Quantifying the Impact of Unscheduled Line Outages on Locational Marginal Prices

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***Abstract*—In this paper, we present a systematic approach for quantifying the impact of unscheduled line outages on real-time Locational Marginal Price (LMP). The probabilistic LMP is formulated with consideration of generation, load, and topology uncertainties. A computationally efficient 2n+1 point estimation method is adopted to calculate statistical moments of LMP due to unscheduled transmission line outages. The proposed approach is demonstrated in a modified PJM five-bus system. Result of such study is beneficial for power market participants in developing a more comprehensive bidding strategy.**

***Index Terms*—Probabilistic LMP; Electricity markets; uncertainty analysis; network topology**

I. Introduction

In competitive electricity markets each participant may make bids based on expected electricity price at the location. The locational marginal price (LMP) model has been adopted in some major Regional Transmission Organizations (RTOs). Since the financial settlements of individual market participants are based on the LMP, thorough understanding of how LMP works, in particular under uncertain situations, is of critical importance in market particiants' decision making process [1].

In major RTOs, energy and ancillary services bids are made at a variety of time scales such as day-ahead, hour-ahead, and ten-minute ahead of market closing. In real-time markets, Security Constrained Economic Dispatch (SCED) is executed every five or ten minutes ahead of the actual operation. One of the by-products of the SCED is the real-time LMPs. Although precise load forecasting methods have been proposed [2-4], still some degrees of uncertainty exist. In [5-6] probabilistic LMP has been proposed to take into account these uncertainties. Impact of demand uncertainty on LMP has been studied in [5] and [6] addressee that of the participants' bid.

Another source of uncertainty is unscheduled network topology change. It is quite possible a given line goes out of service due to permanent fault. Unlike two sources of uncertainties mentioned before (bid of others, and demand), topology change usually causes huge price change. Even though, it does not happen frequently and there is a probability of occurrence associated with it. A systematic approach should be developed to quantify impact of unscheduled outage of the lines on estimated LMP. This analysis is useful for generation companies or load serving entities to formulate their bidding strategies, as well as for the risk hedging policies [5]. In this paper LMP estimation is formulated as an uncertainty analysis problem. Although it is possible to utilize the widely used Monte Carlo Simulation (MCS) to solve this problem, it is computationally expensive as it requires huge number of iterations. Therefore, 2n+1 point estimation method which is computationally efficient is utilized [7]. The result of the method is demonstrated by using modified PJM five-bus system.

The paper is organized as follows. In section II sources of uncertainty in power market are discussed. Impact of unscheduled topology change on LMP is studied in section III and a systematic approach for its quantification is proposed. Section IV presents case study result by using modified PJM five-bus system. Finally Section V concludes the paper.

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II. Power Market in Uncertain Conditions

In this section sources of uncertainties in power market are discussed. Impacts of two sources of uncertainty (demand, participants' bid) are studied briefly. The third source of uncertainty (topology of the network) which is the focus of this paper is discussed in the rest of the paper.

Equation (1) [6] shows the process conducted in an electricity market. The goal is maximizing social welfare while satisfying the constraints. The objective function G is function of demand and supply and their associated price. Uncertainty in participants' bid shows in equation (1-a).

Equating supply and demand based on power flow equations is one of the main constraints. These equations are function of demand and supply among others. Uncertainty in forecasted demand demonstrates itself in these constraints (1-c, 1-d).

Power flow equations are function of network topology. In security limit constraints (1-e), if a line goes out of service, $P_{ij\max}$ and $P_{ji\max}$ become zero.

According to (1), clearing price depends upon the demand among other factors. It is quite possible to get different market prices for different demands. To quantify impact of demand estimation uncertainty on clearing price, performing conventional load-flow computations for every possible or probable combination of demand is impractical due to large computational burden. To solve this problem usually probabilistic load flow is carried out. Instead of deterministic value, a probabilistic distribution function is assigned to each

$$
\begin{array}{ll}
Min \quad G = -(C_D^T P_D - C_S^T P_S) & \text{a) social welfare} \\
F(\delta, V, Q_G, P_S, P_D) = 0 & \text{b) power flow equations} \\
0 \le P_S \le P_{S\max} & \text{c) supply bid limit} \\
0 \le P_D \le P_{D\max} & \text{d) demand bid limit} \\
P_{ij}(\delta, V) \le P_{ij\max} & \text{e) security limit} \\
P_{ji}(\delta, V) \le P_{ji\max} & \\
I_{ij}(\delta, V) \le I_{ij\max} & \text{f) thermal limit} \\
I_{ji}(\delta, V) \le I_{ji\max} & \\
V_{\min} \le V \le V_{\max} & \text{g) voltage limit} \\
Q_{G\min} \le Q_G \le V_{G\max} & \text{h) generator limits}
\end{array}
\quad (1)
$$

where

C_D, C_S supply and demand bids in \$/MWh

P_S, P_D bounded supply and demand power bids in MW

P_{ji}, P_{ij} the power flow through the lines in both directions

I_{ij}, I_{ji} line current limit

δ, V bus phasor voltages and angles,

Q_G generator reactive powers

load and/or generator as well as parameters of the network. Instead of deterministic value for a desired output, its probability distribution is yielded. In electricity market desirable value is the clearing price. In [6] a probabilistic method has been proposed to take into account impact of uncertainty in load forecasting on LMP. LMP has been viewed as a random variable and named probabilistic LMP. The probability mass function (PMF) of LMP is calculated. Having this PMF it is possible to estimate certainty of the price prediction.

Another source of uncertainty in the competitive market is participants' behavior. Each participant bids independently based on its estimate of residual demand (the demand curve each participant faces). The residual demand curve is constructed by calculating horizontal difference of the demand and supply of other participants at each given price, as shown in Fig. 1 [8].

To determine bidding price, the supplier intersects its supply curve (which in ideal competitive market should be its Marginal Cost (MC)) with the residual demand curve. However in real market the supplier tends to bid higher than its MC. As the price increases, the demand decreases. Moreover, other supplier will provide the demand. So, it is not possible to increase the bidding price without a limit. Fig.2 [9] shows the procedure of bidding in real market. The supplier bids higher than its MC until the gain due to price increase becomes equal to loss due to reduction in the demand.

In the above explained procedure a given supplier does not have exact information about demand and supply of other market participants which implies that bidding price is result of uncertain factors. Since only estimate are used, their accuracy depends on accuracy of the method used to estimate such values. In uniform-price auction markets if a supplier is the marginal unit its behavior could affect the clearing price of the market.

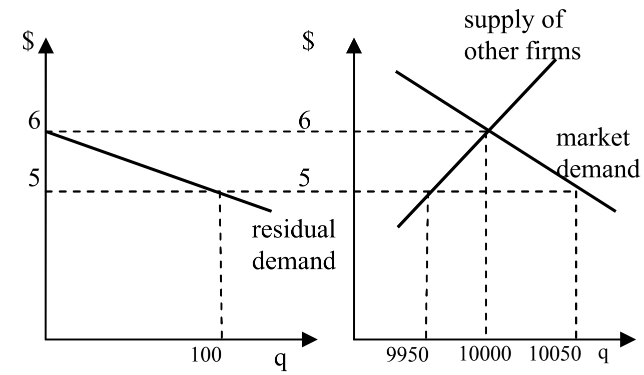

Figure. 1. Residual demand calculation process

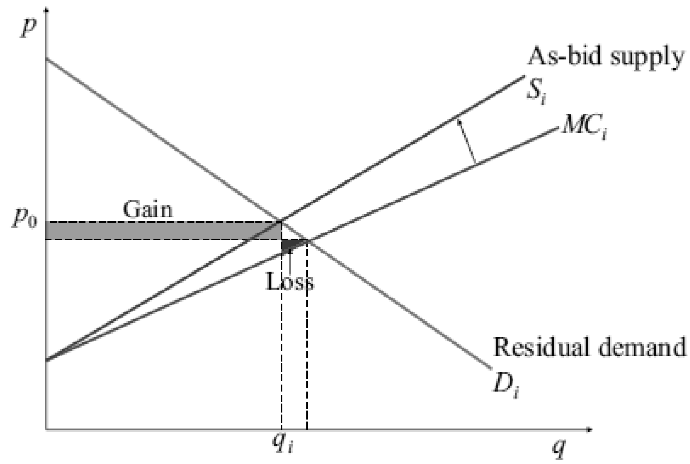

Figure. 2. Process of determining the bid based on residual demand curve

To quantify impact of the uncertainty in participants' bid on the LMP, [6] has used probabilistic optimal power flow. LMP has considered as a probabilistic variable which is function of the participants' bid. Instead of one deterministic value for LMP, its Probability Distribution Function (PDF) is calculated. This information could be used by firms when they making bids

III. IMPACT OF NETWORK TOPOLOGY CHANGE ON LMP

One peculiarity of the electricity market that makes it different from other markets is presence of transmission and distribution systems for delivering the power from the suppliers to the consumers. Power that flows though each line follows the Kirchhoff's laws rather financial contracts between suppliers and consumers. A change in one part of the network can affect power flows on the other parts of the network.

It is quite possible that a given line goes out of the service due to permanent faults or maintenance. Although there is a predefined schedule for the maintenance of the lines, occurrence of the fault is not predictable and may happen at any time.

According to equation (1), security constrained power flow is carried out based on the present topology of the network. Assuming a given topology for the network the optimal power flow is computed while the constraints are taken into account. When an unpredicted outage of the line happens some constraints change. For instance, $P_{ij\max}$ and $P_{ji\max}$ becomes zero for that line. More over outage of a given line changes the power flow equations.

In some cases this change causes drastic variation in the LMPs. Especially in deregulated power system such lines are loaded at their maximum capacities. LMP comprises three components including marginal energy price, marginal congestion price, and marginal loss price [1]. Each of these components can be affected by change in the flow of the power in the lines. If a given line goes out of the service the power that already flows though the line should be distributed through the rest of the lines which may cause congestion of the heavily loaded lines. As a result the LMPs of the power system may change.

It is notable that unscheduled topology change does not happen frequently and there is a probability associated with it. A systematic approach should be developed to quantify impact of unscheduled outage of the lines on LMPs.

It is possible to express LMP at each point as follow:

$$LMP = f(x_1, x_2, \cdots x_n) \tag{2}$$

Where

LMP: Locational Marginal Price

x_i: Factor that affects the LMP. As discussed before some of these factors are as follows:

x_1: Forecasted demand

x_2: Capacity of the line (if the line goes out of the service the capacity becomes zero)

x_3: Bid of others

f(·): the function that relates the input factors(x_i) to the output (LMP). The f(·) can be assumed as Security Constrained Economic Dispatch (SCED) presented in (1). According to (1) LMPs at each nodes of the network are function of uncertain values. For instance, there are always uncertainties associated with forecasted load or it is not possible to exactly estimate behavior of the other participants in the market. Moreover, topology of the network could change unexpectedly due to random occurrence of permanent fault.

To estimate the LMP, performing SCED for every possible combination of loads, parameters of the network, and network topologies is impractical because of the large computational effort required.

A systematic approach should be developed to consider all these uncertainties in the network while still making it computationally affordable. As discussed in section II, the concept of probabilistic LMP (PLMP) has been proposed in the literature to address this issue. The uncertainty in the topology of the network has not been addressed yet which is the focus of this paper. The following procedure is suggested for taking into account the impact of the topology uncertainty on estimated LMP

A. Probability distribution function assignment

In (1), if a line goes out of the service $P_{ij\max}$ and $P_{ji\max}$ become zero. Therefore, Bernoulli distributions could be assigned to the line capacity

Prob (capacity of the line=nominal value)=p

Prob (capacity of the line=0)=q

Where

q is probability of unscheduled outage of the line due to a fault.

According to [10] the probability of fault occurrence on a line can be modeled as the Poisson distribution with a constant fault rate. The probability of not having a fault occurrence in the time period t is given by

$$P_{no} = \frac{e^{-\lambda_0 t}(\lambda_0 t)^0}{0!} = e^{-\lambda_0 t} \tag{3}$$

where

P_{no} : the probability of no fault occurrence

λ_0 : the average fault rate

t :the considered duration

The probability of a fault occurrence in t is

$$P_o = 1 - e^{-\lambda_0 t} \tag{4}$$

If $\lambda_0 t << 1$, the following equation holds:

$$P_o = \lambda_0 t \tag{5}$$

The average fault rate λ_0 can be approximately replaced by the frequency of fault occurrence, which could be obtained from historical records. For a particular transmission line k, the number of faults per unit time (year) and per unit length (100 miles), λ_{k0}, is known. If L_k is the length of the line (in the same units), the expected number of faults on line k per year is [11]

$$\lambda_k = \lambda_{k0} \times L_k \tag{6}$$

λ depends on condition of the weather among others. It is possible a line traverses two regions where Region 1 is in the adverse weather and Region 2 in the less severe weather. Assuming the length exposed to the adverse weather condition is x the total failure rate of the line λ is: x λ_1 + (1-x) λ_2 [12].

As usually λ is a small number and probability of fault occurrence is low. For instance, a 10-mile transmission line with 10 faults per year per 100 miles will have a fault with probability of 0.01% over 1 hour and 0.002% over 10 minutes.

B. Probabilistic LMP calculation

It is possible to conduct widely used Monte Carlo Simulation (MCS) to estimate probabilistic LMP at each bus. However, MCS is computationally expensive and requires huge number of iterations. The alternative method is 2n+1 point estimation method where n is number of uncertain factors. For instance, the five bus PJM system, shown in Fig. 3

[5], has 6 lines, 3 loads, and 5 generators, so in this case the required number of simulation is 29 (2*14+1).

A brief description of the 2n+1 point estimation method is presented here. The details of this method can be found in [7].

For $z = h(X) = h(x_1, x_2, \cdots, x_n)$, where X is a set of random variables x_k, k = 1,2…,n. Assume μ_k, σ_k denote the mean, and standard deviation of variation of x_k respectively and ρ_{ij} is the correlation coefficient between variable x_i and x_j i≠j. Moreover, assume ρ_{ij} =0, i≠j. When $\rho_{ij} \neq 0$, rotational transformation based on the eigenvector of the covariance matrix can be used to transform the set of correlated random variables, X, into an uncorrelated set of random variables, X' [7]. The $p_{k,i}$ is defined as concentrations (or weights) located at $(\mu_1, \mu_2, \cdots, x_{k,i}, \cdots, \mu_{n-1}, \mu_n)$ where

$$x_{k,i} = \mu_k + \xi_{k,i}\sigma_k \quad , i=1,2,..,m \quad k=1,2,\ldots,n \tag{7}$$

Where, m is the number of concentrations per input variable. The standard location $\xi_{k,i}$ and the weight $p_{k,i}$ are obtained by solving the following equations [7]

$$\sum_{i=1}^{m} p_{k,i} = \frac{1}{n} \quad k=1, 2,\ldots,n \tag{8}$$

$$\sum_{i=1}^{m} p_{k,i}(\xi_{k,i})^j = \lambda_{k,j} \quad i = 1, 2,..., m \quad k= 1,2,---,n \tag{9}$$

where $\lambda_{k,j}$ is the ratio of the jth moments about the mean of x_k to $(\sigma_k)^j$ i.e:

$$\lambda_{k,j} = \frac{M_j^{'}(X)}{(\sigma_k)^j} \quad j=1, 2, 3, \ldots. \tag{10}$$

$$M_j^{'}(X) = \int (x-\mu_k)^j f_k(x)dx \tag{11}$$

It is notable that $\lambda_{k,1}$ equals zero, $\lambda_{k,2}$ equals one, and $\lambda_{k,3}$ and $\lambda_{k,4}$ are the coefficient of skewness and coefficient of kurtosis of x_k, respectively.

Once all the $p_{k,i}$ and $x_{k,i}$ are obtained, the jth *raw moment* of the output random variables can be estimated as follow:

$$E(z^j) \cong \sum_{k=1}^{n}\sum_{i=1}^{m} p_{k,i} \times (h(\mu_1, \mu_2, \cdots, x_{k,i}, \cdots, \mu_{n-1}, \mu_n))^j \tag{12}$$

Having the jth *raw moment* it is possible to calculate the jth *central moment* of the output random variable. For instance, mean and standard deviation of the random variable can be calculated as follow:

$$\mu_z = E(z) \cong \sum_{k=1}^{n}\sum_{i=1}^{m} p_{k,i} \times (h(\mu_1, \mu_2, \cdots, x_{k,i}, \cdots, \mu_{n-1}, \mu_n)) \tag{13}$$

$$\sigma_z = \sqrt{E(z^2) - E(z)^2} \tag{14}$$

Skewness, and Kurtosis and other statistical moments of the random variable can also be calculated easily by having jth raw moment [13].

If m = 2 the followings hold:

$$\xi_{k,i} = \frac{\lambda_{k,3}}{2} + (-1)^{3-i}\sqrt{n + (\frac{\lambda_{k,3}}{2})^2} \quad i=1,2 \; k=1, 2,\ldots,n \tag{15}$$

And

$$p_{k,i} = \frac{1}{n}(-1)^i \frac{\xi_{k,3-i}}{\zeta_k} \tag{16}$$

Where

$$\zeta_k = 2\sqrt{n + (\frac{\lambda_{k,3}}{2})^2} \tag{17}$$

It should be noted that in (15) the standard location $\xi_{k,i}$ depends on the number of input random variables. When n becomes large, inaccuracies occur as has been studied in [14]. To overcome this problem, 2n+1scheme has been proposed in [7] and [15]. It requires only one additional evaluation of function compared to the 2n scheme. This scheme is derived from solving (8) and (9) for m=3 with one of the three standard location $\xi_{k,i}$ set to zero.

Let $\xi_{k,3} = 0$. Then, the standard locations and weights are:

$$\xi_{k,i} = \frac{\lambda_{k,3}}{2} + (-1)^{3-i}\sqrt{\lambda_{k,4} - \tfrac{3}{4}\lambda_{k,3}^2} \quad i=1,2 \quad \xi_{k,3} = 0 \tag{18}$$

$$p_{k,i} = \frac{(-1)^{3-i}}{\xi_{k,i}(\xi_{k,1} - \xi_{k,2})} \quad i=1,2 \tag{19}$$

$$p_{k,3} = \frac{1}{n} - \frac{1}{\lambda_{k,4} - \lambda_{k,3}^2} \tag{20}$$

It is notable in (7), setting $\xi_{k,3} = 0$ yields $x_{k,3} = \mu_k$ .So, n of 3n locations are the same point $(\mu_1, \mu_2, \cdots, \mu_k, \cdots, \mu_{n-1}, \mu_n)$. It is enough to run only one evaluation of function at this location, provided that the corresponding weight is updated as follow:

$$p_0 = \sum_{k=1}^{m} p_{k,3} = 1 - \sum_{k=1}^{m} \frac{1}{\lambda_{k,4} - \lambda_{k,3}^2} \tag{21}$$

From (18), it can be seen that the standard location values of the scheme 2n+1do not depend on the number of input random variables, n, as do the m×n type schemes. This is a common feature of all the m×n+1 concentration schemes [15].

IV. CASE STUDY

To demonstrate above mentioned discussions numerically, modified PJM five-bus system, shown in Fig.3, is selected [5]. Tables I and II show parameters of the network.

Suppose a supplier wants to make a decision about its bid for next hour. If normal topology of the network is considered, estimated LMP at bus D becomes $15 as shown in Fig.4.

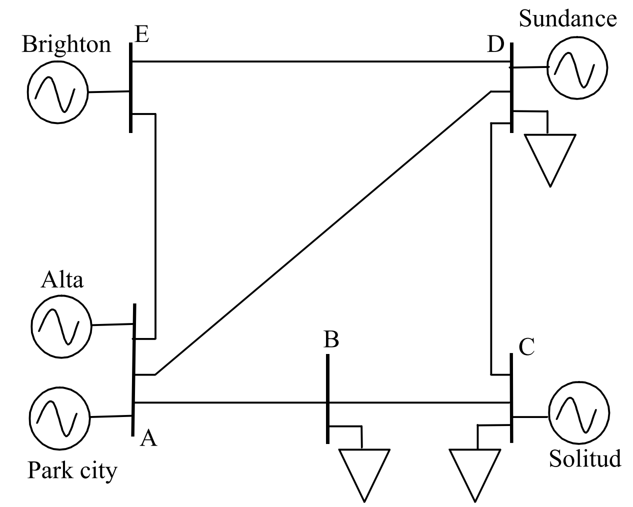

Figure.3. Modified PJM five-bus system

TABLE I
LINE IMPEDANCE AND FLOW LIMITS

Line	AB	AD	AE	BC	CD	DE
X	2.81	3.04	0.64	1.08	2.97	2.97
Limit (MW)	400	--	--	--	--	240

TABLE II
GENERATORS DATA

Generator	A1	A2	C	D	E
MC	14	15	30	35	10
Limit (MW)	40	170	520	200	600

TABLE III
LMP CHANGE AT BUS D DUE TO OUTAGE OF DIFFERENT LINES AT DIFFERENT LOADING CONDITIONS

Line Demand	D-E		D-A	D-C	E-A	A-B	B-C
600 MW	Before After	15 15	15 35	15 15	15 30	15 30	15 15
900 MW	Before After	30 30	30 35	30 30	30 30	30 30	30 30

Line between buses D and E is close to its limit. A possible scenario is that line between buses D and A goes out of service due to permanent fault as shown in Fig.5. In this case line between buses D and E is congested and other lines get closer to their limits. LMP at bus D becomes $35. It is notable that amount of the price change depends upon condition of the system and location of the LMP under study.

Table III shows LMP change at bus D due to outage of different lines at different loading conditions. According to that, outage of line D-E does not have any impact on LMP at bus D. Moreover, while LMP changes from $15 to $30 due to outage of line E-A at demand of 600MW, it does not change at demand of 900MW.

As the goal of this paper is studying impact of unscheduled topology change on the LMP, in (2) x_i s are line capacities.

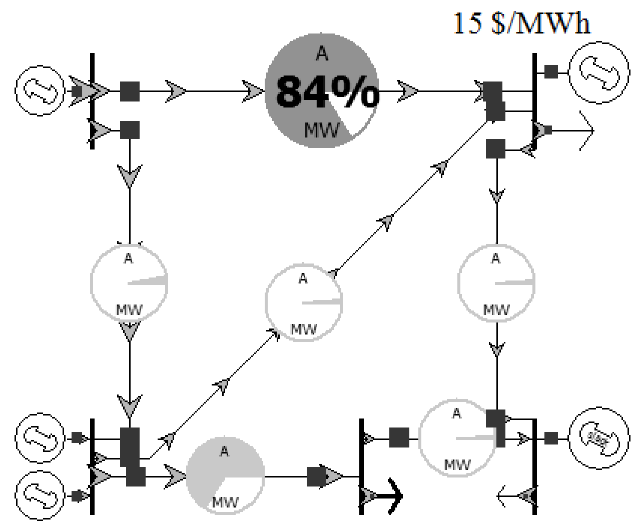

Figure.4. Load flows and LMP at Bus D before outage of line D-A

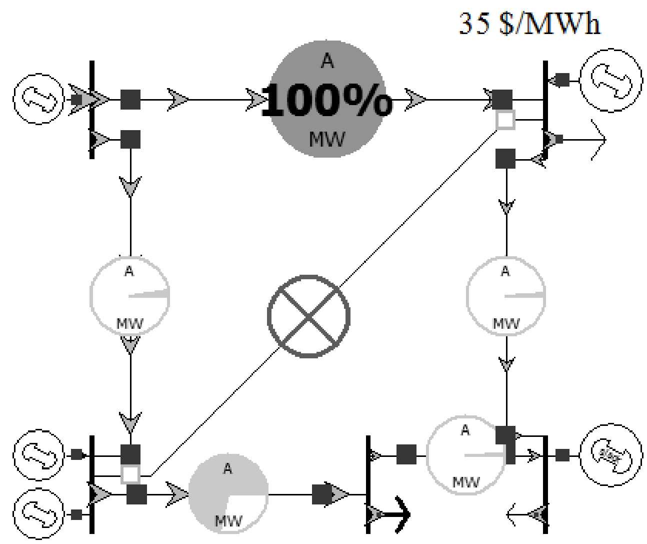

Figure. 5. Load flows and LMP at Bus D after outage of line D-A

As PJM five-bus system, shown in Fig.3, has 6 lines, eq. (2) has 6 input variables as well. Now, according to (12) it is possible to calculate jth *raw moment* of the LMP at bus D.

According to eq. (13) and eq. (14), at demand of 900 MW in hour-ahead market, expected value (μ) and standard deviation (σ) of LMP at bus D are 31.57 and 2.35 respectively. In the case of 10 min-ahead market, they are 30.45 and 1.37 respectively

This information is useful for market participant to develop a better bidding strategy.

V. CONCLUSIONS

In this paper we formulated a probabilistic LMP framework in consideration of network topology uncertainties. In addition to the previous work studying the impact of load uncertainty on LMP, here we proposed a systematic approach to analyze the statistical moments of LMP due to unscheduled transmission line outages. A 2n+1 point estimation method was utilized to calculated statistical moments of LMP. The processes presented in this paper could be beneficial for generation companies and/or load serving entities to develop better bidding strategies.

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VII. Biographies

Saeed Lotfifard (S’08) was born in Karaj, Iran, in1982. He received the B.Sc and M.Sc degrees both in electrical engineering in 2004 and 2006 respectively. Currently, he is a Ph.D student at Texas A&M University.

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Mladen Kezunovic (S’77-M’80–SM’85–F’99) received the Dipl. Ing., M.S. and Ph.D. degrees in electrical engineering in 1974, 1977 and 1980, respectively. Currently, he is the Eugene E. Webb Professor and Site Director of Power Engineering Research Center (PSerc), an NSF I/UCRC.at Texas A&M University He worked for Westinghouse Electric Corp., Pittsburgh, PA, 1979-1980 and the Energoinvest Company, in Europe 1980-1986, and spent a sabbatical at EdF in Clamart 1999-2000. He was also a Visiting Professor at Washington State University, Pullman, 1986-1987 and The University of Hong Kong, fall of 2007. His main research interests are digital simulators and simulation methods for relay testing as well as application of intelligent methods to power system monitoring, control, and protection. Dr. Kezunovic is a Fellow of the IEEE, member of CIGRE and Registered Professional Engineer in Texas.