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Loss of Load Expectation Assessment in Electricity Markets using Monte Carlo Simulation and Neuro-Fuzzy Systems

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1. Introduction

The power systems main emphasis is to provide a reliable and economic supply of electrical energy to the customers (Billinton & Allan, 1996). A real power system is complex, highly integrated and almost very large. It can be divided into appropriate subsystems in order to be analyzed separately (Billinton & Allan, 1996). This research deals with generation reliability assessment in power pool markets, and transmission and distribution systems are considered reliable (Hierarchical Levels-I, HL-I) as shown in Fig. 1.

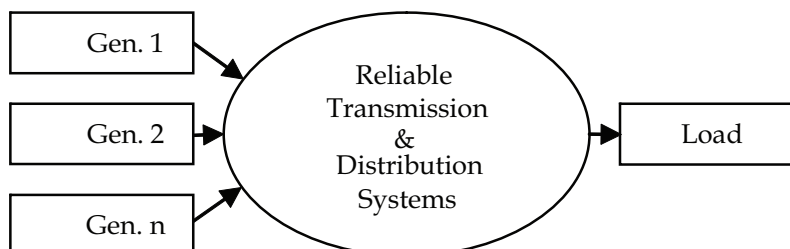


Fig. 1. Power pool market schematic for generation reliability assessment

Most of the methods used for generation reliability evaluation are based on the “loss of load or energy” approach. One of the suitable indices that describes generation reliability level is “Loss of Load Expectation” (LOLE), that is the time in which load is more than the available generation capacity.

Generally, the reliability indices of a system can be evaluated using one of the following two basic approaches (Billinton & Allan, 1992):

- Analytical techniques
- Stochastic simulation

Simulation techniques estimate the reliability indices by simulating the actual process and random behavior of the system. Since power markets and generators’ forced outages have stochastic behavior, Monte Carlo Simulation (MCS), as one of the most powerful methods for statistical analysis of stochastic problems, is used for reliability assessment in this research.

Generation reliability depends absolutely on the generating units specifications. The main function in traditional structure for Unit Commitment (UC) of the generators is to minimize generation costs. Since the beginning of the 21st century, many countries have been trying to deregulate their power systems and create power markets (Salvaderi, 2000), (Mountford & Austria, 1999), (Draper, 1998), (Puttgen et al, 2001), (Mc Clanahan, 2002). In the power markets, the main function of players is their own profit maximization, which severely depends on the type of the market. As a result, generation reliability assessment depends on market type and its characteristics.

Generally, economists divide the markets into four groups, varying between perfect competition market and monopoly market (Pindyck & Rubinfeld, 1995). This study deals with the evaluation of generation reliability in different kinds of power pool markets based on the market concentration. Let's review some of the papers proposed till now.

An optimization technique is proposed in (Wang et al, 2009) to determine load shedding and generation re-dispatch for each contingency state in the reliability evaluation of restructured power systems with the Poolco market structure. The problem is formulated using the optimal power flow (OPF) technique. The objective of the problem is to minimize the total system cost, which includes generation, reserve and interruption costs, subject to market and network constraints.

Reference (Jaeseok et al, 2001) has used "Effective Load Duration Curve" (ELDC) for evaluation of "Loss of Load Expectation" (LOLE) and "Expected Energy Not Served" (EENS) as reliability indices.

Reference (Wang & Billinton, 2001) has presented some reliability models for different players in a power system, where generation system is represented by an equivalent multi-state generation provider (EMGP). The reliability parameters of each EMGP are shown by an available capacity probability table (ACPT), which is determined using conventional techniques. Then, the equivalent reliability parameters for each state (including state probability, frequency of encountering the state and the equivalent available generation capacity) are determined.

Reference (Haroonaabadi & Haghifam, 2009) compares generation reliability in various economic markets: Perfect Competition, Oligopoly and Monopoly power pool markets. Also, due to the stochastic behavior of power market and generators' forced outages, Monte Carlo Simulation is used for reliability evaluation.

In researches dealing with power marketing and restructuring, market behavior and its economic effects on the power system should be considered. Therefore, this research considers power pool market fundamentals and deals with generation reliability assessment in power pool market using MCS and an intelligent system. Also, sensitivity of reliability index to different reserve margins and times will be evaluated. In Section-2, the fundamentals of power pool market will be discussed. In Section-3, the algorithm for generation reliability assessment in power pool market will be proposed, and finally in Section-4, the case study results will be presented and discussed.

2. Power pool markets fundamentals

Market demand curve has negative gradient, and the amount of demand decrease is explained by "price elasticity of demand". This index is small for short terms, and big for

long terms; because in longer terms, customers can better adjust their load relative to price (IEA, 2003). Demand function, generally, is described as $P=a-b.Q$. Therefore, price elasticity of demand is explained as:

$$E_d = \left| \frac{dQ}{dP} \right| = \frac{1}{b} \tag{1}$$

Let’s suppose forecasted load by dispatching center is an independent power from price that equals to Q_n . Therefore, demand function can be obtained as:

$$P = a - b.Q = b.Q_n - b.Q = \frac{Q_n}{E_d} - \frac{Q}{E_d} \tag{2}$$

Typically, as shown in Fig. 2, price elasticity in power markets is 0.1-0.2 for the next 2-3 years and 0.3-0.7 for the next 10-20 years (IEA, 2003).

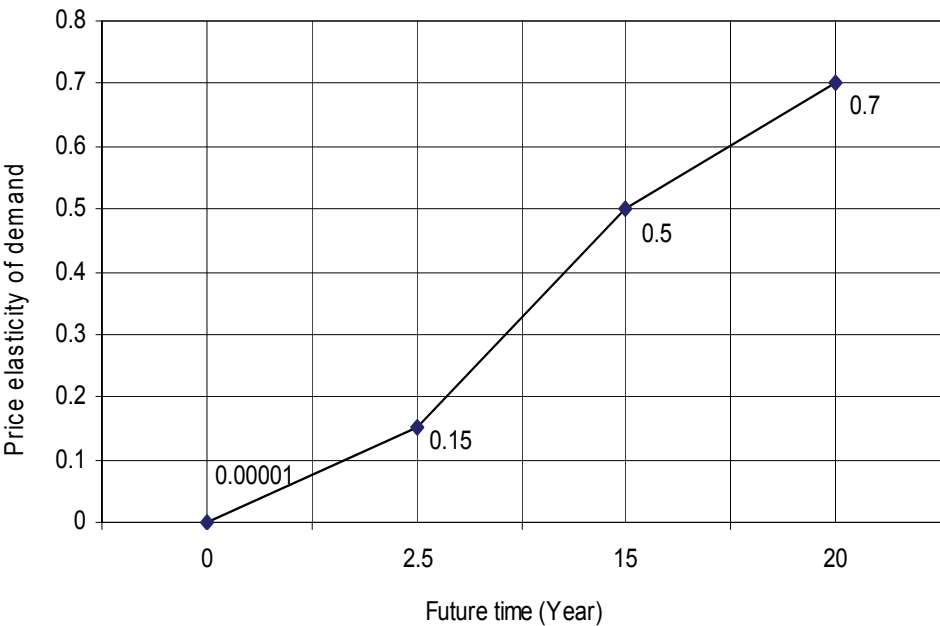


Fig. 2. Price elasticity of demand for various times

Offer curve of a company, which participates in a market without any market power is part of the marginal cost curve that is more than minimum average variable cost (Pindyck & Rubinfeld, 1995). Also, total offer curve of all companies is obtained from horizontal sum of each company’s offer curve. This curve is a merit order function. In economics, if sale price in a market becomes less than minimum average variable cost, the company will stop production; because the company will not be able to cover not only the fix cost but even the variable cost (Pindyck & Rubinfeld, 1995). Due to the changing efficiency and heat rate of power plants, marginal cost is less than average variable cost. Therefore, in power plants, average variable cost replaces marginal cost in economic studies (Borenstein, 1999). In a perfect competition market, equilibrium price and equilibrium amount are obtained from the intersection of total offer curve and demand curve. On the other hand, in a

monopoly market, the monopolist considers the production level, which maximizes his profit. It is proved that the monopolist considers the level of production in which marginal cost of each firm (and total marginal cost of all firms) equals to the marginal revenue of the monopolist (Pindyck & Rubinfeld, 1995):

$$MC_1 = MC_2 = \dots = MC = MR \tag{3}$$

Where:

$$MR = a - 2.b.Q = b.Q_n - 2.b.Q = \frac{Q_n}{E_d} - \frac{2.Q}{E_d} \tag{4}$$

Comparison of (2) and (4) shows that if there is no market power, offer curve of industry for each market (from perfect competition market to monopoly market) will equal marginal cost; but negative gradient of demand exponent curve (DE) varies between b (for demand function in perfect competition market) and $2b$ (for marginal revenue in monopoly market). Therefore, generally, demand exponent curve can be expressed as:

$$DE = a - K.b.Q = \frac{Q_n}{E_d} - \frac{K.Q}{E_d} \tag{5}$$

Where, K varies between 1 and 2.
Fig. 3 shows the typical total offer and demand exponent curves.

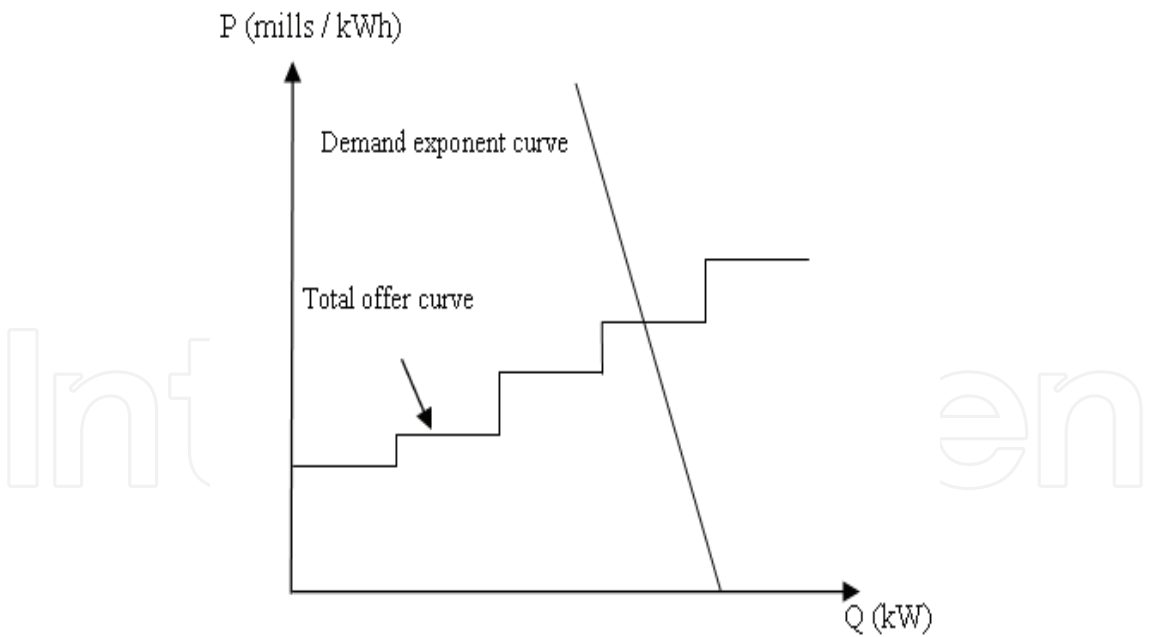


Fig. 3. Typical total offer and demand exponent curves

3. Proposed method for generation evaluation in power markets

In power markets, Hirschman-Herfindahl Index (HHI), which is obtained from (6), is used for market concentration measurement (IEA, 2003):

$$HHI = \sum_M q_i^2$$

(6)

If market shares are measured in percentages, *HHI* will vary between 0 (an atomistic market) and 10000 (monopoly market). According to a usual grouping, the US merger guidelines stipulate an assumption that markets with a *HHI* below 1000 is unconcentrated, a *HHI* between 1000 and 1800 is moderately concentrated, and a *HHI* above 1800 is highly concentrated (FTC, 1992).

As mentioned before, according to the type of market and *HHI* values, negative gradient of demand exponent curve varies between *b* and *2b*. Therefore, for modeling the market, a fuzzy number is proposed in this study to estimate the gradient coefficient of demand exponent curve (*K*) based on the *HHI* values. Membership functions of unconcentrated, moderately concentrated and highly concentrated markets' fuzzy sets and the equation to estimate gradient coefficient are shown in Fig. 4 and (7), respectively.

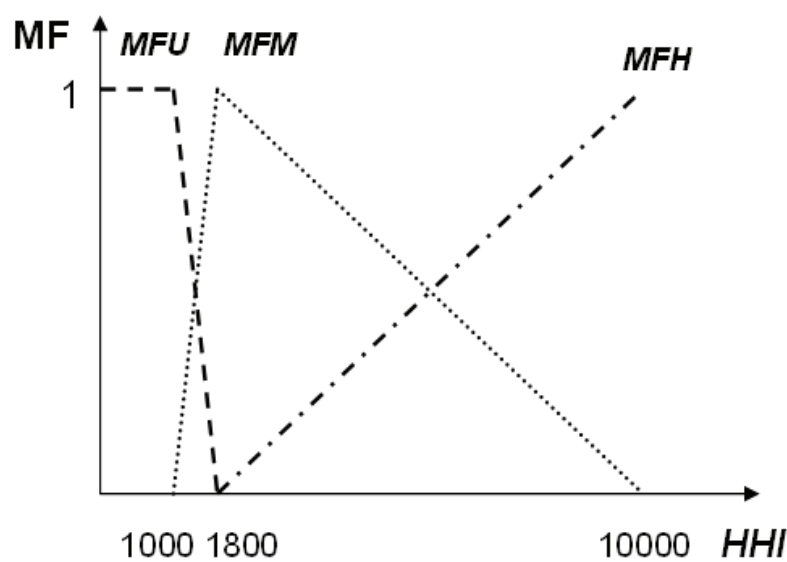


Fig. 4. Membership functions of unconcentrated, moderately concentrated and highly concentrated markets' fuzzy sets

$$K = (MFU + 1.5 \times MFM + 2 \times MFH)$$

(7)

As Fig. 4 and (7) show, while the proposed coefficient (*K*) covers all kinds of markets with different concentration degrees, the changes of these degrees are not sudden, rather they are gradual and continuous. Also, the proposed method and fuzzy logic are valid for all power pool markets.

Generation reliability of a power system depends on many parameters, especially on reserve margin, which is defined as (IEA, 2002):

$$RM\% = \frac{Installed\ Capacity - Peak\ Demand}{Peak\ Demand} \times 100$$

(8)

The algorithm of generation reliability assessment in power pool markets using Monte Carlo simulation and proposed fuzzy logic is as follows (Fig. 5):

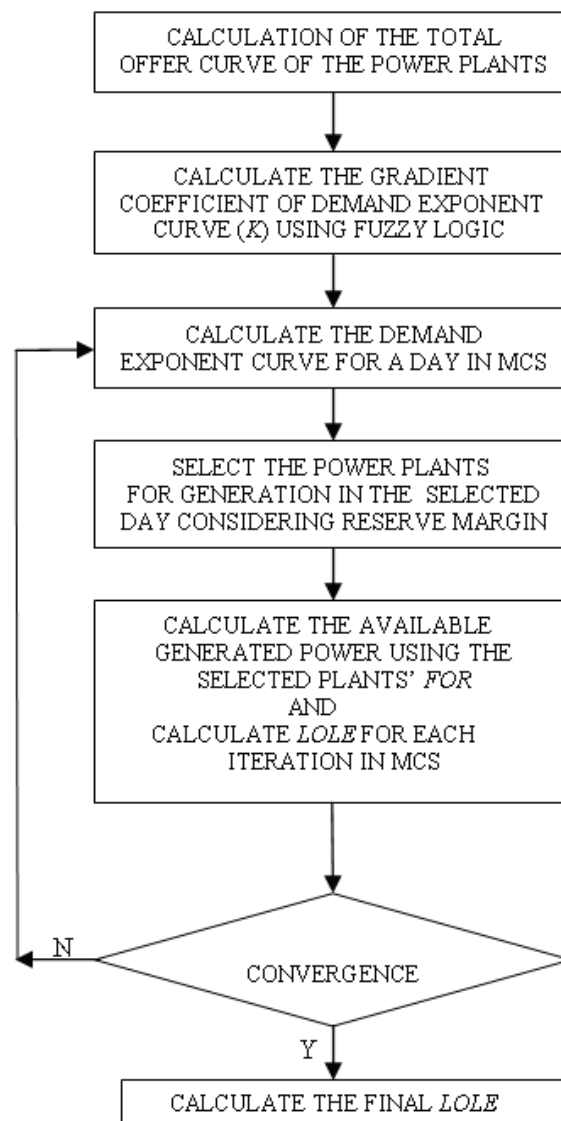


Fig. 5. Flow chart of HLI reliability assessment in power markets using MCS

HHI is obtained based on characteristic of the market. The gradient coefficient of demand exponent curve (K) is calculated using Fig. 4 and (7).

1. Calculation of the total offer curve of power plants.
2. Select a random day and its load (Q_n), and calculate demand exponent curve using (5).
3. The power plants, selected for generation in the selected day, are determined from the intersection of the power plants' total offer curve and demand exponent curve with regards to the reserve margin.
4. For each selected power plant in the previous step, a random number between 0-1 is generated. If the generated number is more than the power plant's Forced Outage Rate (FOR), the power plant is considered as available in the mentioned iteration; otherwise it encounters forced outage and thus can not generate power. This process is performed for all power plants using an independent random number generated for each plant. Finally, sum of the available power plants' generation capacities is calculated. If the sum becomes less than the intersection of power plants' total offer curve and demand exponent curve, we will have interruption in the iteration, and therefore, $LOLE$ will

increase one unit; otherwise, we will go to the next iteration. The algorithm of available generated power and *LOLE* calculations for each iteration in MCS is shown in Fig. 6.

5. The steps 3 to 5 are repeated for calculation of final *LOLE*.

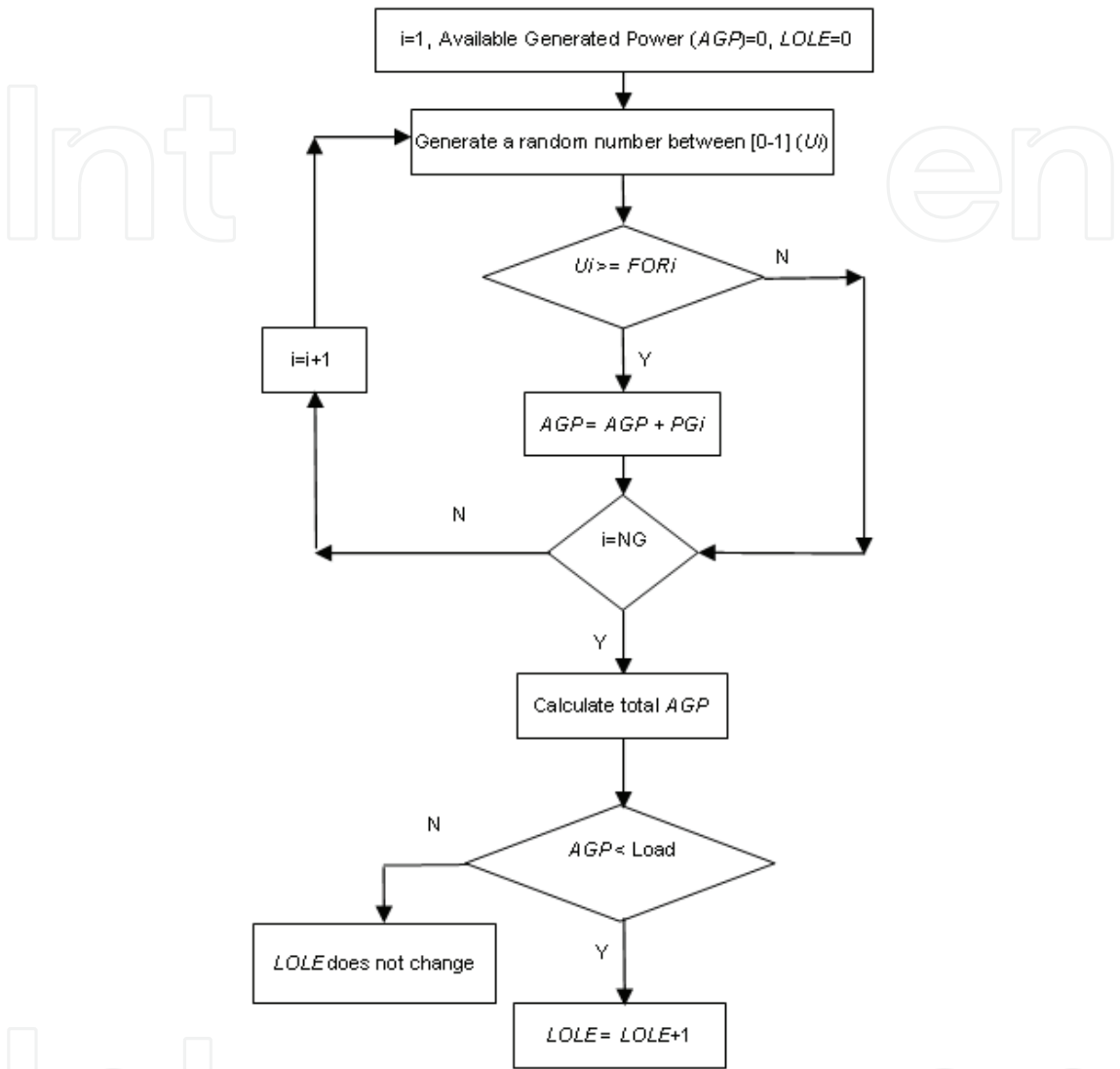


Fig. 6. Algorithm of available generated power and *LOLE* calculations for each iteration using MCS

Now, to create a unique structure, a four-layer perceptron neural network (N.N.) is used for reliability evaluation. The number of the neurons in each layer is 20, 15, 12 and 1, respectively (Fig. 7). All the neurons in the first, third and last layers have POSLIN transfer function, and the second layer has TANSIG transfer function. Inputs of the neural network include:

- Gradient coefficient of demand exponent curve (*K*)
- Simulated future time (*FT*)
- Reserve margin (*RM*)

Also, neural network's output is *LOLE* index.

Parts of the MCS results, obtained from the mentioned algorithm, are used for neural network training.

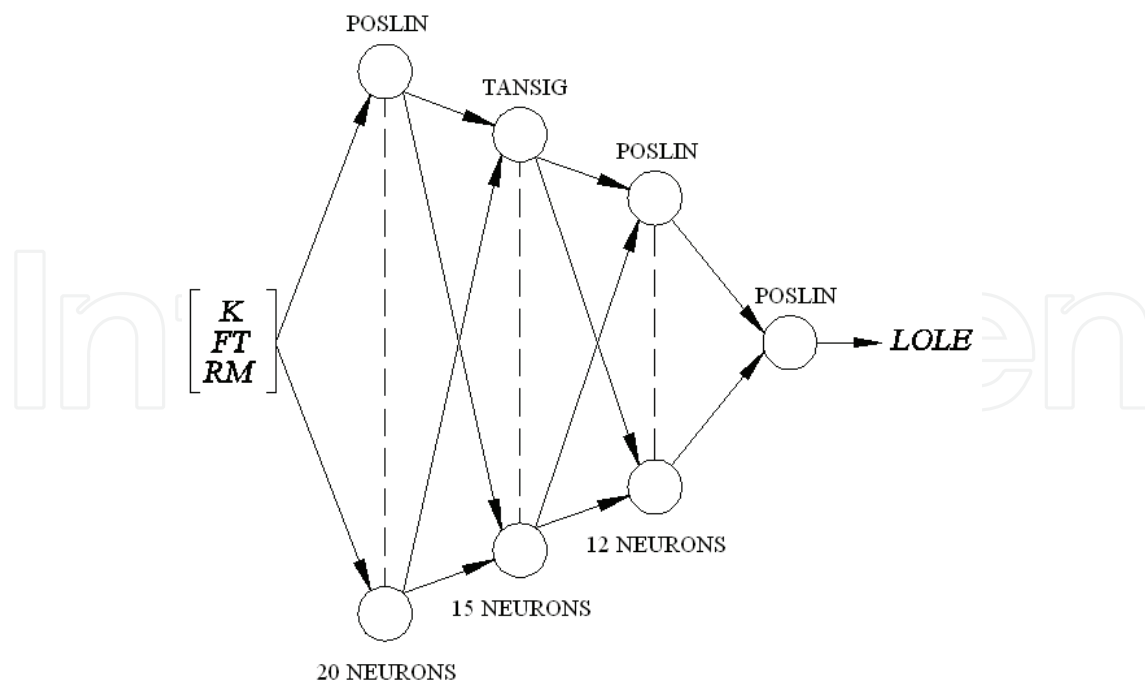


Fig. 7. Proposed N.N. for HLI reliability evaluation

4. Numerical studies

IEEE - Reliability Test System (IEEE-RTS) is used for case studies. The required data for IEEE-RTS can be found in (Reliability Test System..., 1979). The following assumptions are used in various case studies:

1. All case studies are simulated for the second half of the year, based on the daily peak load of the mentioned test system.
2. All simulations are done with 5000 iterations.
3. Neural network is trained with TRAINLM method in MATLAB 7.0 software with 150 epochs. In this research, the neural network reached 0.2 Mean Square Error (MSE) after training.
4. Each case study is simulated for two different times (present time and the 2nd next year) and two different reserve margins (0%, 9%).
5. Annual growth rates of the power plants' generation capacity and consumed load are considered as 3.4% and 3.34%, respectively.
6. Annual growth rates of oil and coal costs are considered as 4% and 1%, respectively. Nuclear fuel cost (including uranium, enrichment and fabrication) is considered as a fixed rate. Also, annual growth rate of variable Operating and Maintenance (O&M) cost is considered as 1%.

In the first case study, each power plant is assumed as an independent company. Therefore, *HHI* equals 634, and the market is unconcentrated. Using Fig. 4 and (7), *K* is calculated as 1, as shown in Fig. 8. Based on this assumption and using MCS algorithm and the proposed neural network, *LOLE* values are obtained versus different times and reserve margins as shown in Fig. 9 and Fig. 10, respectively.

The error between the *LOLE* values obtained from MCS and neural network in the first study is 0.4%.

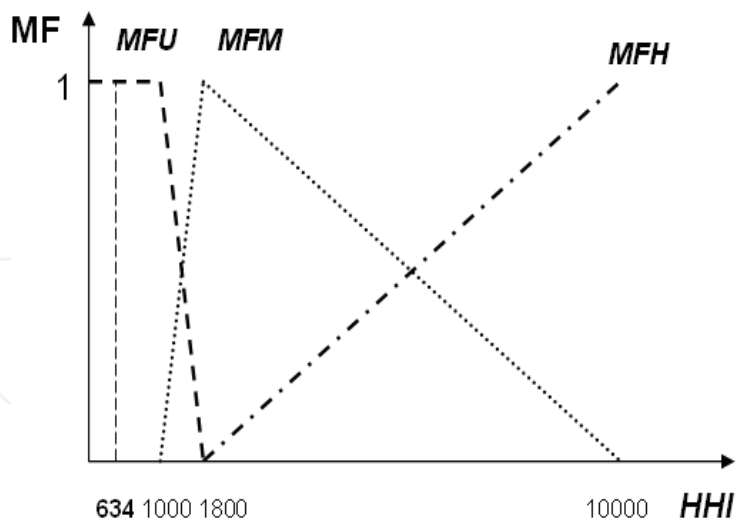


Fig. 8. The gradient calculation of demand exponent curve using membership functions for the first study

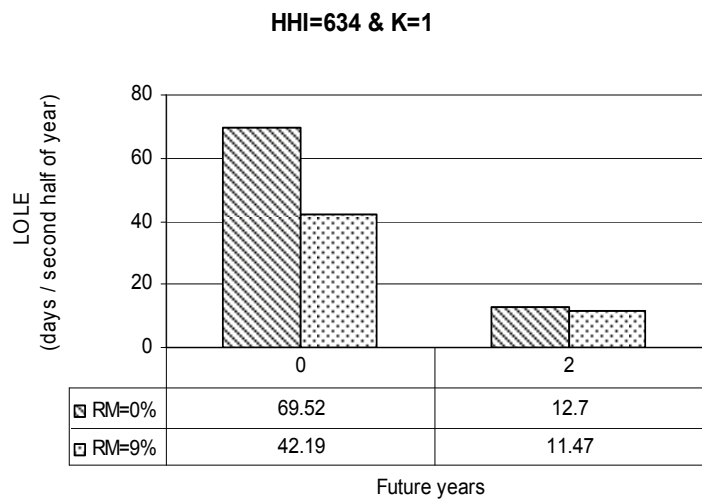


Fig. 9. LOLE values for the first study using MCS

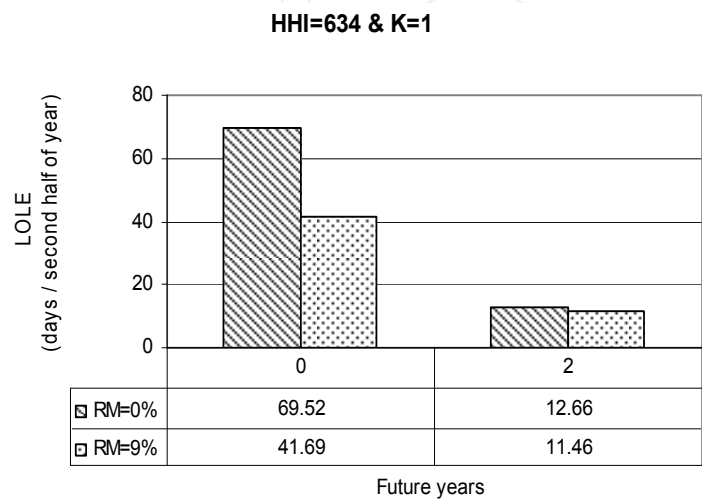


Fig. 10. LOLE values for the first study using N.N.

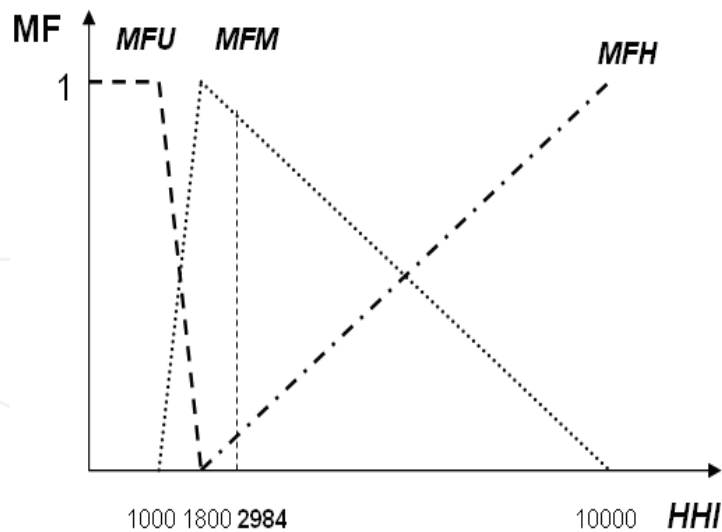


Fig. 11. The gradient calculation of demand exponent curve using membership functions for the second study

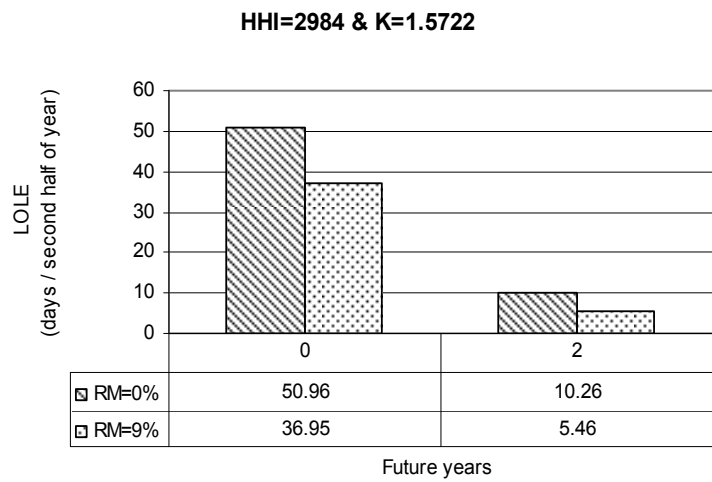


Fig. 12. LOLE values for the second study using MCS

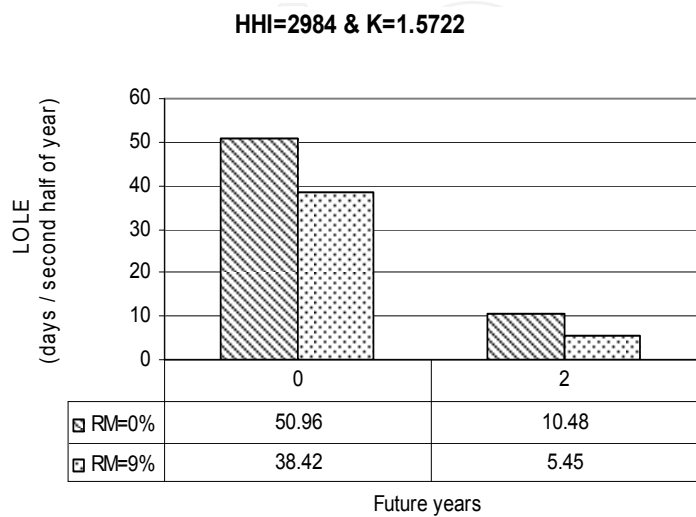


Fig. 13. LOLE values for the second study using N.N.

In the second study, all the power plants based on their types (including oil, coal, nuclear and water plants) are classified. Therefore, HHI equals 2984, and K is calculated as 1.5722 (Fig. 11). Based on this assumption and using MCS algorithm and the proposed neural network, $LOLE$ values are obtained versus different times and reserve margins as shown in Fig. 12 and Fig. 13, respectively.

The error between the $LOLE$ values obtained from MCS and neural network in the second study is 1.64%.

In the third study, all fossil power plants (including oil and coal power plants) are classified in one company, and other power plants are as in the second case study. Therefore, the types of power plants are fossil, nuclear and water. As a result, HHI equals 5290, and K is calculated as 1.7128 (Fig. 14). Based on this assumption and using MCS algorithm and the proposed neural network, $LOLE$ values are obtained versus different times and reserve margins as shown in Fig. 15 and Fig. 16, respectively.

The error between the $LOLE$ values obtained from MCS and neural network in the third study is 1.53%.

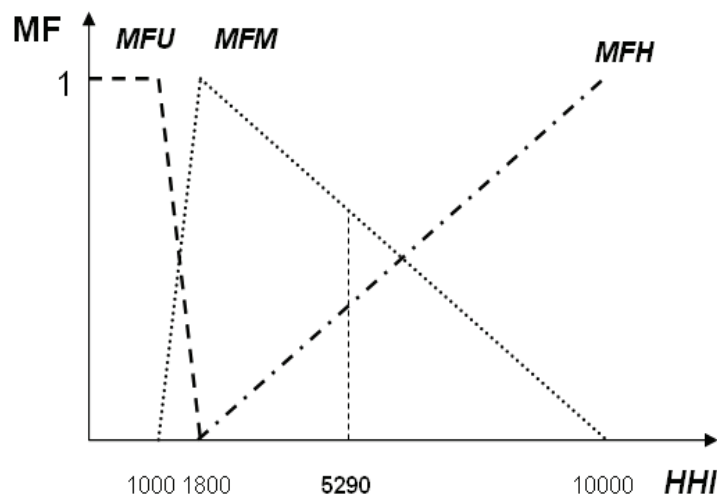


Fig. 14. The gradient calculation of demand exponent curve using membership functions for the third study

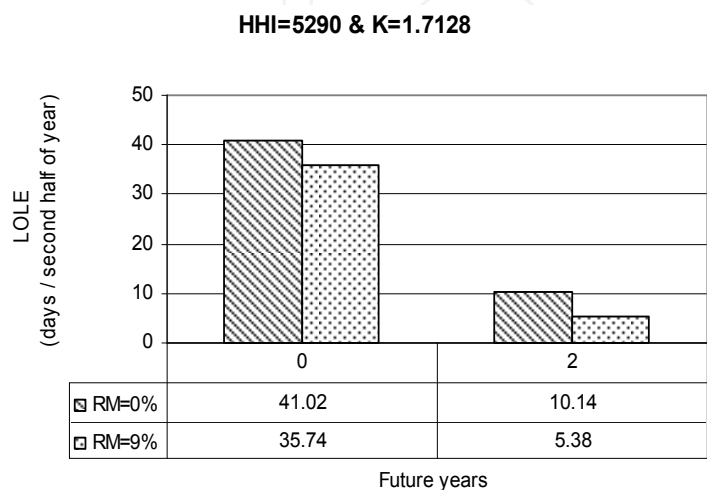


Fig. 15. $LOLE$ values for the third study using MCS

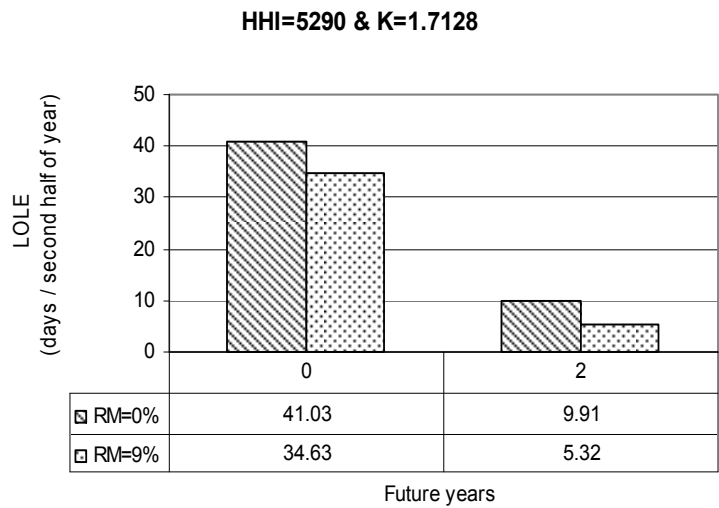


Fig. 16. *LOLE* values for the third study using N.N.

In the fourth study, it is assumed that all power plants belong to a monopolist, and the market is fully concentrated and monopoly. Therefore, *HHI* equals 10000, and *K* is calculated as 2 (Fig. 17). Based on this assumption and using MCS algorithm and the proposed neural network, *LOLE* values are obtained versus different times and reserve margins as shown in Fig. 18 and Fig. 19, respectively. The error between the *LOLE* values obtained from MCS and neural network in the fourth study is 0.5%.

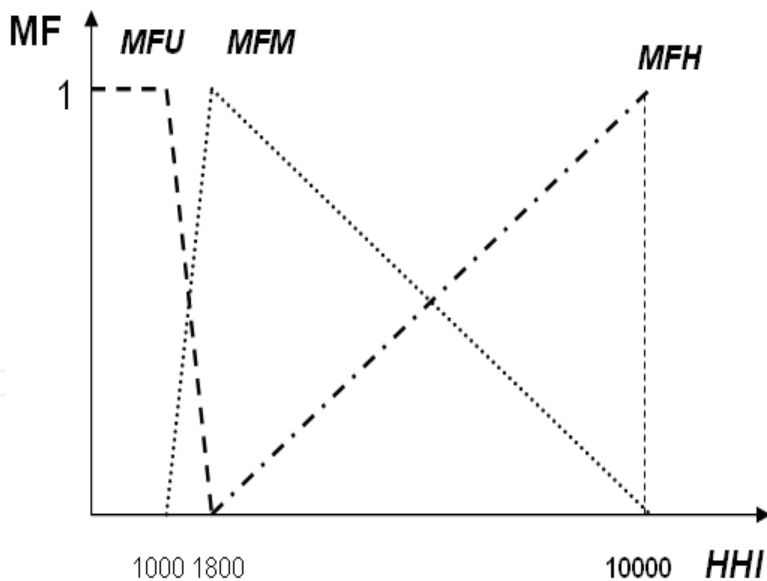


Fig. 17. The gradient calculation of demand exponent curve using membership functions for the fourth study

As it is shown in all case studies, *LOLE* values in the neural network method are very similar to MCS values. Evidently, the neural network's specifications depend on the power system's characteristics, and the proposed neural network is valid for the mentioned power system. Therefore, neural network's specifications may be changed in another power system based on the power system parameters.

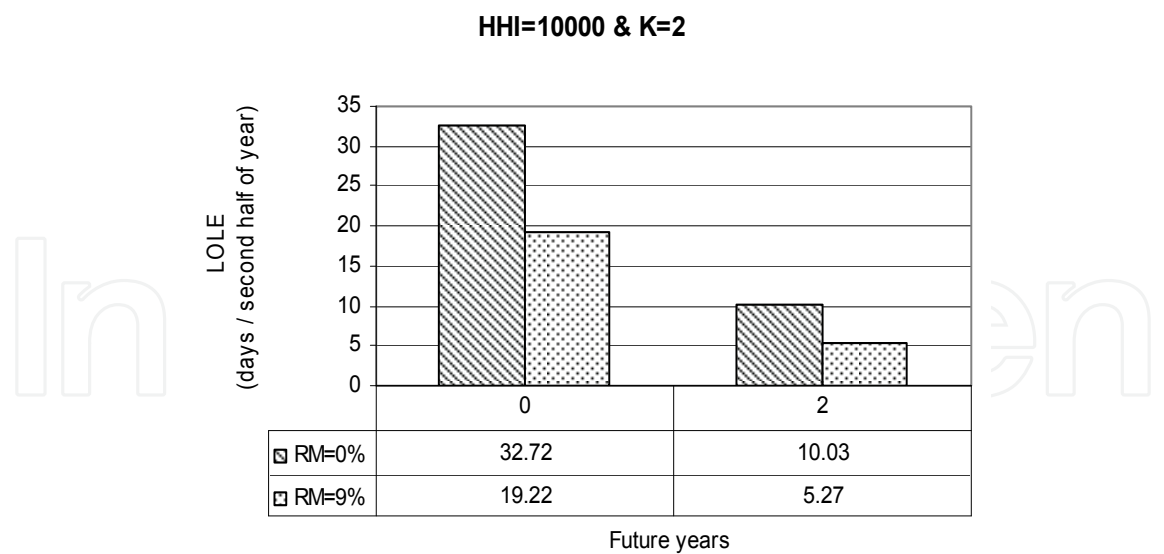


Fig. 18. *LOLE* values for the fourth study using MCS

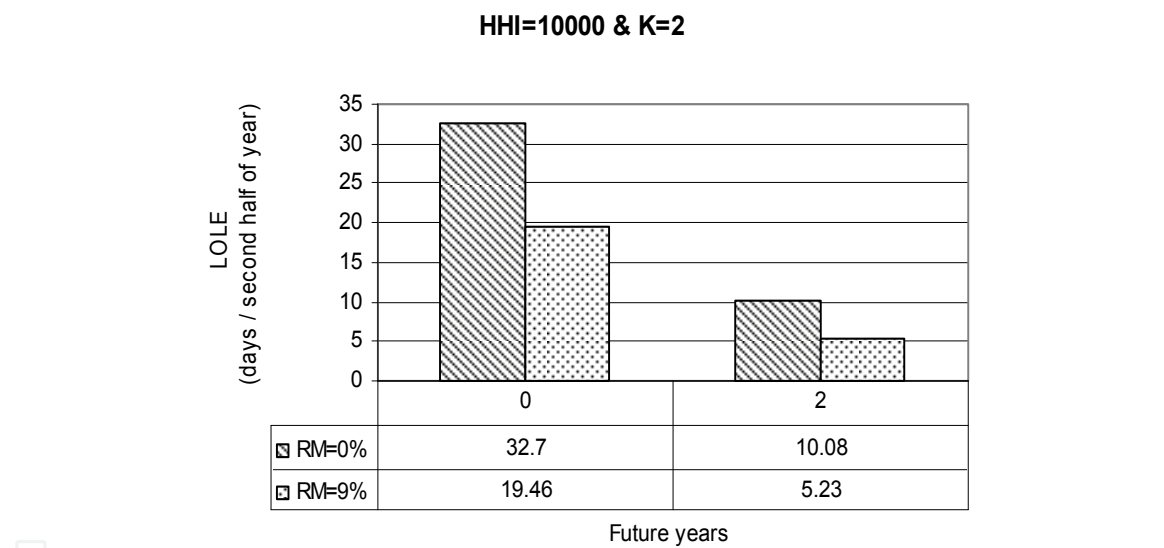


Fig. 19. *LOLE* values for the fourth study using N.N.

In all case studies, if reserve margin increases, *LOLE* will decrease and reliability will improve.

As mentioned before, in longer terms, customers can better adjust their load relative to the price. Therefore, price elasticity increases in longer terms, and according to (5), demand exponent curve reaches less gradient. As a result, intersection of the power plants’ total offer curve and demand exponent curve will occur at less demand. This matter leads to operate from fewer power plants. Therefore, in each case study, if time increases, *LOLE* will decrease.

If market becomes more concentrated or *HHI* becomes bigger, *K* will find bigger value. Therefore, according to (5), intersection of the power plants’ total offer curve and demand exponent curve will occur at less demand. Therefore, *LOLE* will decrease. So that in the fourth study (monopoly market), *LOLEs* are the least values comparing to the other case studies.

It is to be noted that since available capacity of hydro plants in IEEE-RTS are different in the first and the second halves of the year, therefore, simulations were done for the second half of the year. Evidently, the proposed method can be utilized for every simulation time. Also, in this study, it was supposed that the annual additional generation capacity is uniformly distributed between all the present generators.

5. Conclusion

This research deals with generation reliability assessment in power pool market using Monte Carlo simulation and intelligent systems. Since changes of market concentration in power markets are gradual, a fuzzy logic was proposed for calculation of the gradient coefficient of demand exponent curve. Due to the stochastic behavior of market and generators' *FOR*, MCS was used for the simulations. Also, for creation of a unique structure for reliability assessment, a neural network was used, which its outputs were very similar to MCS results. In this research, *LOLE* was used as reliability index and it was shown that if market becomes more concentrated, *LOLE* will decrease and reliability will improve. Also, if price elasticity of demand increases, *LOLE* will decrease.

Follows can be considered for future researches:

1. Reliability indices evaluate in HL-II zone in which both generation and transmission systems are considered.
2. Bilateral contracts consider in the power market as well as pool market.
3. If the generation planning scenarios in a power system are specified, then they can be used instead of uniformly distribution of annual additional generation capacity.
4. Reserve market can be considered as an independent market of the main energy market.

6. Symbol list:

MC: Marginal cost (mills/kWh)

MR: Marginal revenue (mills/kWh)

Q: Quantity of power (kW)

P: Electrical energy price (mills/kWh)

RM: Reserve margin (%)

E_d : Price elasticity of demand (kW²h/mills)

Q_n : Forecasted load (kW)

LOLE: Loss of load expectation (days/second half year)

FOR: Forced outage rate of power plants

q_i : Share of i^{th} company in the pool market (%)

M : Number of independent companies in the market

a : Demand exponent curve cross of basis (mills/kWh)

b : Demand exponent curve gradient (mills /kW²h)

HHI: Hirschman - Herfindahl index

DE: Demand exponent curve

K : Gradient coefficient of demand exponent curve

MFU: Membership function of unconcentrated market

MFM: Membership function of moderately concentrated market

MFH: Membership function of highly concentrated market

FT: Simulated future time (year)

NG: Number of selected plants for generation in the market

AGP: Available generated power

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Edited by Prof. Shaul Mordechai

ISBN 978-953-307-691-1

Hard cover, 950 pages

Publisher InTech

Published online 28, February, 2011

Published in print edition February, 2011

In this book, Applications of Monte Carlo Method in Science and Engineering, we further expose the broad range of applications of Monte Carlo simulation in the fields of Quantum Physics, Statistical Physics, Reliability, Medical Physics, Polycrystalline Materials, Ising Model, Chemistry, Agriculture, Food Processing, X-ray Imaging, Electron Dynamics in Doped Semiconductors, Metallurgy, Remote Sensing and much more diverse topics. The book chapters included in this volume clearly reflect the current scientific importance of Monte Carlo techniques in various fields of research.

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H. Haroonabadi (2011). Loss of Load Expectation Assessment in Electricity Markets using Monte Carlo Simulation and Neuro-Fuzzy Systems, Applications of Monte Carlo Method in Science and Engineering, Prof. Shaul Mordechai (Ed.), ISBN: 978-953-307-691-1, InTech, Available from:
<http://www.intechopen.com/books/applications-of-monte-carlo-method-in-science-and-engineering/loss-of-load-expectation-assessment-in-electricity-markets-using-monte-carlo-simulation-and-neuro-fu>

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