

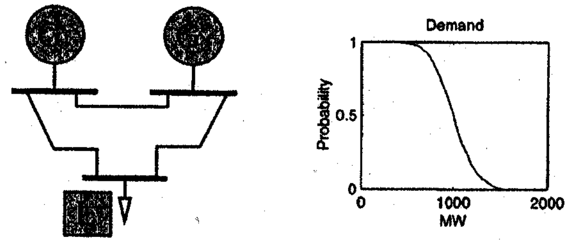

Figure 5. A 3-bus system and the load duration curve of load L.

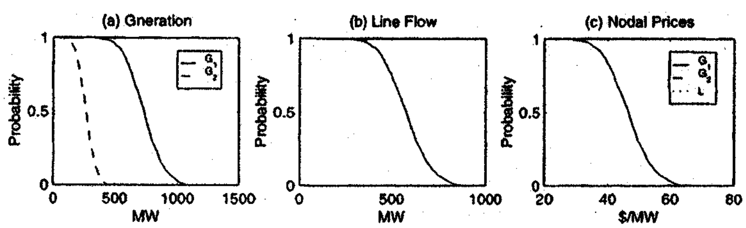

Figure 6. Monte Carlo simulation—Case 1: No line flow constraint.

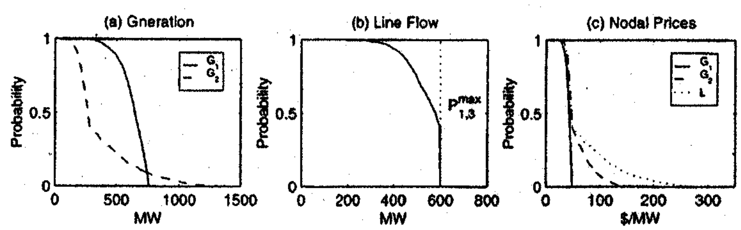

Figure 7. Monte Carlo simulation—Case 2: Imposing 600 MW line flow constraint on line G_1-L.

Then we plot the distributions of the corresponding OPF solutions as shown in Figure 6. Figures 6(a), 6(b) and 6(c) show the probability distributions of the two generator outputs, the line flow on line G_1-L and nodal prices at three buses respectively. Since the system is lossless and unconstrained, as expected, all three nodal prices are identical.

In the second case, the flow on transmission line G_1-L is bounded by a 600 MW limit. Figure 7 show the Monte Carlo simulation results. As illustrated in Figure 7(c), the nodal price at the load bus L has some probability of reaching as high as 200 $/MW due to the congestion.

6.1.2. Two-Stage Approach for Monte Carlo Simulations

When applying the Monte Carlo method to large power systems, an immediate problem is the difficulty of constructing probability density functions f_{P_L}. Because of the metering problems, electricity demands at individual load buses are usually not measured in real-time; instead, usually only the total system demand is recorded. These historical total load data for different systems are public information and can be downloaded via the Internet (FERC, 1999). Therefore, one can assume that the probability density function $f_{P_L^{tot}}(P_L^{tot})$ of total system demand is available.

As the system becomes larger, the number of variables increases (generators and loads) so that more sample points are needed for the Monte Carlo method to converge. In addition, longer simulation time is needed to obtain the OPF solution for each sample case. Therefore, applying the traditional Monte Carlo technique to solve large network cases is apparently a very time-consuming process. Even though some efficient ways to solve an OPF problem in large power systems have been proposed (Baldick et al., 1998), it is still not plausible to use brute-force Monte Carlo simulations. In order to get around these problems, we propose a two-stage approach to efficient Monte Carlo simulations.

6.1.2.1. Basic Assumptions. The proposed two-stage approach is based on the observation that at each load level, there usually exists a nominal load pattern, which represents system load conditions, for example, peak load pattern, off-peak pattern *etc.* These load patterns describe how total system demand is distributed at each load bus. A nominal pattern can also be interpreted as the mean value of random load conditions at a specific load level. Of course, there are deviations from the nominal pattern at all load buses. The actual system loads are the sum of nominal patterns and zero-mean random perturbations at individual load buses. In order to further simplify the problem, it is assumed that congestion is caused by the nominal patterns and not by the random deviations.

At the first stage a set of discrete load patterns that represent nominal system load conditions at different levels of the cumulative load duration curve is used. Detailed OPF solutions are calculated based on these nominal patterns. These OPF solutions give a rough approximation of generation probability distributions. At stage two, random deviations from the nominal load patterns are taken into account. By using incremental linearized OPF solutions, a large number of simulation sample points can be obtained efficiently.

6.1.2.2. Stage One: Coarse Computations. First, we identify several basic load patterns in the system, for instance, peak load pattern, normal load pattern and off-peak pattern, and ranges of system load levels for which these patterns are most likely to occur. Based on these, a fuzzy set representing the typical load patterns at different system load levels and their membership functions η are obtained (Pedrycz, 1993; Klir et al., 1995). As shown in Figure 8, if the total system load is larger than $P^{[4]}$, it follows peak load distribution; if system load falls between $P^{[2]}$ and $P^{[3]}$, it follows the normal load distribution; and if system load is less than $P^{[1]}$, off-peak load pattern is used to depict the load distribution. The load pattern between $P^{[1]}$, $P^{[2]}$ or $P^{[3]}$, $P^{[4]}$ can also be obtained by combining the two adjacent patterns weighted by their membership functions.

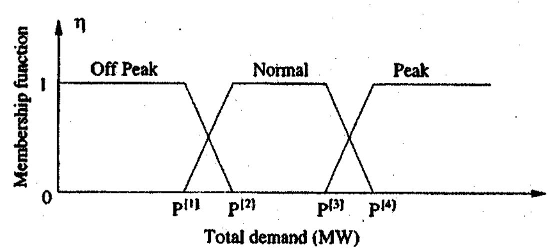

Figure 8. Membership functions representing the loads of peak load, normal, and off peak.

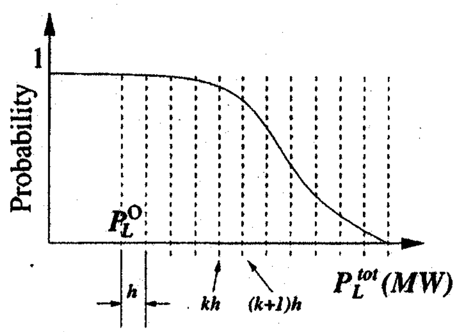

Figure 9. Discretized load duration curve.

Next, we discretize the system load every h MW starting from P_L^0 MW, i.e., $P_L^{tot}(k) = P_L^0 + kh$, Figure 9. Thus, the typical patterns of different load levels can be computed by using the following equation:

$$P_L^{[k]} = P_L^{tot}(k)\left(\eta^{[N]}\frac{P_L^{[N]}}{1^T P_L^{[N]}} + \eta^{[OP]}\frac{P_L^{[OP]}}{1^T P_L^{[OP]}} + \eta^{[PK]}\frac{P_L^{[PK]}}{1^T P_L^{[PK]}}\right) \tag{34}$$

The probability of each discrete load pattern occurrence is

$$\begin{aligned} Prob\{P_L^{[k]}\} &= Prob\{P_L^0 + kh \le P_L^{tot} \le P_L^0 + (k+1)h\} \\ &= G_{P_L^{tot}}(P_L^0 + (k+1)h) - G_{P_L^{tot}}(P_L^0 + kh) \\ &= \int_{P_L^0+kh}^{P_L^0+(k+1)h} f_{P_L^{tot}}(P_L)\, dP_L \end{aligned} \tag{35}$$

Thus, we have computed OPF solutions for each load level. Based on the corresponding probabilities calculated in (35), the cumulative distribution curves for these OPF solutions can be constructed.

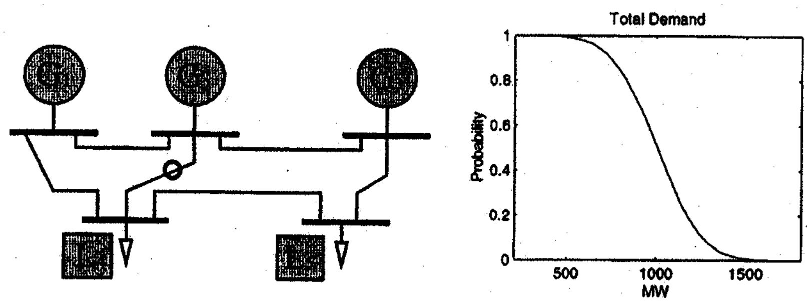

Figure 10. A 5-bus system and the load duration curve for the simulation case.

6.1.2.3. Stage Two: Refined Computations. The objective of refined computations is to improve coarse solutions to a better approximation by including perturbations at each discrete load pattern level. First, we generate a set of zero-mean random deviation, ΔP_L around a nominal pattern, $P_L^{[k]}$ and use this to compute the incremental changes of OPF solutions. It can be shown that if generation cost curves are approximated by quadratic functions (i.e., linear marginal cost curves) under the assumption made, the incremental OPF solution is simply a linear function of load deviations (Yu, 1999), i.e.,

$$\Delta P_G^* = V^{[k]} \Delta P_L \tag{36}$$

The matrices $V^{[k]}$ can be obtained when computing kth coarse solution. Therefore, a refined solution is

$$P_G = P_G^{[k]} + V^{[k]} \Delta P_L \tag{37}$$

Since refining computations are just linear transformations, it is possible to handle a large number of simulation points. By combining coarse and refined solutions, we can approximate the continuous load distribution functions within a reasonable computing time.

6.1.3. Numerical Example

To illustrate the idea of the two-stage approach, we have simulated a simple five bus system with three generators and two loads shown in Figure 10.[7] Next, we assume the distribution of the total system demand to be normal with a 1000 MW mean and a 200 MW variance exhibiting two basic load patterns: (1) peak load pattern, L_4 60% and L_5 40% of total demand, and (2) off-peak load pattern, L_4 50% and L_5 50% of total demand. A fuzzy membership function of the occurrence of the two basic load patterns at different load levels is shown in Figure 11.

In this example, we assume that there are two inexpensive generators, G_1 and G_2, with a generator marginal cost function, $\frac{\partial c(P_G)}{\partial P_G} = 0.1 P_G + 10$, and one expensive generator G_3

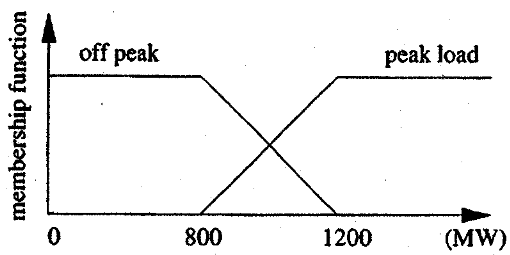

Figure 11. Fuzzy membership function of the occurrence of the two basic load patterns at different load levels.

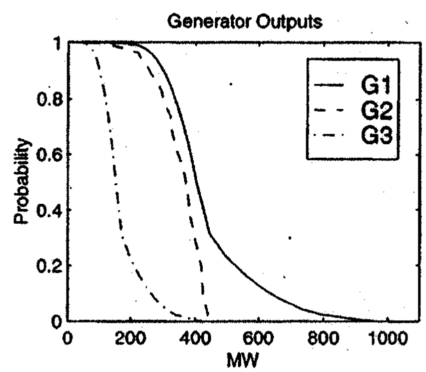

Figure 12. Probability distributions of three generator outputs.

with a marginal cost function, $\frac{\partial c(P_G)}{\partial P_G} = 0.2P_G + 20$. Also, we assume that a transmission line $G_2 - L_4$ is the one most likely to be congested and its maximum capacity is $F^{max}_{G_2-L_4} = 350$ MW.

At a coarse computation stage, we discretize the total system load every 50 MW starting from 500 MW to 1500 MW. We use (34) and (35) to find the typical patterns corresponding to the discretized load levels and the probability of the occurrence of each load pattern. Next, we generate a set of zero-mean random deviations for L_4 and L_5 around each load pattern. These random load deviations could be any type distributions and also could be independent or correlated. In this case, random deviations are assumed to be independent and normally distributed with a 2% variance around the nominal values.

Figures 12, 13, and 14 show the probability distributions of all generator outputs, transmission line flows, and nodal prices respectively. As illustrated in Figure 12, generation of G_2 is limited by the transmission flow constraint. Figure 13 shows that the probability of the system being congested is around 32%. Furthermore, the constraint causes the

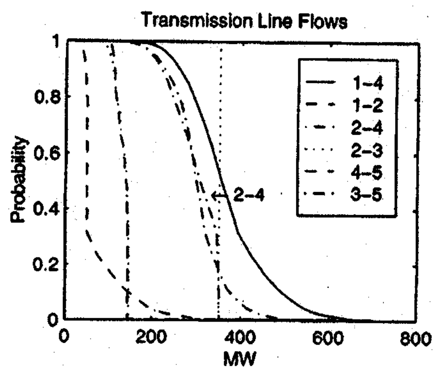

Figure 13. Probability distributions of six transmission line flows (line G_2-L_4 is the one constrained).

Figure 14. Probability distributions of nodal prices.

nodal price at L_4 to reach as high as 200 $\$/MW$, while the nodal price at G_2 is always the lowest.

Next, we take the differences of the nodal prices to evaluate the value of each transmission path. Figure 15 shows the probability distributions of the values of six possible node-to-node transactions. The result shows that these transmission paths have non-zero values only when system is congested. As expected, the link between G_2 and L_4 is the most valuable one. However, an interesting fact is that the link between G_1 and L_5 has the lowest value even though it is the most distant path in the system.

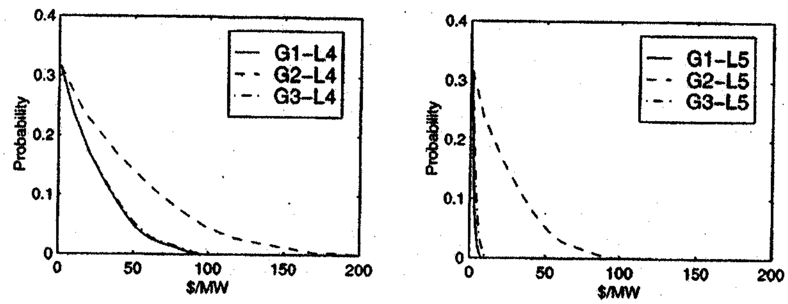

Figure 15. Probability distributions of nodal price differences for different node-to-node transactions.

6.1.4. *Uncertain Generator Cost Curves*

In the previous derivations, we assumed that all cost functions of generators are given. However, in a competitive energy market, a generator cost curve is usually confidential. It is possible, however, to estimate the cost curve of a generator using public knowledge concerning the generation technology, the fuel used, the current fuel prices, *etc.*; still, estimation errors are unavoidable. As shown in Figure 16, by applying fuzzy theory, an uncertain marginal cost curve can be characterized by its upper and lower bounds and a most likely band. Therefore, given any possible nodal price, there will be a corresponding uncertain generation output with the same distribution shape, Figure 16. This way, the uncertain cost curves are mapped into uncertain generation.

Assume that the membership function of uncertain generation and the corresponding probability function have the same shape. In other words, $\eta_i = \eta_j$ implies $f_i = f_j$. Next, we use P_G^{err} to indicate the uncertain generation output deviating from its nominal value P_G^{nom}, i.e., $P_G = P_G^{nom} + P_G^{err}$. By inspection, the probability distribution of P_G^{err} can be calculated by the following formula, Figure 17:

$$f_{err}(P_G^{err}) = \frac{\eta(P_G^{err} + P_G^{nom})}{\int_{P_G^{LB}}^{P_G^{UB}} \eta(P_G)\, dP_G} \tag{38}$$

Note that this kind of uncertainty results from the imperfect human knowledge of the marginal cost curves. Introducing this kind of uncertainty in the POPF computation will decrease the accuracy of the results.

6.2. *A DEDS Model for Congestion Management of Bilateral Transactions*

The congestion management of bilateral transactions can be viewed as a discrete event supervisory control problem (Ramadge et al., 1987). First, each bilateral transaction is discretized into several bilateral transaction units. These transaction units are associated

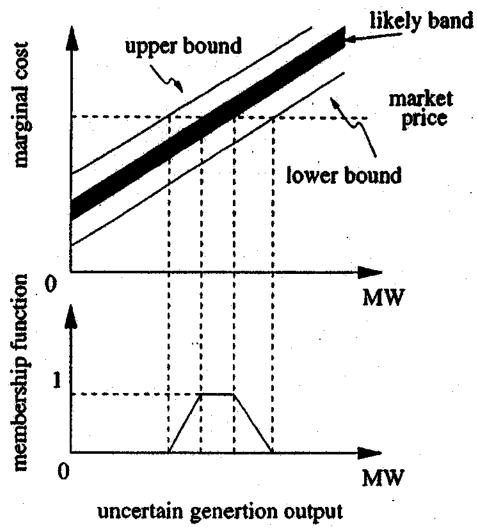

Figure 16. Uncertain generation cost curve.

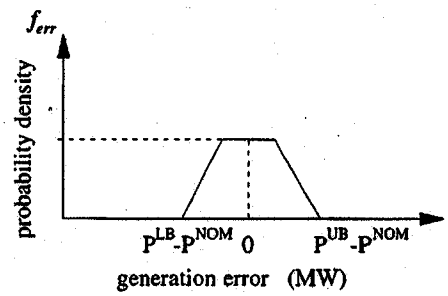

Figure 17. Uncertain generation output deviation from the nominal value.

with different levels of firmness and can be denied (curtailed) by a system operator if the transmission system is congested. In other words, each of these transaction units could be viewed as controllable events; therefore, a system operator could "enable" or "disable" some of these transactions to maintain line flows within constraints.

A simple 3-bus example is used to illustrate this idea, Figure 18. Assume that a transmission line between bus 2 and bus 3 is the most likely congested line (bottleneck) and the three transmission lines have the same parameters. With a transaction between bus 1 and

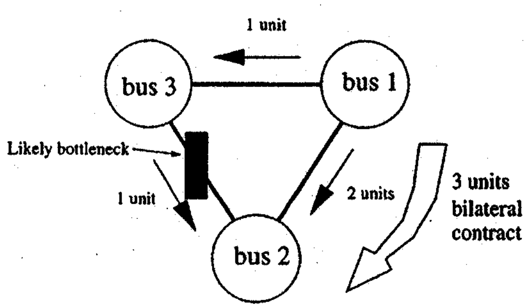

Figure 18. A 3-bus example.

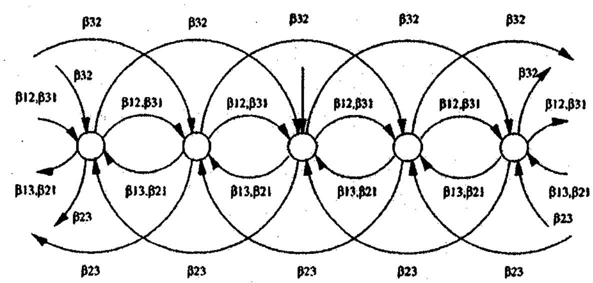

Figure 19. The DEDS model for a transmission line.

bus 2, $\beta 12$, 1 unit of power will flows through the transmission line whose congestion is in question. With a transaction between bus 3 and bus 2, $\beta 32$, 2 units of power will flow through the bottleneck of interest. Now, let us define all possible trading events β_{ij} between i and j, shown in Table I.

Next, the power flow on transmission line 2-3 could be modeled as a queue with a N-unit capacity limit, as shown in Figure 19. Thus, the objective of congestion management is to keep the line flow on the suspected bottleneck within

$$-N\text{units} \leq F_{flow} \leq N\text{units} \tag{39}$$

Table I. Possible bilateral trading events in the 3 bus example.

$\beta 12, \beta 31$	→	+1 unit	line flow increase
$\beta 13, \beta 21$	→	−1 unit	line flow decrease
$\beta 32$	→	+2 units	line flow increase
$\beta 23$	→	−2 units	line flow decrease

This model could be used to develop DEDS methods for curtailing when necessary so that the entire transmission network is operated in the most efficient fashion.

6.3. Priority Service-Based Menus for Bilateral Transactions

Next, the idea of priority insurance contracts introduced by Wilson, Chao and Peck, (Chao et al., 1987; Wilson, 1989; Wilson, 1997) is applied for managing transmission for long term bilateral transactions. Unlike these previously proposed schemes, this priority insurance contract is used exclusively while acquiring transmission services and it is completely separated from the energy contracts. The feature of this type of pricing scheme is that it specifies an order in which customers requiring transmission services are served. Therefore, instead of giving a single price for transmission service, a price menu that lists a set of prices corresponding to different levels of firmness is provided. A customer indirectly reveals the value of the bilateral transaction to the grid operator by selecting a priority level for the transmission service. This information helps a system operator manage congestion more economically.

6.3.1. The Optimal Menu Design Problem

Variable $\mu_{i,j}$ is used here as the index of different priority levels. Each $\mu_{i,j}$ value requests random nodal price difference between buses i and j under different load and generation conditions; namely, it represents the random value of a transmission path. The definition of $\mu_{i,j}$ is:

$$\mu_{i,j} = p_j - p_i \tag{40}$$

where p_i is the nodal price at bus i.

The value of a transmission path is very volatile in real time operations. It varies with the system congestion condition, which is dependent on uncertain loading, generation market and network outages. The value of each node-to-node transmission path $\mu_{i,j}$ is modeled as a random variable with certain probability density distribution $f_{i,j}(\mu_{i,j})$. One way to obtain these probability density functions is to apply the probability optimal power flow (POPF) technique described above.

A price menu, $M_{i,j}$, for the priority insurance service corresponding to a transmission path from bus i to bus j consists of the following three components:

- $R_{i,j}(\mu_{i,j})$: The probability of the bilateral transaction being implemented. This is a function of $\mu_{i,j}$ for different levels of firmness.
- $P_{i,j}(\mu_{i,j})$: The price for network users to subscribe to level $\mu_{i,j}$ transmission service.
- $I_{i,j}(\mu_{i,j})$: The insurance payment to a network user when the subscribed level $\mu_{i,j}$ bilateral transaction is curtailed by a system operator due to congestion.

If a customer selects a priority level $\mu^0_{i,j}$, the associated marginal willingness-to-pay, from a menu, then he expects the insured transaction to be implemented when the random spot transmission value $\mu_{i,j}$ falls in the region $\Omega_{i,j}(\mu^0_{i,j}) = \{\mu_{i,j}\colon \mu_{i,j} \le \mu^0_{i,j}\}$ and to be curtailed when the spot transmission value falls in $\overline{\Omega}_{i,j}(\mu^0_{i,j})$, the complement region of $\Omega_{i,j}(\mu^0_{i,j})$. In other words, if the spot value of transmission is higher than the profit made by implementing the bilateral transaction, the grid user is willing to be curtailed rather than pay for access.

Therefore, the probability of implementation with respect to priority level $\mu^0_{i,j}$ can be derived as follows:

$$\begin{aligned} R_{i,j}(\mu^0_{i,j}) &= Prob\{\mu_{i,j} \le \mu^0_{i,j}\} \\ &= \int_{-\infty}^{\mu^0_{i,j}} f_{i,j}(\mu_{i,j})\, d\mu_{i,j} \\ &= G(\mu^0_{i,j}) \end{aligned} \tag{41}$$

where $G(\mu_{i,j})$ is the cumulative distribution function of the random variable $\mu_{i,j}$. Note that $R_{i,j}$ is nondecreasing in $\mu_{i,j}$ since $G(\mu_{i,j})$ is nondecreasing, i.e.,

$$\text{If} \quad \mu^I_{i,j} \le \mu^{II}_{i,j} \quad \text{then} \quad R_{i,j}(\mu^I_{i,j}) \le R_{i,j}(\mu^{II}_{i,j}) \tag{42}$$

Next, consider the insurance payment $I_{i,j}$. This payment is designed to partially or fully compensate the losses of customers when their insured contracts are curtailed. Therefore, when a customer chooses $\mu^0_{i,j}$ as a desired level of priority, the insurance payment is

$$I_{i,j}(\mu^0_{i,j}) = \alpha\mu^0_{i,j} \tag{43}$$

where α is the percentage of loss recovery, i.e., $\alpha = 100\%$, 90%, or 80% *etc.* Here we consider the fully insured cases. Thus, equation (43) becomes

$$I_{i,j}(\mu^0_{i,j}) = \mu^0_{i,j} \tag{44}$$

Therefore, the expected total charge for a system user to require transmission service is $P_{i,j}(\mu_{i,j}) - (1 - R_{i,j}(\mu_{i,j}))I_{i,j}(\mu_{i,j})$. For proper menu design, the incremental expected charge should equal the incremental gain/losses incurred when a customer selects higher/lower priority, i.e.,

$$P_{i,j}(\mu^0_{i,j}) - (1 - R_{i,j}(\mu^0_{i,j}))I_{i,j}(\mu^0_{i,j}) = \int_{-\infty}^{\mu^0_{i,j}} \mu_{i,j}\, dR_{i,j}(\mu_{i,j}) \tag{45}$$

This yields the price for priority insurance service

$$P_{i,j}(\mu^0_{i,j}) = \int_{-\infty}^{\mu^0_{i,j}} \mu_{i,j}\, dR_{i,j}(\mu_{i,j}) + (1 - R_{i,j}(\mu^0_{i,j}))I_{i,j}(\mu^0_{i,j}) \tag{46}$$

Note that if a customer signs up for a 100% firm transmission service, the price for this service is

$$P_{i,j} = \int_{-\infty}^{\infty} \mu_{i,j}\, dR_{i,j}(\mu_{i,j}) \tag{47}$$

$$= \mathcal{E}(\mu_{i,j}) \tag{48}$$

The customer is willing to pay the expected spot transmission price.

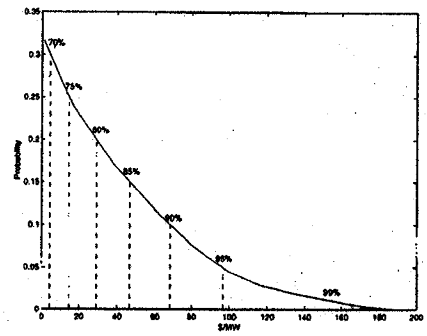

Figure 20. The cumulative probability distribution curve of $\mu_{2,4}$ and the corresponding reliability levels.

6.3.2. A Numerical Example

In this example, we use the same 5 bus system shown in Figure 10. Assuming that the random load condition follows the same distribution as in the POPF example above, we use the results of the probabilistic optimal power flow calculation as a starting point.

Here we consider the problem of designing an effective pricing menu for bilateral transactions between nodes 2 and 4. First, we use the distribution curve of nodal price difference between nodes 4 and 2 to obtain $\mu_{2,4}$ values corresponding to different levels of reliability, Figure 20.

Next, by using (42), (44) and (46), one can compute the transmission prices and insurance payments of the bilateral transaction from nodes 2 to 4 with respect to different levels of reliability, Figures 21 and 22. The optimal menu design is listed in Table II.

Table II. The price menu for bilateral transactions from bus 2 to bus 4.

Priority Level	Price ($/MWh)	Insurance ($/MWh)
99%	15.4989	155.4658
95%	14.6582	96.3301
90%	12.7578	68.1500
85%	10.2656	46.5161
80%	7.3804	29.0937
75%	4.1895	14.6701
70%	1.3544	4.3608

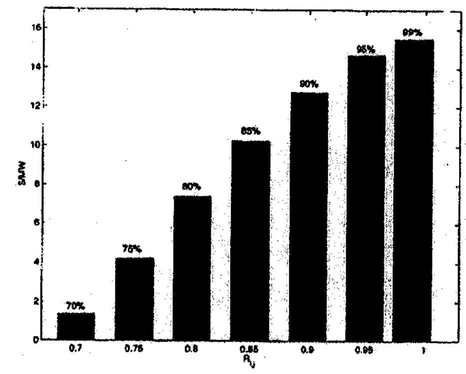

Figure 21. The transmission prices for bilateral transactions from bus 2 to bus 4 for different levels of reliability.

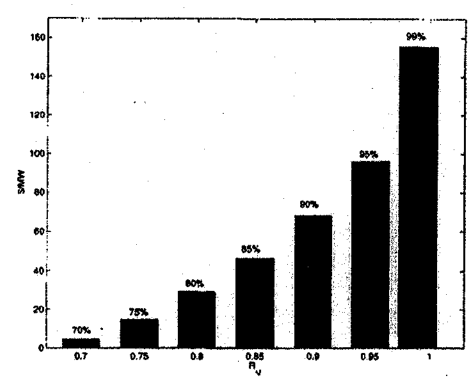

Figure 22. The insurance payments of bilateral transactions from bus 2 to bus 4 for different levels of reliability.

6.4. *Hybrid Bilateral/Spot Real-Time Congestion Management As a Dynamic Programming Problem*

Assume that priority insurance services for transmission are sold seasonally to long-term bilateral customers and the short-term spot market is cleared hourly. As the transmission system becomes congested, a system operator will have to relieve the constrained situation in an efficient way based on the energy bids on the spot market and the economic values of each bilateral transaction. In addition, since the priority insurance contracts are committed ex ante, a system operator will have to manage this process dynamically without violating the contracts over the entire season, Figure 23.

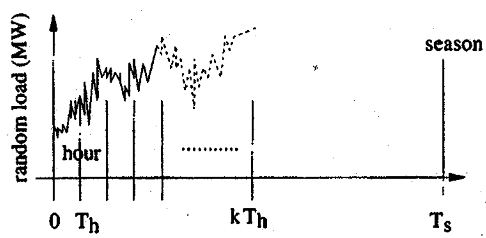

Figure 23. Time line of the real-time congestion management.

Here we choose the state variable $x_i[k]$ to represent the number of hours remaining for bilateral transaction i to be curtailed by a grid operator without violating the priority contract. For example, if a customer subscribes to a 90% firm transmission service over a season, then there is total of 216 hours during which this transaction is allowed to be curtailed. Therefore, $x_i[0] = 216$. Let the control variable $u_i[k]$ represent the curtailment decision made by a transmission system operator, i.e.,

$$u_i[k] = \begin{cases} 1 & \text{if the transaction is curtailed} \\ 0 & \text{if the transaction is implemented} \end{cases} \tag{49}$$

The state transition equation is simply:

$$x_i[k+1] = x_i[k] - u_i[k] \quad (x_i[k] \geq 0) \tag{50}$$

Recall that when a bilateral transaction i is curtailed, the transmission provider has to pay back the insurance $I_i[k]$. Therefore, the total insurance paid is $\sum_{i=1}^{N_{trans}} u_i[k]I_i[k]$ where N_{trans} is the total number of bilateral transactions. Next, let $MS_{[k]}$ be the merchandise surplus of hour k which indicates the congestion revenue collected from the real-time spot market (Hogan, 1992; Cadwalader et al., 1998).

At each stage, we define the social welfare loss function:

$$L_{[k]} = \sum_{i=1}^{N_{trans}} u_i[k]I_i[k] + MS_{[k]}(u[k], P_L[k]) \tag{51}$$

The objective function of the dynamic programming is to minimize the cumulative welfare loss $L_{[k]}$ over the N total stages. Thus, the DP algorithm becomes

$$J_{[N]}(x[N]) = L_{[N]}(x[N]) \tag{52}$$

$$J_{[k]}(x[k]) = \min_{u[k]} \mathcal{E}\{L_{[k]}(x[k], u[k], P_L[k]) + J_{[k+1]}(f_{[k]}(x[k], u[k], P_L[k]))\}$$

$$k = 0, 1, \ldots, N-1 \tag{53}$$

Since the amount of merchandise surplus will also depend on the generator bids in a spot market, a perfect competition assumption is made in order to make the DP problem solvable. In other words, a generator will submit its bid based solely on the remained capacity that is not yet committed in the bilateral deals, and its marginal cost curve.

7. Conclusions

We have stated in this paper that the general problem of dynamic transmission provision for the newly evolving industry cannot be tackled without re-visiting this problem in the coordinated industry. The general lack of dynamic decision-making tools under uncertainties for the coordinated industry is taking on new importance under competition. Tools for long-term network use and investments are of critical importance. This paper attempts to formulate the basis for developing such tools.

The most novel aspect of the transmission provision under restructuring is the idea of giving economic signals (prices for using transmission) to the transmission system users so that they can evaluate their requests and adjust to the system conditions. This is an alternative to the operator only taking technical actions, such as using suboptimal generation to supply anticipated demand, or even not serving portions of load demand, in order to keep system variables within the acceptable technical limits.

Different transmission pricing possibilities have a common characteristic in that, as soon as congestion appears on the grid, power does not have the same value at each node but it is traded on the power market as if it did. The congestion management scheme, whichever it is, thus is required to incorporate these differences. The transmission rent will appear, under one form or another, in all congestion schemes as an economic reality. This rent could serve as a basis for developing a uniform approach to long term transmission investment incentives.

A definition of the value of transmission capacity is not straightforward. In the short-run, demand and cost functions can be considered deterministic. However, a transmission provider has no exact knowledge of their value. The main issue in setting the value of the coordinating variables μ_l, therefore, is in the information asymmetries. Many diverse mechanisms have been proposed to price transmission based on its market-value. Most of them are based on information exchanges between the coordinating entity and market participants. Not surprisingly, strategic behavior issues and convergence issues are the most often quoted issues associated with these pricing schemes.

Also unsurprising is the fact that all congestion management schemes lead in theory to the same dispatch of generation resources. We cannot differentiate between them at the equilibrium or under the assumptions of perfect market conditions. The most suitable structure for value-based transmission pricing should, on the contrary, be judged on its ability to mitigate market power, to handle uncertainty in demand, and to converge toward equilibrium prices.

Acknowledgments

The financial support provided by the MIT Consortium for "New Concepts and Software for Competitive Power Systems" has made this research possible and it is greatly appreciated.

Notes

1. Throughout this paper we assume no stability problems in moving from one system equilibrium to the next.
2. This amounts to replacing the social welfare criterion with controllable cost; it is easy to include price-elastic demand as an active decision variable if desired (Wu et al., 1994).
3. The basis for defining these constraints for a given system is outside the scope of this paper.
4. In section 6.1 an approximate computing method for obtaining the expected short-term optimum is introduced by means of solving a probabilistic optimal power flow (Yu, 1999).
5. In this formulation, only transmission investment is of interest; generation is assumed given. For optimal generation/transmission investment see (Leotard, 1999).
6. A similar approach could be used to define access charges for new power plants.
7. The detailed system data and large system simulations can be found in (Yu, 1999).

References

Allan, R. N., Borkowska, B., and Brigg, C. H. 1974. Probabilistic analysis of power flows. *IEE Proceedings* 121(12): 1551–1555.

Allan, R. N., Leite da Silva, A. M., and Burchett, R. C. 1981. Evaluation methods and accuracy in probabilistic load flow solutions. *IEEE Transactions on Power Apparatus and Systems* PAS-100(5): 2539–2546.

Baldick, R., Kim, B. H., Chase, C., and Loo, Y. 1998. A fast distributed implementation of optimal power flow. *IEEE Transactions on Power Systems*. PE-167-PWRS-0-04-1998.

Bensoussan, A. 1981. Singular perturbation results for a class of stochastic control problems. *IEEE Transactions on Automatic Control* AC-26: 1071–1080.

Bertsekas, D. P. 1995. *Dynamic Programming and Optimal Control*, vol. 1. Athena Scientific.

Bertsekas, D. P., and Tsitsikiis J. 1996. *Neuro-Dynamic Programming*. Athena Scientific.

Borkowska, B. 1974. Probabilistic loadflow. *IEEE Transactions on Power Apparatus and Systems* PAS-93(3): 752–759.

Gadwalader, M. D., Harvery, S. M., Pope, S. L., and Hogan, W. W. 1998. Market coordination of transmission loading relief across multiple regions. Draft.

Caramanis, M. C. 1981. Investment planning under optimal spot pricing of electricity. MIT Energy Laboratory working paper MIT-EL 81-051WP.

Chao, H., and Wilson, R. 1987. Priority service, investment, and market organization. *The American Economic Review* 77(5): 899–916.

Chao, H., and Peck, S. 1996. A market mechanism for electric power transmission. *Journal of Regulatory Economics* 10(1): 25–59.

Chao, H. and Peck, S. 1997. An institution design for an electricity contract market with central dispatch. *The Energy Journal* 18(1): 85–110.

Crew, M., and Kleindorfer, P. R. 1979. *Public Utility Economics*. New York: St. Martin Press.

Delebecque, F., and Quadrat, J. P. 1978. Contribution of stochastic control singular perturbation averaging and team theories to an example of large-scale systems: Management of hydropower production. *IEEE Transactions on Automatic Control* AC-23: 209–221.

Delebecque, F., Quadrat, J. P. 1981. Optimal control of Markov chains admitting strong and weak interactions. *Automatica* 17: 281–296.

Descamps, F., and Feltin, L. 1995. A new model to assess the composite adequacy and the operating costs of large interconnected power systems. *Proceedings of the Powertech Conference*. Stochdem, Sweden.

Dixit, A. K., and Pindyck, R. S. 1994. *Investments Under Uncertainty*. New York: Princeton University Press.

FERC World Wide Web site. http://www.ferc.fed.us

Guan, X., and Luh, P. B. 1999. Integrated resource scheduling and bidding in deregulated electric power market: New challenges. *The Journal on Discrete Event Dynamic Systems*, this issue.

Haddad, A. H., and Kokotović, P. V. 1977. Stochastic control of linear singularly perturbed systems. *IEEE Transactions on Automatic Control* AC-22: 815–821.

Hogan, W. W. 1992. Contract networks for electric power transmission. *Journal of Regulatory Economics* 4: 211–242.

Khalil, H., and Gajić, Z. 1984. Near-optimum regulators for stochastic linear singularly perturbed systems. *IEEE Transactions on Automatic Control* AC-29: 531–541.

Kirchmayer, L. K. 1985. *Economic Operation of Power Systems*. John Wiley & Sons Inc.

Klir, G., and Yuan, B. 1995. *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. New Jersey: Prentice-Hall PTR.

Lecinq, B. 1996. Peak-load pricing for transmission. Master thesis, MIT Department of Technology and Policy Program.

Lecinq, B., and Ilić, M. D. 1997. Peak-load pricing for electric power transmission. *Proceedings of the Hawaii Conference on System Sciences*, pp. 624–632.

Leite da Silva, A. M., Arienti, V. L., and Allan, R. N. 1984. Probabilistic load flow considering dependence between input nodal powers. *IEEE Transactions on Power Apparatus and Systems* PAS-103(6): 1524–1530.

Leotard, J.-P. 1999. Transmission pricing and incentives for investments under uncertainty in the deregulated power industry. Master thesis, MIT Department of Technology and Policy Program.

Lerner, P. A., and Ilić, M. D. 1997. On the value of transmission systems: Incentives for investment under open access. *Proceedings of the 18th Annual North American Conference on International Energy Markets, Competition and Policy*. San Francisco, CA.

McGuire, B. 1999. Power grid decentralization. University of California Energy Institute, POWER Report PWR-065.

Oren, S. 1997. Economic inefficiency of passive transmission rights in congested electricity systems with competitive generation. *The Energy Journal* 18(1).

Pedrycz, W. 1993. *Fuzzy Control and Fuzzy Systems*. England: Research Studies Press LTD.

Ramadge, P. J., and Wonham, W. M. 1987. Supervisory control of a class of discrete event processes. *SIAM J. Control and Optimization* 25(1): 206–230.

Ross, S. 1980. *A Course in Simulation*. New York: Macmillan.

Rubenstein, R. 1981. *Simulation and the Monte Carlo Method*. New York: John Wiley.

Sauer, P. W. 1982. Constrained stochastic power flow analysis. *Electric Power Systems Research* 5: 87–95.

Schweppe, F. C., Caramanis, M. C., Tabors, R. D., and Bohn, R. E. 1988. *Spot Pricing of Electricity*. Kluwer Academic Publishers.

Visudhiphan, P., and Ilić, M. D. 1999. Dynamic games-based modeling of electricity markets. *Proceedings of the IEEE PES Winter Meeting*. New York, NY.

Wellman, M. P., Walsh, W. E., Wurman, P. R., and MacKie-Mason, J. K. 1998. Some economics of market-based distributed scheduling. *Proceedings of the Eighteenth International Conference on Distributed Computing Systems*. Amsterdam.

Wilson, R. 1989. Efficient and competitive rationing. *Econometrica* 57(1): 1–40.

Wilson, R. 1997. Implementation of priority insurance in power exchange markets. *The Energy Journal* 18(1): 111–123.

Wu, F., Varaiya, P., Spiller, P., and Oren, S. 1992. Folk theorems on transmission open access: Proofs and counter examples. University of California Energy Institute. POWER report PWP-023.

Yu, C.-N. 1999. Hierarchical congestion management for a deregulated power industry. PhD Thesis, MIT Department of Mechanical Engineering.