Valuation Model for Generation Investment in an Oligopoly Electricity Market

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Abstract- This paper proposes a new explicit, step-by-step approach for a generating company to evaluate investments considering uncertainties and future expected investment from its competitors. The new framework consists of i) defining some potential investments to be evaluated; ii) anticipating competitors' future expansion plans using dynamic programming; iii) generating future cash-flow for each investment alternative by clearing the market every year considering the anticipated system expansion over the life time of the plant; iv) computing each plan's rate of return. The evaluation has been carried out on three different technologies i.e. nuclear, coal and combined cycle power plants. We also introduce a probabilistic valuation model to incorporate risk assessment in the evaluation. We extend the framework to consider uncertainties in future load growth and plant technologies' fuel cost and use a Monte Carlo simulation to capture the statistical fluctuations of the rate of return. We also use a rigorous technique to approximate the load duration curve with a step-function. In order to model an oligopoly market, we assume that at higher loads, the generators submit bids higher than their marginal cost. A price duration curve from PJM market is used to extrapolate the bid price of these units.

1.0 INTRODUCTION

Capacity investment decisions in a restructured and liberalized electricity market are more complex to model than in a traditional centralized industry. In this new environment, the decision to build a new plant can be taken by any participating company in the market independently of what its competitors might decide to do. Since each generating company has limited information on its competitors' investment strategy, it has to anticipate what they might do in the future. Moreover, each generating company also has to forecast what is likely to happen over the lifetime of the plant in terms of demand, fuel cost and the bidding strategies of its competitors. The uncertainties on all these variables must be carefully modelled for a proper individual expansion assessment.

The traditional levelised cost methodology has been widely used as an assessment method for investment. However this approach alone does not take risk into account in an effective way. Therefore it needs to be complemented by approaches that account for risks in future cost and revenues [1]. The classic economic theory has also been further extended by means of probabilistic analysis to take into account the risk and uncertainty in valuing the investment. The authors of [2] use a probabilistic analysis to compare investments in three base-load technologies (combined cycle gas turbine (CCGT), coal and nuclear). The authors of [3, 4] extend the traditional probabilistic production costing model to incorporate probabilistic evaluation and risk assessment and in [5] a probabilistic model to price the risks of bidding strategies in auction for long term electricity contract is proposed. Real option theory, which is a technique borrowed from financial options theory, has recently been used to estimate future uncertainty in prices given the observed volatility. For example, the authors of

[6-8] have used it to determine an investor's optimal generation investment decision in restructured power systems.

This paper proposes an investment model for a generating company to evaluate power investment in competitive electricity market considering future investment from the competitors. Instead of simplifying the technique of calculating electricity spot price such as using random distribution of electricity prices [2, 4], trend extrapolation [9] or a stochastic process such as in real option theory, which do not take into account possible new plants and closure of old ones in the next few years, this paper adopts an explicit approach for calculating the electricity price by clearing the market considering the expected change in the system. This paper also uses a probabilistic analysis to evaluate the investment risks.

2.0 MODEL DESCRIPTION

2.1 Overview of Investment Evaluation in a Competitive Electricity Market

Fig. 1 shows a flow diagram of an investment evaluation by a generating company, which we shall call company A. This process in general includes stages for investment options identification, investment evaluation and decision-making. In the investment options identification, the generating company defines some potential investment options to be evaluated. When evaluating each possible investment, the generating company needs to consider the fact that other plants will be built and retired over the lifetime of the plant that the company is evaluating. A prototype investment plan for all the companies is then defined using dynamic programming. An expected retirement schedule of the existing plants is provided as input data to the dynamic programming. This prototype is based on the assumption that overall generation expansion will minimize the total cost of expansion and operation over the planning horizon.

In the evaluation framework, the generating company forecasts the load duration curve (LDC), the future load growth and the fuel cost. An optimal step-function approximation to fit the LDC based on the minimization of total penalty function using dynamic programming [10] is used prior to the investment evaluation. On the other hand, the electricity prices are a by-product of the market clearing process every year. In this process, the generators in the system are stacked in order of bidding price to meet the demand and the price is determined by the marginal generator. Based on these prices, the revenue produced by a new plant can be calculated for every year of its expected lifetime and used to determine the internal rate of return (IRR) and the net present value (NPV) of this investment. Finally, in the decision framework, the generating company compares the profitability of different investments and makes decision on which plant to build.

The proposed model can be extended to consider uncertainties using Monte Carlo simulation as also shown in Fig. 1. The uncertainties are modelled as probability distributions and a Monte Carlo simulation is used to determine the distribution of IRR for the investment plan.

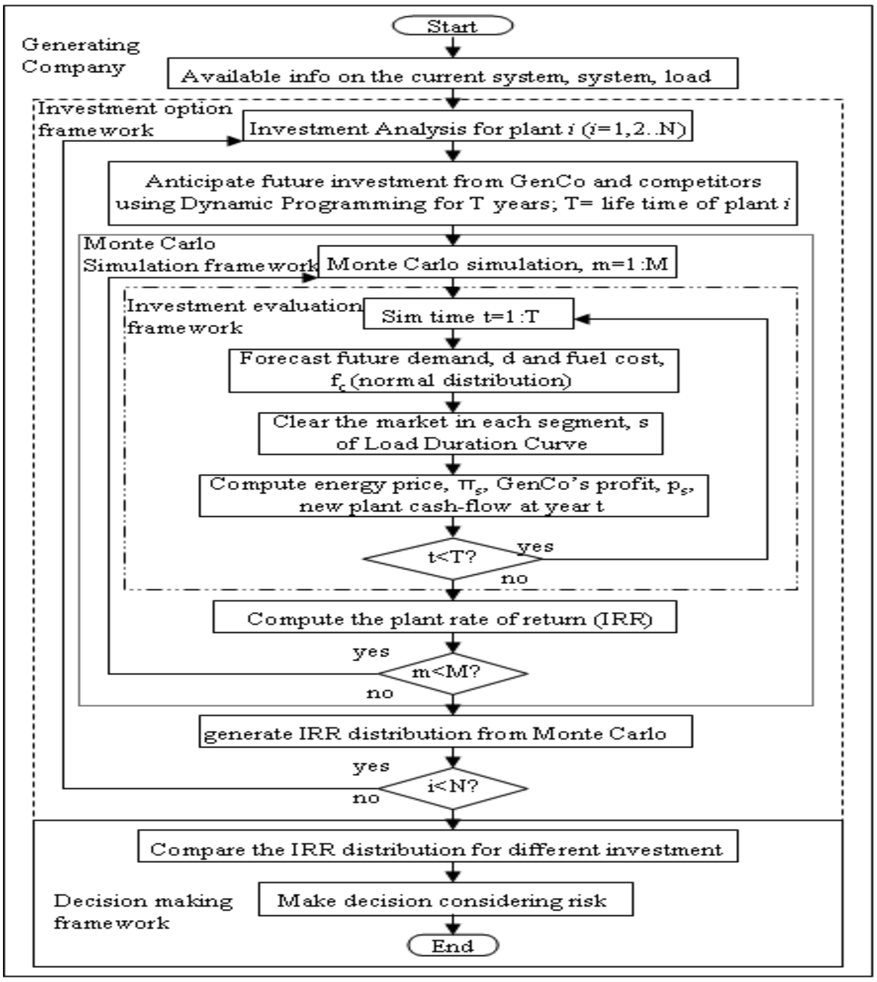

Fig. 1 Overview of investment evaluation

2.2 Anticipate System Changes Using Dynamic Programming

In evaluating an investment plant over its lifetime, Company A needs to consider the generating plants that will be built by its competitors and itself over the lifetime of the plant that it is evaluating. The new investment plan must therefore be evaluated against a "prototype investment schedule" for the entire sector because these future investments will affect the price of electricity and hence the profitability of the new plant. In this model, the prototype investment schedule for all the companies in the future is defined using dynamic programming (DP). An expected retirement schedule of the existing plants is provided as input data to the DP. This expected investment and retirement schedule from DP are used by the generating company as a base to calculate the revenue of the investment plant every year over its lifetime.

DP was one of the most widely used algorithms in expansion planning before the restructuring of the electricity supply industry [11-13]. Some commercial packages like WASP [14] use DP to find the "optimal" generation expansion planning strategy. DP is applied over a time horizon to find a set of optimal decisions to minimize the objective function subjects to several constraints. This paper uses a similar technique for finding the optimal generation expansion using DP in developing the prototype investment schedule. This prototype assumes that generation expansion by company A and its competitors will approximately minimize the total cost of generation expansion while meeting a minimum reserve capacity requirement for the system. In other words, it is assumed that the industry will behave in a rational manner in the long term and will not let the reserve capacity decrease below a level that might endanger the security of supply and hence trigger intervention by the regulator of the government. A set of potential investment technologies available to each generating company is defined at each year of the optimization horizon.

The total generation expansion cost is defined as follows:

$$TC = \min \sum_{t=1}^{T} \{ PC(X_t)_t + IC(U_t)_t + FOM(X_t)_t + VOM(X_t)_t \} \tag{1}$$

where TC is the total cost of expansion over the planning horizon, PC_t is the total production cost at year t, IC_t is the total investment cost at year t, FOM_t is the total fixed O&M cost at year t, VOM_t is the total variable O&M cost at year t, X_t is the cumulative capacity (MW) vector in year t, U_t is the capacity addition vector in year t and T is the number of periods in the simulation horizon. The production cost of each unit is given by the product of the marginal cost unit times the power produced. The power produced each year is computed by clearing the market at each segment of the LDC as will be explained in section 2.3.

This objective function is subject to several constraints:

$$X_t = X_{t-1} + U_t \text{, } \forall t \in \mathrm{T} \tag{2}$$

$$R^{\min} \leq R(X_t) \leq R^{\max} \text{, } \forall t \in \mathrm{T} \tag{3}$$

$$U_t \leq C_t \text{, } \forall t \in \mathrm{T} \tag{4}$$

where R is the reserve margin with X_t at year t and C_t is the available investment capacity in year t.

The first constraint in equation (2) shows that the cumulative capacity in year t is updated by adding the previous capacity with the new capacity addition in year t. For each year, Equation (3) constrains the installed capacity to be within the minimum and maximum reserve requirements allowed in the system. The maximum reserve constraint is set in the formulation only to reduce the state space of the DP simulation. Equation (4) shows that the capacity addition in each year is subjected to the investment availability in year t.

2.3 Modelling a Competitive Electricity Market

The market is cleared for each segment of the LDC at each year. The market clearing process is modelled as an optimization problem [16] in which the total yearly operating cost is minimized:

$$\min \left\{ \sum_{s=1}^{S} \sum_{i=1}^{I} \left(MCb_i \; p_{i,s} \; d_s \right) \right\} \tag{5}$$

where S is the number of segments in the LDC, I is the number of generating units participating in the market, MCb_i is the bidding price of generating unit i, $p_{i,s}$ is the power produced by generating unit i at segment s and d_s is the duration in hours of segment s.

The objective function is subject to several constraints:

$$\sum_{i=1}^{I} p_{i,s} = pd_s \tag{6}$$

$$P_i^{\min} \le p_{i,s} \le P_i^{\max} \tag{7}$$

$$\sum_{i=1}^{I} r_{i,s} \ge rd_s \tag{8}$$

where pd_s is the system demand at segment s and rd_s is the spinning reserve requirement for segment s.

The first constraint is enforced so that the selected generation meets the load demand of segment *s;* as in equation (6). Each of the generating unit is also constrained by its minimum stable generation and its maximum capacity as in equation (7). Since the market clears simultaneously energy and spinning reserve, constraint (8) needs to be enforced.

The market-clearing price is the cost of providing an additional megawatt of energy, and is thus assumed to be the marginal cost of the marginal energy producer. The spinning reserve price is the net cost of getting an additional megawatt of reserve. Fig. 2 shows an example of market clearing, and the energy and spinning reserve price at a given load.

The model assumes that each generating company bids at a price that covers both its variable and quasi-fixed production costs. Since the actual power produced by each generator is not known prior to the actual clearing process, it is assumed that the generators bids hedge for the minimum stable generation as follows:

$$MCb_i = f_c\, m_i + \frac{f_c b_i}{P_i^{\min}} \tag{9}$$

where m_i is the slope of the linearized input-output characteristic of generating unit i (MBtu/MWh), b_i is the y-offset of the linearized input-output characteristic of generating unit i (MBtu/h), f_c is the fuel cost ($/MBtu) and P_i^{min} is the minimum stable generation of generating unit i (MW).

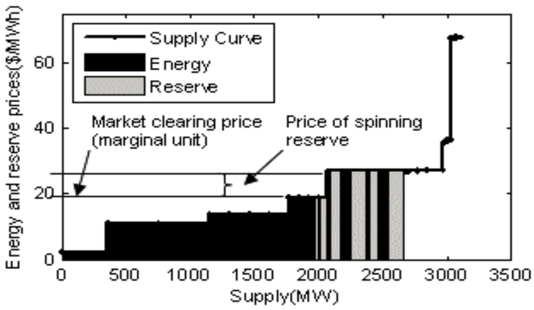

Fig. 2 Example of market clearing and spinning reserve price at a given load

2.4 Decision Making Process

The decision making process consist of determining which investment option is the most profitable. Therefore information about the expected revenues and costs for each investment plant are required. The market clearing process is performed at each year of the plant's lifetime. After simulation of the market clearing process, the profits made by the company are computed as follows:

$$P_{GenCo} = \sum_{\forall j \in J} (ER_j + SR_j - PC_j - FOM_j - VOM_j - NWC_j - CC_j) \tag{10}$$

where J is the set of generating units that belong to a given generating company, ER_j is the yearly revenue made from energy market, SR_j is the yearly revenue made from providing spinning reserve, PC_j is the yearly production cost of generating unit j, FOM_j is the yearly fix O&M cost of generating unit j, VOM_j is the yearly variable O&M cost of generating unit j, NWC_j is the yearly nuclear waste cost of nuclear technology and CC_j is the yearly carbon emission cost of coal and combined cycle technologies.

The yearly energy revenues, revenues derived from providing spinning reserve, production cost, fix and variable O&M cost, nuclear waste cost and carbon emission cost are given by:

$$ER_j = \sum_{s=1}^{S} \pi_{clear,s}\ p_{j,s}\ d_s \tag{11}$$

$$SR_j = \sum_{s=1}^{S} (\pi_{SR})(P_j^{\max} - p_j) d_s \tag{12}$$

$$PC_j = \sum_{s=1}^{S} \left(f_c m_j + \frac{f_c b_j}{p_{j,s}} \right) p_{j,s}\ d_s \tag{13}$$

$$FOM_j = F_{O\&M,j} P_j^{\max} \tag{14}$$

$$VOM_j = \sum_{s=1}^{S} V_{O\&M,j}\, p_{j,s} d_s \tag{15}$$

$$NWF_j = \sum_{s=1}^{S} WF \times p_{j,s} d_s \tag{16}$$

$$CC_j = \sum_{s=1}^{S} CO_{2,j} CT \times p_{j,s} d_s \tag{17}$$

where $\pi_{clear,s}$ and π_{SR} are the market clearing prices for energy and reserve at segment s of the LDC, $F_{O\&M,j}$ is the annual fix O&M cost per MW capacity of generating unit j, $V_{O\&M,j}$ is the variable O&M cost per MWh of energy produce by generating unit j, WF is the nuclear waste fee per MWh of energy produce by nuclear technology, CO_2 is the amount of carbon dioxide emission per MWh of energy produce by coal and combined cycle technologies and CT is the carbon tax set by government for every tonne of carbon produce by coal and combined cycle technologies.

This approach therefore does take into account the effect that a new plant might have on the revenues generated by other plants in Company A's portfolio. Once all these quantities have been computed over the lifetime of a possible new plant, the IRR and the NPV of the generated cash-flow are calculated. The IRR and NPV are calculated using the following expressions:

$$0 = \sum_{t=0}^{T} \frac{CF_t}{(1+r)^t} \tag{18}$$

$$NPV = \sum_{t=0}^{T} \frac{CF_t}{(1+k)^t} \tag{19}$$

where CF_t is the net cash-flow at year t, T is the number of years of cash-flow in investment's life, t is the year in which the cash-flow CF_t occurs, r is the IRR of the investment and k is the discount rate.

This revenue evaluation takes into account the prototype investment scheduled produced using DP and the retirement of generating plants that have reached their expected lifetime. If a generating company is evaluating two plants for expansion, the plant with NPV>0 and greater IRR will be selected.

2.5 Investment Evaluation under Uncertainty

2.5.1 Modelling Uncertainty in Load Demand and Fuel Cost

When assessing an investment under uncertainty, the future demand and fuel costs must be predicted considering their volatility. In this research, the forecast load demand and fuel costs are modelled as normal probability distributions function. The LDC is modelled with uncertainties not only on the amplitude but also on the duration of each segment. The magnitude of segment s is given as $A_s = N(\mu_s, \sigma_s^2)$ with duration $d_s = N(\mu_d, \sigma_d^2)$; where μ is the expected value and σ is the standard deviation. Since the LDC has a length of 1 year, the following equality must hold:

$$\sum_{s=1}^{S} d_s = 8760 \tag{20}$$

Similarly the uncertainty on the fuel cost is modelled by a Gaussian distribution, $f_c = N(\mu_f, \sigma_f^2)$ where μ_f is the expected fuel cost and σ^2_f is its variance.

2.5.2 Probabilistic Evaluation and Risk Assessment

A Monte Carlo simulation is used to determine the probability distribution of IRR. The IRR of the cash flow for each scenario is calculated for randomly selected demands and fuel costs using the specified probability distributions. This Monte Carlo simulation characterizes the probability distribution of IRR. The resulting IRR probability distribution provides investor a much richer analytical framework to assess power generation investment.

Fig. 3 and Fig. 4 show an illustrative example of IRR probability and cumulative distribution function for a power plant. Instead of finding the Value at Risk (VaR) with a given probability as usually considered in financial analysis as defined in [17], we provides the VaR equal to Minimum Acceptable Rate of Return (MARR). From the distribution, for a given value of MARR, the probability of getting an IRR less or greater than MARR can be computed. In other words, this answers the following question: *"Considering all the risks involved, what is the confidence level associated with investing in a project with an IRR of x%?"*. The example shows that the project provides a confidence level of 95% of getting an IRR≥12%. The decision to accept or reject this project depends on the investor's perspective towards the risk. The risk-averse investor may accept a project with lower but more probable IRR, while a risk-taking investor may prefer a higher return despite a probability distribution with a high standard deviation. Different project may have different risk distributions, which lead to different IRR distributions. With the aid of this IRR distribution, the company may decide how much market risk the company is willing to take before any investment decision is made.

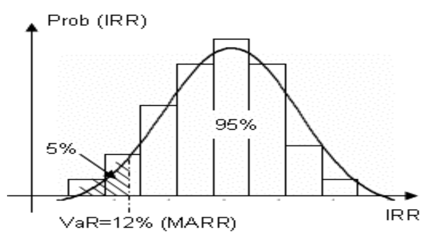

Fig. 3 IRR probability distribution function

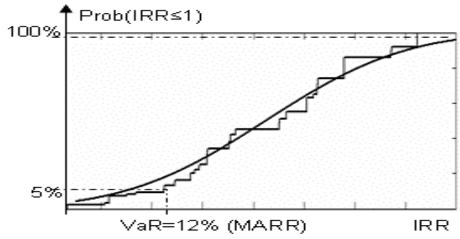

Fig. 4 IRR cumulative distribution function

3.0 OPTIMAL STEP FUNCTION APPROXIMATION TO LOAD DURATION CURVE

In scheduling energy generation, the LDC is usually approximated using a step-function. In general this approximation is usually produced by sketching or in some other ad hoc manner. However, because the expected profitability of any investment plan is very dependent on the shape of this discretized LDC, it is necessary to use a rigorous technique to discretize the LDC. Some techniques have been developed to find an optimal step function that fit the LDC. The first attempt was proposed by Loney [18] who used dynamic programming with a six step approximation. The authors of [10, 19] extended Loney’s algorithm. In our model, the algorithm proposed by [10, 19] to discretize the LDC based on the minimization of total penalty function is used prior to the investment evaluation.

3.1 Formulation and Algorithm

A three step-function of a typical LDC as in Fig. 5 [10, 19] is used to illustrate the methodology.

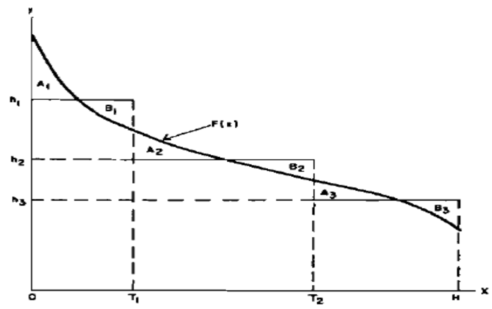

Fig. 5 Typical load duration curve with a three step approximations

The LDC is denoted by *F* and the interval *0* to *H* is the number of hours being considered. The three segments are defined by the break points defined by T_1 and T_2 and the corresponding height h_1, h_2 and h_3. Since the area under the LDC is equal to the total electrical generation in the period, the area under the step function approximation should be equal to the area under the LDC for each step.

In Fig. 5, area A_1 in the first segment under the LDC can be interpreted as representing the deficiency of electrical generation and B_1 above the LDC as representing the excess of generation. Areas A_2, B_2, A_3 and B_3 are interpreted the same way.

The authors of [10, 19] also introduce a penalty function, $p(e(x))$, to solve the optimization problem where $p(e(x))$ is the penalty to be paid per unit of mismatch at x and $e(x)$ is the amount of mismatch at x. From Fig.5, $e(x)$ can be expressed as $|F(x) - h(x)|$. The total penalty for the step-function approximation is given by;

$$P = \int_{T=0}^{H} p(e(x))e(x)dx \tag{24}$$

The goal of this optimization problem is to find the value of T_1 and T_2 in such a way that this total penalty is minimized.

3.2 Results of the Optimal Step-Function Approximation Using DP

The simulations were carried out for a six step approximation of the LDC using a penalty function, $p(e(x)) = 1$. The hourly load data is from the PJM RTO regions [20] for the load from 1st January 2008 to 31st December 2008 with the total hours of 8784 hours. Fig. 6 shows the six step approximation of LDC from PJM market with the break points and the total error are tabulated in Table I.

Steps	Break Points	Total Error
6 step-function of LDC	300 1511 3416 6001 7672	0.03218222

Table I Break points and total error of six step-function approximation of LDC in PJM market

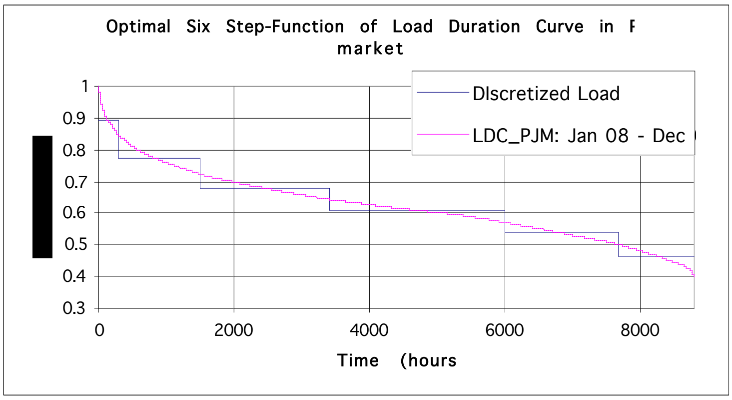

Fig. 6 Optimal six step-function approximations of LDC in PJM market

Various shapes of discretized LDC have been tested in the investment model, for example an LDC with more steps at the higher loads; we found that the profitability of the investment plants is very sensitive to the shape of this discretized LDC.

4.0 MODELLING AN OLIGOPOLY MARKET

The market model explained in section 2.3 represents an electricity market with perfect competition. Generators are thus expected to bid at their marginal cost. However, under an oligopoly markets, the players in the market may employ restrictive trade practices such as collusion, market sharing, and various strategies to raise the price. For this reason, in modelling an oligopoly market we estimate the bidding behaviour of the generators using a price duration curve from a real market such as PJM market.

4.1 Extrapolating the Bid Price of Generating Units in an Oligopoly

Lucas and Taylor [21] found that generators with lower running costs are bid below their marginal cost, while the more expensive ones are bid higher than their marginal cost. Generators that are technically flexible can start and shut down quickly when needed. However they tend to be more expensive. These generators command a premium for their flexibility, therefore owners of these plants can afford to bid high and still expect the plants to be run. Furthermore, these generators have less competition in setting the price at the higher loads since most of the generators with lower marginal cost have been committed to supply energy at lower loads. This provides them an opportunity to bid high but still expect the plants to be committed. In modelling this kind of bidding behaviour in an oligopoly market, we assume that the bid price of each unit will imitate the bidding behaviour in a real market such as PJM. Since the shape of the mathematically (PDC) is dependent on the production cost of generating units, load, generation availability, unit commitment, transmission constraints and strategic bidding [22], we used the PDC from the PJM market to extrapolate the bid price of the generating units, whereas the production cost and load have been considered in determining the market price as in section 2.3.

The PJM weighted average real time locational marginal price data [23] from 1st January 2008 to 31st December 2008 with a total of 8784 hours was used to construct the PDC. This PDC was then discretized using a six step approximation as shown in Fig. 7 where the break points are the same as those obtained for the six step LDC of section 3.2. The PDC under the perfect competition is then determined from the investment model. The bid price factor at each of the higher load segments is computed so that the shape of the PDC under the perfect competition follows the trend of the PDC in the PJM market but the price at the lowest load segment is unchanged i.e. the bid factor is equal to one. The implicit assumption made was that the power suppliers submit bid at their marginal cost at the lowest load segment but submit bid higher than their marginal cost at the higher load segments. The new bid prices in the oligopoly market are then obtained by multiplying the bid factor with the marginal cost of the generators at each of the load segments.

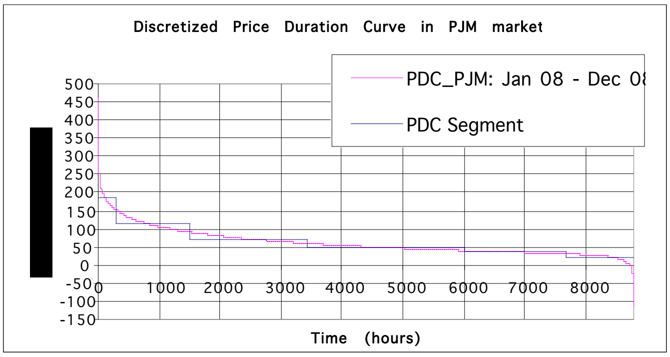

Fig. 7 Six step-function of PDC in PJM market

Fig. 8 shows the PDC under oligopoly market which has higher prices at higher load segments than the PDC under the perfect competition market model resulting from the bidding behaviour of the generators considered in the system.

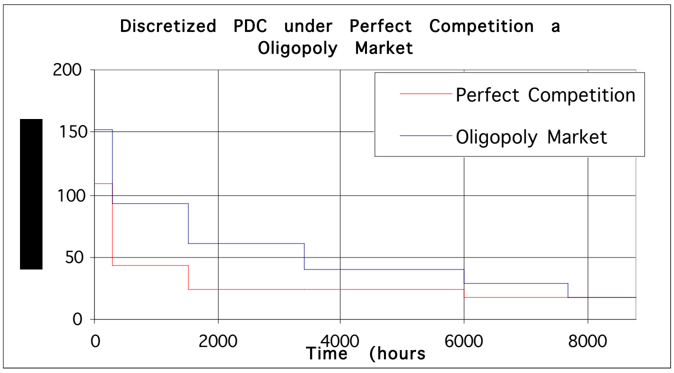

Fig. 8 PDC under perfect competition and oligopoly market

The bid factors and the new market clearing prices under oligopoly market are endogenously computed in the model every year of the lifetime of the investment plant with the assumption that the bidding behaviour of the generators at each of the load segments remains the same over the evaluation years. Fig. 9 shows the PDC under the oligopoly market for the ten years of nuclear investment plant's lifetime.

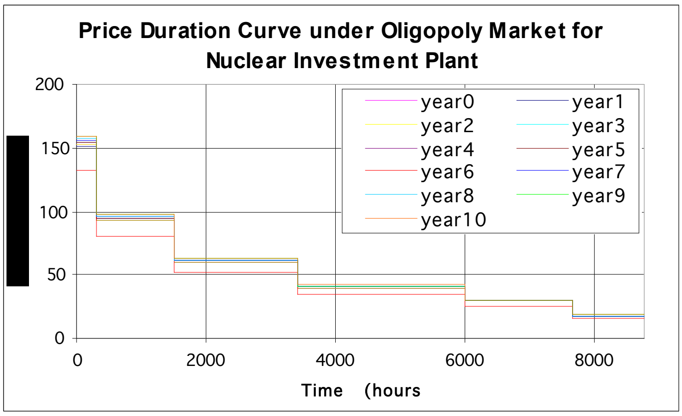

Fig. 9 PDC under oligopoly market for the 10 years of nuclear investment plant's lifetime

5.0 RESULTS AND ANALYSES

Three types of analyses have been carried out using the model described in the previous sections. These include; 1) a comparative investment evaluation for nuclear, coal and combined cycle technologies; 2) a study of the effect of various scenarios of future changes in the system on the profitability of the investment; and 3) an evaluation of investments under uncertainty.

5.1 Investment Evaluation for Nuclear, Coal and Combined Cycle Technologies

This analysis is carried out for a generating company wishing to compare investments in three different technologies i.e. nuclear, coal and combined cycle gas turbine.

5.1.1 Test Data

The analysis has been carried out on the IEEE-RTS [24] omitting the hydro generation, which consist of 26 generating units and a total of 3105MW of installed capacity. The existing technologies in the system are listed in Table II. It is assumed that three generating companies compete in this market and that their portfolios are as follows: Company B owns the set of generating units {Unit_01-10}, Company A owns the set {Unit_11-20} and Company C owns the set {Unit_21-26}. Company A is the company evaluating a new investment; Company B and Company C are its competitors in the market.

Unit Group	Size, MW	Unit Name	Unit type	Heat rate offset, Mbtu/h	Heat rate, Mbtu/MWh	Remaining lifetime, years	Investment Cost, $/kW	Fix O&M Cost, $/MW/yr	Variable O&M Cost, $/MWh
U12	12x5	Unit_01 - 05	Oil/Steam	2.81	3.07	15	800	21500	3.17
U20	20x4	Unit_06 - 09	Oil/CT	13.87	4.49	10	800	21500	3.17
U76	76x4	Unit_10 - 13	Coal/Steam	44.38	8.82	17	1175	20630	3.063
U100	100x3	Unit_14 - 16	Oil/Steam	24.03	2.23	8	800	21500	3.17
U155	155x4	Unit_17 - 20	Coal/Steam	64.88	7.28	14	1175	20630	3.063
U197	197x3	Unit_21 - 23	Oil/Steam	26.59	2.81	15	800	21500	3.17
U350	350x1	Unit_24	Coal/Steam	12.12	1.37	25	1175	20630	3.063
U400	400x2	Unit_25 - 26	Nuclear	211.27	7.69	33	1810	57140	0.365

Table II Existing unit's technology and cost

Company A assumes that nine generation technologies can be selected by the DP each year for the prototype system expansion schedule. Each of these plants belongs to a specific company. The characteristics of these technologies are given in Table III.

Unit	Owned by Company	Size, MW	Unit type	Heat rate offset, Mbtu/h	Heat rate, Mbtu/MWh	Investment Cost, $/kW	Lifetime, years	Fix O&M Cost, $/MW/yr	Variable O&M Cost, $/MWh
PGF_17	A	155	Coal/Steam	64.881	7.9044	1175	25	20630	3.063
PGF_10	B	76	Coal/Steam	44.386	8.8288	1175	25	20630	3.063
PGF_21	C	197	Oil/Steam	26.597	2.8134	800	25	21500	3.17
PGF_01	B	12	Oil/Steam	2.8099	3.0774	800	25	21500	3.17
PGF_24	C	350	Coal/Steam	70.124	6.679	1175	25	20630	3.063
PGF_06	B	20	Oil/Steam	13.871	4.4939	800	25	21500	3.17
PGF_14	A	100	Oil/Steam	24.029	2.2303	800	25	21500	3.17
PGF_17	A	155	Coal/Steam	64.881	7.9044	1175	25	20630	3.063
PGF_10	B	76	Coal/Steam	44.386	8.8288	1175	25	20630	3.063

Table III Available investment technologies for DP

The three possible investment technologies that are considered by Company A are shown in Table IV. The technical and cost characteristics of these candidates are given in [2]. The optimal six step-function of LDC obtained in section 3.2 and shown in Fig. 6 is used in the investment evaluation. It is assumed that the magnitude of each segment of the LDC increases by 2.3% every year. The NPV of each investment plan is calculated using 10% of discount rate. In this analysis, Company A considers making investment in an oligopoly market as previously modeled in section 4.0. The prototype future system expansion schedule from DP is obtained considering the installed capacity is within the 18% minimum and 30% maximum reserve requirements. Uncertainties in the load demand and fuel cost are not considered.

Parameters	Units	Nuclear	Coal	NGCC
Technical Parameters				
Net capacity	MW	300		
Heat rate	MBTU/MWh	10.4	8.6	7
Construction period	years	5	4	2
Plant life time	years	40	30	20
Carbon intensity	tC/MBTU	0	0.0258	0.0145
Cost Parameters				
Overnight cost	$/kW	1810	1175	452
Fixed O&M	$/kW/yr	57.14	20.63	14.29
Variable O&M	$/MWh	0.365	3.063	0.476
Fuel cost	$/MBTU	0.55	2.06	5.24
Fuel escalation rate	%	0.5	0.5	1.2
Nuclear waste fee	$/MWh	0.95	0	0
Financing Parameters				
Discount rate	%	10		
Regulatory Action				
Carbon tax	$/tC	63.5		

Table IV Technical and cost characteristic of investment plants

5.1.2 Test Results

Fig. 10 shows the expected cash flow for an investment in a nuclear plant over its expected lifetime. In this system, the plant collects revenue by selling energy and by providing spinning reserve. The revenue collected by the plants each year is based on the energy and spinning reserve prices resulting from the market clearing process each year with respect to the expected changes in the system from the DP calculation. Since each new plant enters the system at a different year, the DP gives a different optimal solution of the prototype system expansion and hence different expected energy prices for each plan under evaluation. The results of the DP will be discussed in detail in the next analysis.

Being a base unit in the system, the revenue of the nuclear plant depends mostly on the price of energy. This is shown in Figures 10 and 11 where the expected revenue of the nuclear plant follows the trend of the energy prices over its lifetime. On the other hand, the revenues of the coal and combined cycle plants, which are intermediate and peak units respectively, depend on both the energy and spinning reserve prices.

Comparing the three technologies, the combined cycle plant, which has lower investment and O&M costs and a shorter lifetime, provides higher rates of return than nuclear and coal technologies. On the other hand, the coal plant, which has a high investment and O&M cost as well as a high cost for carbon emissions, is a less desirable investment. Although the nuclear plant has a high investment cost, being a base unit in the system and providing clean energy makes it the second most profitable investment after the combined cycle power plant. Table V shows the IRR and the NPV for all the investment plans.

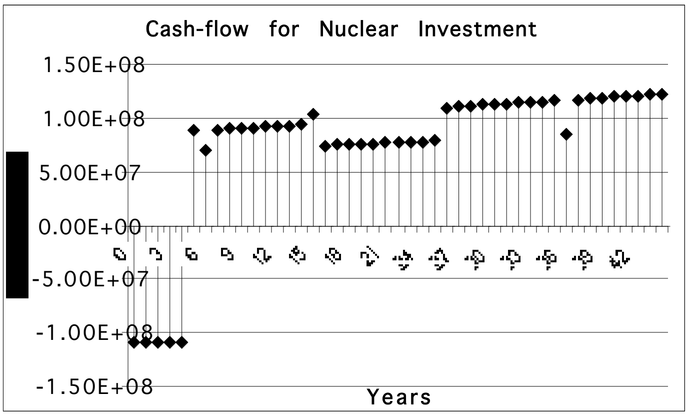

Fig. 10 Expected cash-flow of nuclear investment plant

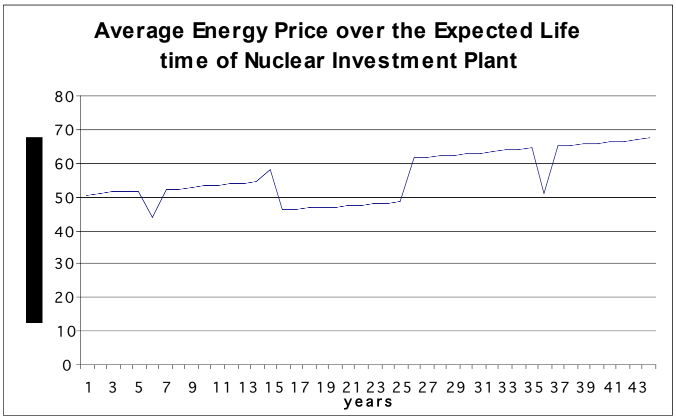

Fig. 11 Average energy price over the expected life time of nuclear investment plant

	IRR (%)	NPV ($)
Nuclear	12.41	1.39E+08
Coal	8.4767	-3.21E+07
Combined Cycle	32.705	2.66E+08

Table V IRR, and NPV of the investment plants

5.2 Anticipate System Changes Using DP at Various Load Growths

This analysis is carried out by Company A to perform a sensitivity analysis on the profitability of the investment plans with respect to various scenarios of future changes in the system. These scenarios are obtained from the DP considering different forecasted rates of load growths.

5.2.1 Test Data

Similar test data, LDC, market model and assumptions as in 5.1.1 have been used in this analysis. Since the objective of this analysis is to study the effect of future changes in the system on the profitability of the new plant, the analysis is carried out for the nuclear plant only. Three different scenarios of forecasted load growth i.e. 2.7%, 2.3% and 1.5% have been tested.

5.2.2 Test Results

Fig. 12 shows the first 15 years of the 44 years of the prototype system expansion schedule resulting from the DP assuming a 2.3% load growth each year. The nuclear plant being evaluated by Company A comes on line at year 5 after its construction is completed. The DP is carried out for the lifetime of nuclear investment plant, i.e. 40 years. The upper block of Fig. 12 shows the plants addition by all the companies over the simulation horizon, while the lower block shows the retirement of the units that have reached their expected lifetime. It is expected that Company B will build PGF_01 and PGF_10 and Company A will build two units of PGF_17 that will come on line in year 1. No new plant will be added to the system at year 6 and 7 as the nuclear plant considered by Company A will enter the market at year 5 is enough to cater the load growth for the coming years. More new plants will be added to the system at year 9, 11, and 15 to replace some of the existing units that retire.

Fig. 13 shows the prototype system expansion schedule considering the case with a higher load growth (2.7%) in the system, which in average shows more new plants will be added to the system. On the other hand in the case of a smaller load growth i.e. 1.5%, it is expected that fewer new plants will be built over the planning horizon. This is shown in Fig.14.

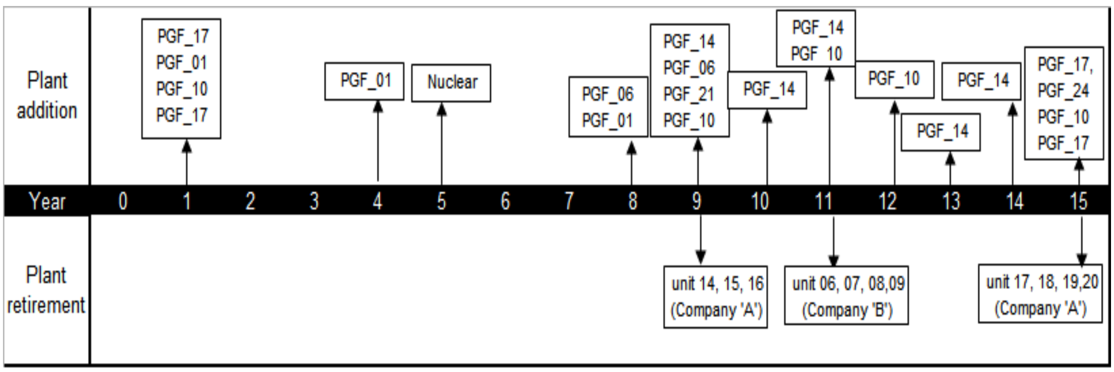

Fig. 12 Prototype system expansion schedule at 2.3% load growth

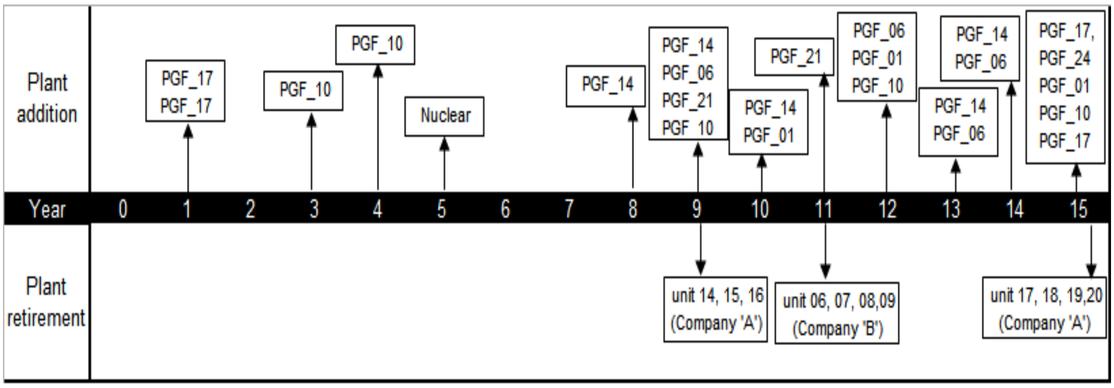

Fig. 13 Prototype system expansion schedule at 2.7% load growth

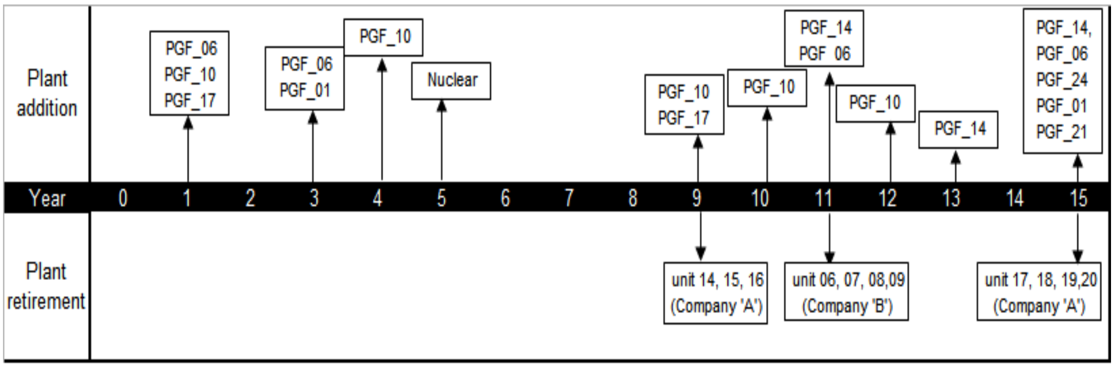

Fig. 14 Prototype system expansion schedule at 1.5% load growth

It is expected that a bigger installed capacity in each year with a 2.7% load growth considered in the system than 2.3% and 1.5% load growth as shown in Fig. 15. The reserve margin in the system remains within the required limit for all the load growth cases. Figure 16 shows that the DP simulation keeps the system reserve just above the minimum requirement i.e. 18% in order to minimize the total cost of expansion and operation in the system over the simulation horizon.

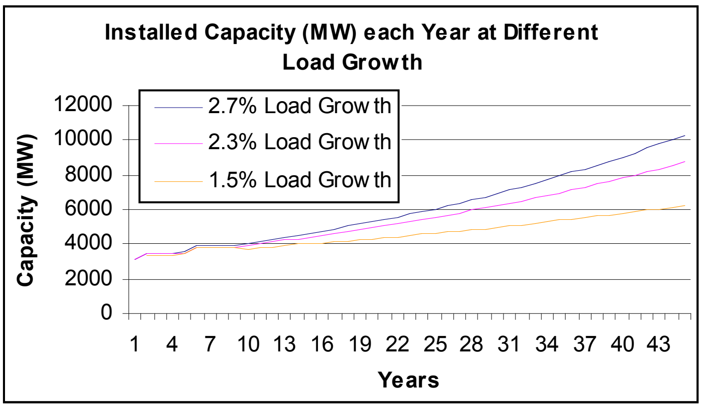

Fig. 15 Installed capacity in the system at various load growths

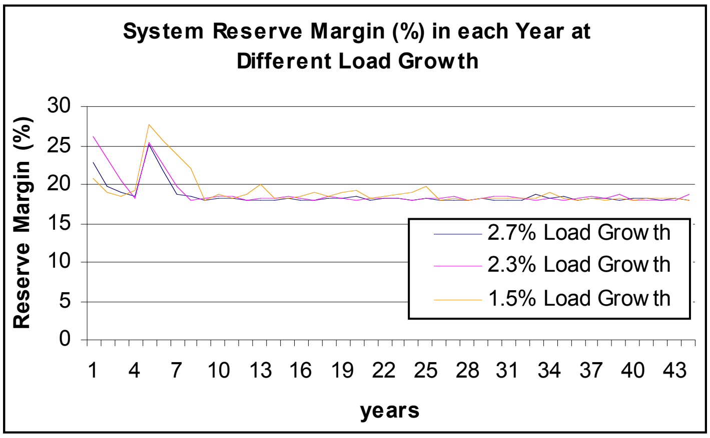

Fig. 16 System reserve margin at various load growths

The expected average energy price fluctuates but overall increases as the demand increases over the planning horizon. A higher load growth in the system provides expensive generators the opportunity to dispatch energy and hence leads to higher market clearing prices. This is shown in Fig. 17 where the 2.7% load growth in general results in higher energy prices than the smaller load growths and hence provides higher rate of return for the nuclear plant. Table VI shows that the rate of return of the nuclear plant increases slightly when bigger load growths are forecasted.

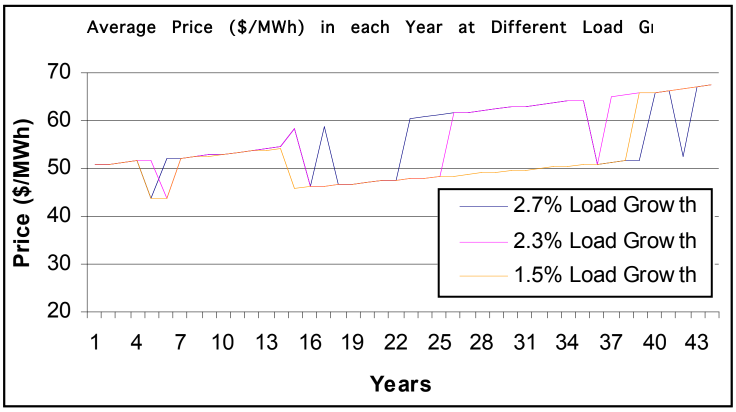

Fig. 17 Expected average energy price at various load growths

Load Growth	IRR (%)	NPV ($)
2.70%	12.58	1.51E+08
2.30%	12.41	1.39E+08
1.50%	11.58	9.38E+07

Table VI IRR and NPV of nuclear investment plant at various load growths

5.3 Investment Evaluation under Uncertainty in a Competitive Electricity Market

The analysis is further extended to carry out an investment evaluation in a competitive electricity market considering uncertainties in future load demand and fuel cost using a Monte Carlo simulation.

5.3.1 Test Data

The analysis has been carried out on the same test system as in 5.1.1. Company A considers investing in one of two possible generating plants for the current year. Both are coal power plant but with 250 MW or 155 MW capacities. Table VII shows the technical and cost characteristic of these two plants.

Plant name	Size, MW	Unit type	Invest, $/kW	Construction lead time	Heat rate offset, Mbtu/h	Heat rate, Mbtu/MWh	MARR, %	Expected lifetime, years
Plant_1	155	Coal	1000	3	64.881	7.2892	12	25
Plant_2	250	Coal	1000	3	70.124	6.679	12	25

Table VII Investment plant's technology and cost

The characteristics of the investment technologies that can be selected by the DP for the prototype system expansion are given in Table VIII.

Unit	Owned by Company	Size, MW	Unit type	Heat rate offset, Mbtu/h	Heat rate, Mbtu/MWh	Investment Cost, $/kW	Lifetime, years
PGF_17	A	155	Coal/Steam	64.881	7.9044	1175	25
PGF_10	B	76	Coal/Steam	44.386	8.8288	1175	25
PGF_21	C	197	Oil/Steam	26.597	2.8134	800	25
PGF_01	B	12	Oil/Steam	2.8099	3.0774	800	25
PGF_24	C	350	Coal/Steam	70.124	6.679	1175	25
PGF_06	B	20	Oil/Steam	13.871	4.4939	800	25
PGF_14	A	100	Oil/Steam	24.029	2.2303	800	25

Table VIII Available investment technologies for DP

The LDC has been discretized into 5 non-optimised segments. The peak value is assumed to be 2577.2 MW at year 0 and it is assumed that the magnitude of each segment of the LDC increases by 2.3% per year. In this analysis the market is assumed to be perfectly competitive. The uncertainties in the LDC are modeled as Gaussian distributions with a mean value equal to the magnitude of the segment times the demand peak value and a standard deviation of 1% of the mean value. Similarly, the fuel costs are modeled with a Gaussian distribution with the following mean values: 2.31 $/MBtu for coal, 13.5 $/MBtu for oil and 5.54 $/MBtu for gas [25]; and a standard deviation of 1% of the mean value of the fuel. The LDC used for the prototype calculation using DP has the same values and increases at the same rate but uncertainty is not considered. The minimum and maximum reserve requirements in the DP are set at 18% and 30% respectively. It is assumed that all the existing generating units are sunk costs at year 0. At least 1000 trials of the Monte Carlo simulation are performed.

5.3.2 Test Results

Fig. 18 shows 12 of the 28 years of the prototype system expansion schedule resulting from the DP calculation. The new plant being evaluated by Company A (Plant_1) comes on line after construction is completed at year 4. The DP is carried out for the lifetime of Plant_1 i.e. 25 years. It is expected that Company B will build PGF_10 in year 6 follow by Company A with PGF_14 in year 7 and so on. More plants will be built at years 9 and 11 to replace some of the existing units that are retired. When Plant_2 with a different capacity is evaluated, the DP gives a different solution of prototype system expansion.

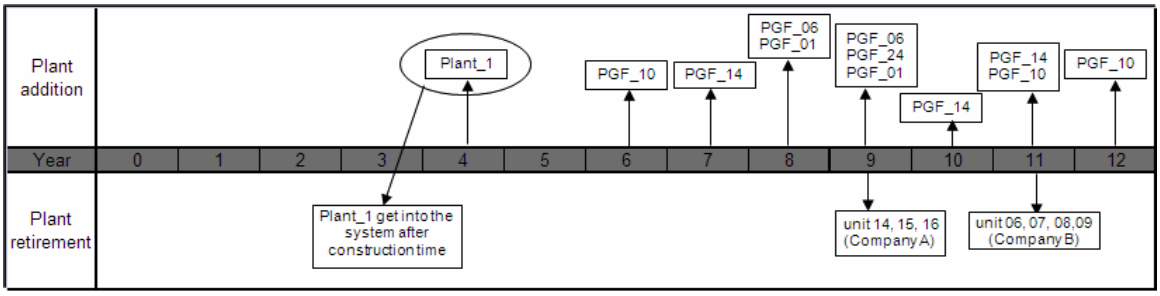

Fig. 18 Prototype system expansion using DP over the lifetime of Plant_1

The average energy price over 28 years resulting from the simulated market clearing process with respect to the expected changes in the system (Fig. 18) is shown in Fig. 19.

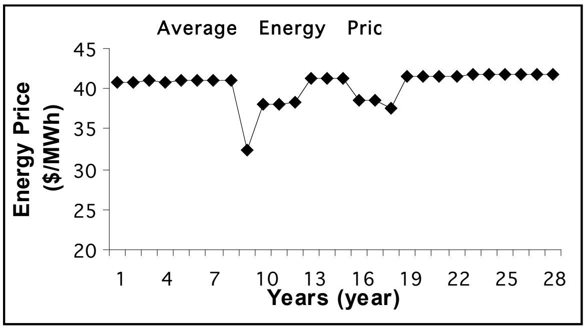

Fig. 19 Average energy price over the lifetime of Plant_1

Fig. 20 and Fig. 21 show the IRR probability density and cumulative distributions function of Plant_1 and Plant_2 respectively with similar uncertainties applied to both investments. The IRR distribution of Plant_1 is skewed to the left compared to the distribution of Plant_2. This indicates that the probability of getting a smaller rate of return is greater with Plant_1. If the VaR of the investments is assumed to be equal to the MARR of both of the plants (i.e. 12%), then the plot of IRR cumulative distribution function of Plant_1 gives a confidence level of 63% to get a return greater than 12%. On the other hand Plant_2 provides a confidence level of 98.9%. The lower confidence level of Plant_1 indicates that investing in Plant_1 represents a higher risk than investing in Plant_2. Both of the IRR distributions are spread almost equally since they are from the same coal fuel technology. However, if we compare plants with different technologies, for example combined cycle and coal, the IRR distribution of each plant might spread differently depending on the distribution of the gas and coal prices.

By comparing the two plants, Company A may thus decide to invest in Plant_2 which is less risky and guarantees a higher return. However all decision depends on the acceptable confidence level of Company A and the financial risk that the company is prepared to take.

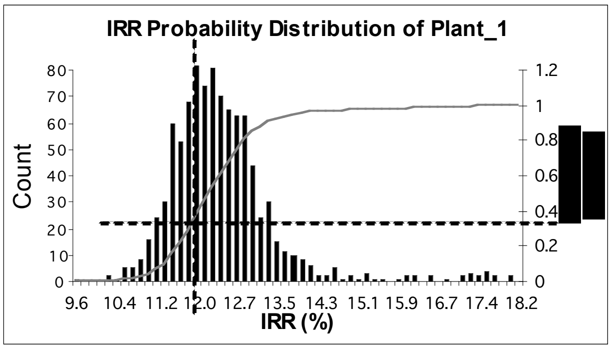

Fig. 20 IRR probability distribution for Plant_1

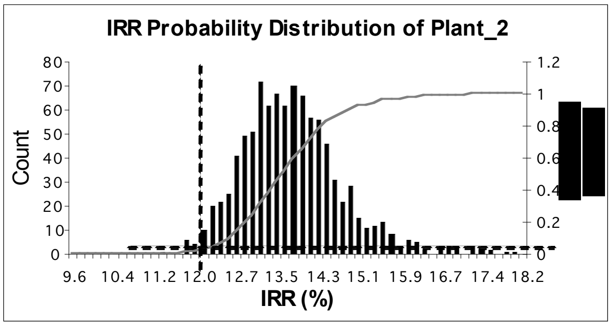

Fig. 21 IRR probability distribution for Plant_2

6.0 CONCLUSIONS

This research proposes a technique to carry out investment analysis and to provide a generating company a framework for incorporating risk assessment in investment decisions in a competitive electricity supply industry. The investment analysis also takes into account the expectation of what the competitors might decide to do with respect to investments and retirements. These are indeed important factors that must be considered in evaluating new investment in a competitive electricity market. The proposed technique is also able to model the electricity market price and its dependence on changes in the system. A rigorous technique to discretize the LDC based on the minimization of total penalty function is used for the investment evaluation. An interesting extension of the analysis is to consider the uncertainty in the competitors' expectation from DP.

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