An Algorithm for Implementing Transmission Rights in a Competitive Power Industry

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Abstract: In this paper an algorithm for evaluating the long-term (seasonal, annual) values of transmission rights is described. The algorithm is based on simulating the probable line flows ahead of time using probabilistic optimal power flow (POPF). An efficient Monte Carlo approach, which computes the value of transmission links and line-flow probability distributions based on a given load duration curve and public knowledge of power plant characteristics is developed by linearizing OPF solutions at different system load levels. This knowledge is used by a system provider to establish likely value of transmission rights characterized by different levels of firmness. If a system provider is to post this information publicly, system users could estimate the value of the transmission rights to themselves.

The second part of the algorithm is intended to facilitate ISOs in deciding between not serving system users who own transmission rights of certain firmness and curtailing short-term transactions in case there is congestion. The developed algorithm facilitates efficient relief of network congestion in short-term operations without violating prior obligations in long-term transmission right markets.

Keywords: Transmission Rights, Probabilistic Optimal Power Flow, Transmission Congestion Management, Priority Insurance Service.

I. Introduction

Most of the newly formed Independent System Operators (ISOs), such as Pennsylvania-New Jersey-Maryland (PJM), California (CAISO), and New England (ISO-NE), are required to offer some type of long-term transmission rights to the users willing to pay for future use of the grid. Current industry concerns are if these rights should be solely financial or they must be physical and firm. As the rules regarding these concerns evolve, it is essential to develop computer-based tools to assist ISOs in implementing these rights as an integral part of transmission system operations and planning.

A definition of the values of transmission rights is not straightforward. Many diverse mechanisms have been proposed to price these rights based on their market values. For instance, in some of the energy markets currently in operation, the prices for transmission rights are determined through auction processes depending upon what system users offer in their bids for purchasing these rights. Not surprisingly, strategic behaviors and convergence problems are the most often quoted issues associated with this type of pricing scheme. It is suggested in this paper that a transmission service provider should be an active decision maker in this auction process as well. It is essential that the provider's decisions be based on realistic estimates of how many rights are likely to be available and of the price at which these rights should be sold. The proposed algorithm is a basic tool to a transmission provider for this purpose.

In this paper, a theoretical setup for implementing physical transmission rights is presented. A transmission provider needs to respond to the market participants requesting the network use for some future period of time (typically season or year ahead). This is additional to the responsibility to manage daily, or hourly requests for access. Customers are obligated to obtain the transmission rights before implementing their long-term bilateral contracts. The approach taken is adopted from the recently proposed priority-based pricing scheme. Estimation of the values and availabilities of transmission rights between certain nodes in the transmission network for the future season is defined in terms of the probability of the occurrence of system congestion.

This paper is organized as follows: First, Section II introduces a method for predicting long-term system conditions using a probabilistic optimal power flow-based approach as an essential tool for long-term transmission provision. The probabilistic information obtained from this tool could help a transmission provider estimate the value and the availability of these transmission rights. Next, in Section III, we show how this probabilistic information could be used to design the menus for selling priority insurance service of different firmness for obtaining the transmission rights. 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 transmission network or paying back the owners of long-term rights for not being served. In Section IV, a dynamic programming-based formulation for an efficient relief of network congestion in real-time operations without violating prior obligations in long-term transmission right markets is presented.

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II. Tool for Projecting Long-term Values of Transmission Services

To begin with, a new algorithm which helps both market participants and transmission right sellers to evaluate long-term (seasonal, annual) value of transmission paths is developed. The proposed approach simulates the operation of the electricity market under competition via probabilistic optimal power flow (POPF).

Historically, optimal power flow (OPF) analysis has been used 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 estimate market equilibrium and calculate so-called locational-based marginal prices (LBMPs) [1], [2]. Recall that traditional OPF is a static optimization problem assuming load demand $P_L = [P_{L_1}, \cdots, P_{L_{nd}}]$ to be known, solving for the optimal dispatch of available generation resources $P_G^* = [P_{G_1}^*, \cdots, P_{G_{ng}}^*]$:

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

subject to the load flow constraints. 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.

Traditional OPF is applied based on a snapshot of time[1] and it does not give any information regarding the degree of importance or likelihood of each violation. In actual operating practice, total electricity demand always deviates away from these snapshot conditions in a random fashion. Several efforts have been made over years to obtain a probabilistic-based load flow solution [3], [4], [5], [6].

A. Two-stage Approach for Monte Carlo Simulations

In this paper, we introduce a two-stage, Monte Carlo-based method to efficiently solve probabilistic optimal power flow (POPF) [7], [8]: At the first stage, a set of discrete load patterns that represent nominal system load conditions at different load levels is used. Detailed OPF solutions are computed based on these nominal load patterns and these OPF solutions give a rough approximation of generation probability distributions. At stage two, random deviations from these nominal patterns are taken into account. By using incremental linearized OPF equations, a large number of simulation samples can be obtained efficiently.

Basic Assumptions

When applying Monte Carlo methods to large power systems, an immediate problem is the difficulty of constructing probability density functions. Because of metering problems, electricity demands at individual load buses are usually not measured; only the total system demand is recorded. Historical total load data for different systems are public information [9]. Utility companies could use this information to construct the so-called load duration curve[2] such as that shown in Figure 1.

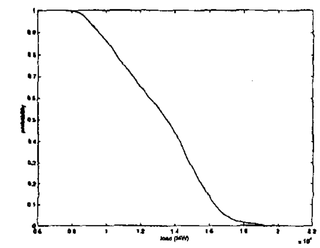

Fig. 1. The load duration curve constructed from NEPOOL total load data of 1997.

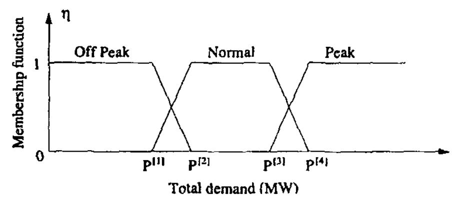

Fig. 2. Membership functions representing the loads of peak load, normal, and off peak.

In order to overcome this problem, we assume that there exists a nominal load pattern, which describes how total system demand is distributed at individual load buses, e.g., peak-load pattern, off-peak pattern *etc.* A nominal pattern can also be interpreted as the mean value of the random load around a specific load level. Of course, there are deviations from the nominal pattern at these load buses. The actual system loads are the sum of nominal patterns and zero-mean random perturbations at individual load buses. To further simplify the problem, it is assumed that congestion is caused solely by the nominal patterns and not by the random deviations.

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 [10], [11]. As shown in Figure 2, 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

[1] i.e., for calculating optimal generation dispatches for average or extreme loading conditions only.

[2] It is basically a cumulative distribution function, For example, the values read from the Y-axis of Figure 1 indicate the probabilities of demand at L exceeding corresponding X-axis value., e.q., 45% probability of load exceeding 14000MW.

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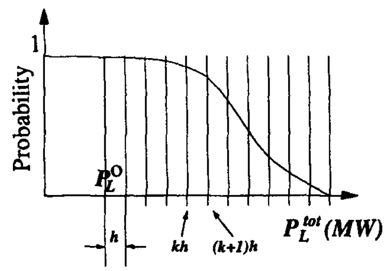

Fig. 3. Discretized load duration curve.

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.

Next, we discretize the system load every hMW starting from P_L^0MW, i.e., $P_L^{tot}(k) = P_L^0 + kh$, Figure 3. Thus, the typical patterns of different load levels is computed by using the following equation:

$$P_L^{[k]} = P_L^{tot}(k)\left(\eta^{[N]}\frac{P_L^{[N]}}{1^T P_L^{[N]}} + \eta^{[OP]}\frac{P_L^{[OP]}}{1^T P_L^{[OP]}} + \eta^{[PK]}\frac{P_L^{[PK]}}{1^T P_L^{[PK]}}\right) \tag{2}$$

and the probability of each discrete load pattern occurrence is

$$\begin{aligned} Prob\{P_L^{[k]}\} &= Prob\{P_L^0 + kh \le P_L^{tot} \le P_L^0 + (k+1)h\} \\ &= G_{P_L^{tot}}(P_L^0 + (k+1)h) - G_{P_L^{tot}}(P_L^0 + kh) \\ &= \int_{P_L^0+kh}^{P_L^0+(k+1)h} f_{P_L^{tot}}(P_L)dP_L \end{aligned} \tag{3}$$

Next, we compute OPF solutions for each load level. Based on the corresponding probabilities calculated in (3), the cumulative distribution curves for these OPF solutions can be constructed.

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 above, the incremental OPF solution is simply a linear function of load deviations [8], i.e.,

$$\Delta P_G^* = V^{[k]}\Delta P_L \tag{4}$$

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

$$P_G = P_G^{[k]} + V^{[k]}\Delta P_L \tag{5}$$

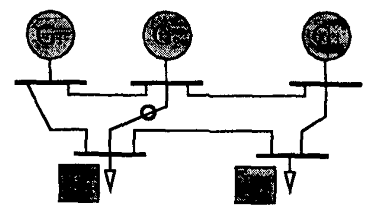

Fig. 4. A 5-bus system

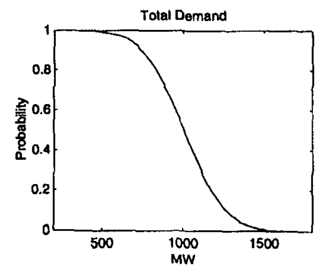

Fig. 5. The total load duration curve for the simulation case

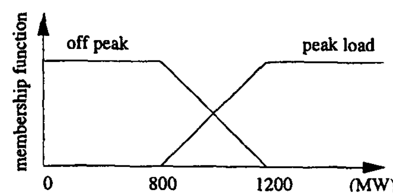

Fig. 6. Fuzzy membership function of the occurrence of the two basic load patterns at different load levels.

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.

B. A Numerical Example

To illustrate the idea of the two-stage approach, we have simulated a simple 5-bus system with three generators and two loads shown in Figure 4.[3] Next, we assume the estimated distribution of the total system demand for the next season to be normal with a 1000MW mean and a 200MW 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. The fuzzy membership function for the occurrence of the two basic load patterns at different load levels is shown in Figure 6.

In this example, we assume that there are two inexpensive generators, G_1 and G_2, with a generator marginal

[3]The detailed system data and large system simulations can be found in [8].

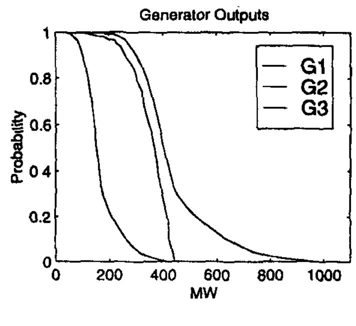

Fig. 7. Probability distributions of three generator outputs.

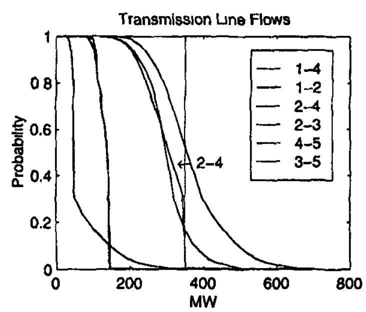

Fig. 8. Probability distributions of six transmission line flows (line G_2-L_4 is the one constrained).

cost function, $\frac{\partial c(P_G)}{\partial P_G} = 0.1P_G + 10$, and one expensive generator G_3 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 50MW starting from 500MW to 1500MW. We use (2) and (3) 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 7, 8, and 9 show the probability distributions of all generator outputs, transmission line flows, and nodal prices respectively. As illustrated in Figure 7, generation of G_2 is limited by the transmission flow constraint. Figure 8 shows that the probability of the system being congested is around 32%. Furthermore, the constraint causes the 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 10 shows the probability distributions of the values of six possible

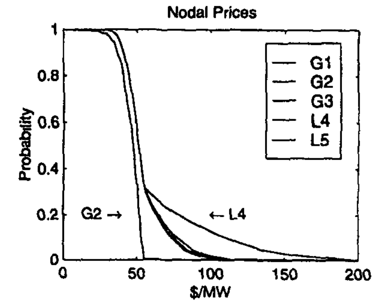

Fig. 9. Probability distributions of nodal prices.

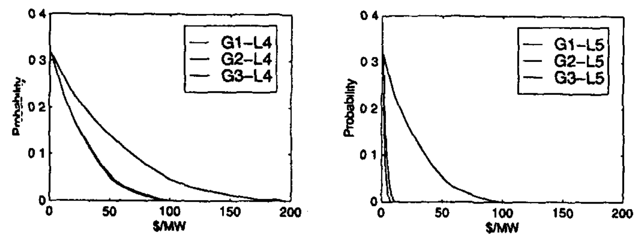

Fig. 10. Probability distributions of nodal price differences for different node-to-node transactions.

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.

C. *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 11, 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 11. 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^{err}_G to indicate the uncertain generation output deviating from its nominal value P^{nom}_G, i.e., $P_G = P^{nom}_G + P^{err}_G$. By inspection, the probability distribution of P^{err}_G can be calculated by the following

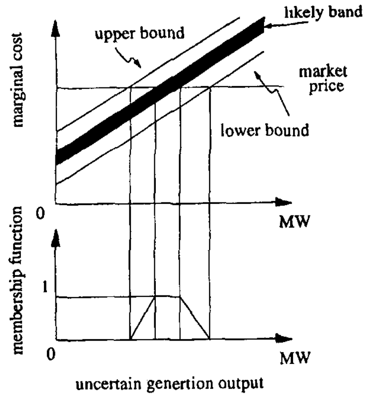

Fig. 11. Uncertain generation cost curve.

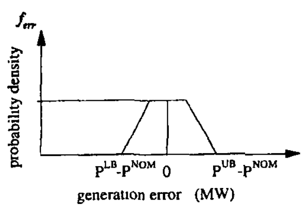

Fig. 12. Uncertain generation output deviation from the nominal value.

formula, Figure 12:

$$f_{err}(P_G^{err}) = \frac{\eta(P_G^{err} + P_G^{nom})}{\int_{P_G^{LB}}^{P_G^{UB}} \eta(P_G)dP_G} \tag{6}$$

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.

III. Priority Insurance Service for Long-Term Transaction Rights

Next, the idea of priority insurance contracts introduced by Wilson, Chao and Peck, [12], [13], [14] is applied for selling transmission rights for long-term bilateral transactions. The feature of this type of pricing scheme is that it specifies an order in which customers requiring transmission services are served. Therefore, in our setup, instead of giving a single price for a node-to-node transmission right, a price menu that lists a set of prices corresponding to different levels of firmness is provided. A customer is obligated to obtain a transmission right via selecting an insurance level before implementing the long-term bilateral transaction. Then, the customer indirectly reveals the value of its bilateral transaction to the ISO during the self-selecting process. This information helps the ISO manage congestion more economically.

A. Optimal Menu Design

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:

$$\mu_{i,j} = p_j - p_i \tag{7}$$

where p_i is the nodal price at bus i.

The value of a transmission path 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 $f_{i,j}(\mu_{i,j})$. The way to obtain these probability density functions is to apply the probability optimal power flow (POPF) technique described in the previous section.

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

- $\mathcal{R}_{i,j}(\mu_{i,j})$: The probability of the bilateral transaction being implemented.
- $\mathcal{P}_{i,j}(\mu_{i,j})$: The price for network users to subscribe to level $\mu_{i,j}$ transmission service.
- $\mathcal{I}_{i,j}(\mu_{i,j})$: The insurance payment to a network user when the subscribed level $\mu_{i,j}$ service can not be implemented due to system congestion.

If a customer selects a priority level $\mu_{i,j}^0$, 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 $\Omega_{i,j}(\mu_{i,j}^0) = \{\mu_{i,j} : \mu_{i,j} \leq \mu_{i,j}^0\}$ and to be interrupted when the spot transmission value falls in $\bar{\Omega}_{i,j}(\mu_{i,j}^0)$, the complement region of $\Omega_{i,j}(\mu_{i,j}^0)$. 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 $\mu_{i,j}^0$ can be derived as follows:

$$\begin{aligned} \mathcal{R}_{i,j}(\mu_{i,j}^0) &= Prob\{\mu_{i,j} \leq \mu_{i,j}^0\} \\ &= \int_{-\infty}^{\mu_{i,j}^0} f_{i,j}(\mu_{i,j})d\mu_{i,j} \\ &= G(\mu_{i,j}^0) \end{aligned} \tag{8}$$

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

$$\text{If} \quad \mu_{i,j}^I \leq \mu_{i,j}^{II} \quad \text{then} \quad \mathcal{R}_{i,j}(\mu_{i,j}^I) \leq \mathcal{R}_{i,j}(\mu_{i,j}^{II}) \tag{9}$$

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

$$\mathcal{I}_{i,j}(\mu_{i,j}^0) = \alpha\mu_{i,j}^0 \tag{10}$$

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 (10) becomes

$$\mathcal{I}_{i,j}(\mu_{i,j}^0) = \mu_{i,j}^0 \tag{11}$$

Therefore, the expected total charge for a system user to require transmission right is $\mathcal{P}_{i,j}(\mu_{i,j}) - (1 - \mathcal{R}_{i,j}(\mu_{i,j}))\mathcal{I}_{i,j}(\mu_{i,j})$. For proper menu design, the incremental expected charge should equal the incremental gain/losses incurred when a customer selects higher/lower priority [12], i.e.,

$$\mathcal{P}_{i,j}(\mu_{i,j}^0) - (1-\mathcal{R}_{i,j}(\mu_{i,j}^0))\mathcal{I}_{i,j}(\mu_{i,j}^0) = \int_{-\infty}^{\mu_{i,j}^0} \mu_{i,j} d\mathcal{R}_{i,j}(\mu_{i,j}) \tag{12}$$

This yields the price for obtaining level $\mu_{i,j}^0$ transmission rights

$$\mathcal{P}_{i,j}(\mu_{i,j}^0) = \int_{-\infty}^{\mu_{i,j}^0} \mu_{i,j} d\mathcal{R}_{i,j}(\mu_{i,j}) + (1-\mathcal{R}_{i,j}(\mu_{i,j}^0))\mathcal{I}_{i,j}(\mu_{i,j}^0) \tag{13}$$

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

$$\mathcal{P}_{i,j} = \int_{-\infty}^{\infty} \mu_{i,j} d\mathcal{R}_{i,j}(\mu_{i,j}) \tag{14}$$

$$= \mathcal{E}(\mu_{i,j}) \tag{15}$$

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

B. A Numerical Example

In this example, we use the same 5-bus system shown in Figure 4. 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 the starting point.

Here we consider the problem of designing an effective pricing menu for selling transmission rights 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 13.

Next, by using (9), (11) and (13), one can compute the prices and insurance payments of the rights from nodes 2 to 4 with respect to different levels of reliability. The optimal menu design is listed in Table I.

IV. Hybrid Real-time Congestion Management as a Dynamic Programming Problem

Assume that priority insurance for transmission rights is sold seasonally to long-term transmission customers and

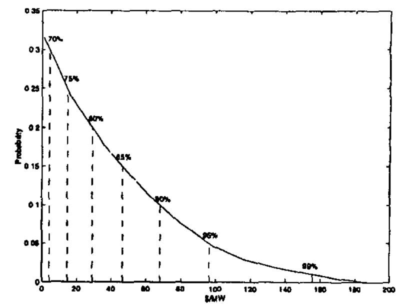

Fig. 13. The cumulative probability distribution curve of $\mu_{2,4}$ and the corresponding reliability levels.

TABLE I

THE PRICE MENU FOR 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

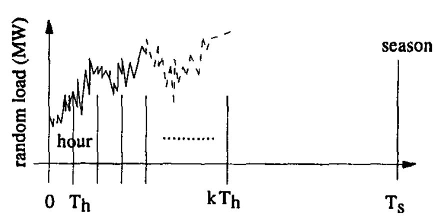

Fig. 14. Time line of the real-time congestion management

the short-term spot market is cleared hourly. As the transmission system becomes congested, an ISO has to relieve the constrained situation in an efficient way based on the energy bids in the spot market and the economic values of each long-term bilateral transaction. In addition, since the priority insurance contracts are committed *ex ante*, the ISO also has to manage this process dynamically without violating the contracts over the entire season, Figure 14.

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 transmission right contract. For instance, if a customer holds the right to a 90% firm transmission service over a season, then there is total of 216 hours during which this service is allowed to be interrupted. Therefore, $x_i[0] = 216$. Let the control variable $u_i[k]$ represent the interruption decision made by the ISO, i.e.,

$$u_i[k] = \begin{cases} 1 & \text{if the transaction is interrupted at hour } k \\ 0 & \text{if the transaction is implemented at hour } k \end{cases} \quad (16)$$

The state transition equation is simply:

$$x_i[k+1] = x_i[k] - u_i[k] \quad (x_i[k] \geq 0) \qquad (17)$$

Recall that if a bilateral transaction i is interrupted, the transmission provider has to pay back the insurance $I_i[k]$ to the transmission right holder. Therefore, the total insurance paid equals $\sum_{i=1}^{N_{trans}} u_i[k]I_i[k]$ 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 [2], [15].

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

$$L_{[k]} = \sum_{i=1}^{N_{trans}} u_i[k]\mathcal{I}_i[k] + MS_{[k]}(u[k], P_L[k]) \qquad (18)$$

The objective function of the dynamic programming is to minimize the cumulative welfare loss $L_{[k]}$ over the N total stages. Thus, the corresponding dynamic programming (DP) algorithm can be formulated as [16]:

$$J_{[N]}(x[N]) = L_{[N]}(x[N]) \qquad (19)$$

$$\begin{aligned} J_{[k]}(x[k]) \; = \; & \min_{u[k]} \mathcal{E}\{L_{[k]}(x[k], u[k], P_L[k]) \qquad (20) \\ & + J_{[k+1]}(f_{[k]}(x[k], u[k], P_L[k]))\} \\ & k = 0, 1, \cdots, N-1 \end{aligned}$$

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 is assumed to submit its spot energy bid based on the remained capacity that is not yet committed in the long-term bilateral deals, and its marginal cost curve.

V. Conclusions

The 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, most of the methods are either useful only for short-term optimal use of the network, like deterministic optimal load flow, or for long-term planning methods but not capable of optimal scheduling in short-term operations.

In this paper, the possibility of valuing long-term transmission services is recognized; a recently proposed priority-based insurance service idea based on a bottom-up auction mechanism to purchasing long-term transmission rights is posed here as a dynamic decision making problem under uncertainties of competitive energy markets. Proposed algorithm helps an ISO relieve short-term network congestion efficiently without violating prior obligations in long-term transmission right markets.

VI. Acknowledgments

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VII. References

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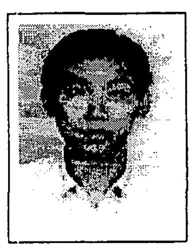
VIII. Biographies



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