The Effects of Multi-temporal Electricity Markets on Short- and Long-Term Bidding

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***Abstract*—In this paper we discuss the generator investment problem for a newly proposed energy-only market structure comprising both spot and forward sub-markets as an alternative long-term resource adequacy solution. The investment problem is modeled as stochastic dynamic programming problem for a profit maximizing generator over a long time horizon. The long-term growth and short-term deviation of demand are represented as stochastic processes. The spot market is modeled as bilevel non-cooperative game and the forward market is formulated based on mean-variance criteria and market equilibrium arguments. The interrelated dynamics of different markets and its effect on investment decision and profitability of market participants are analyzed and comparisons with other market structures such as spot only energy markets are investigated as well.**

***Index Terms*—Forward markets for electricity, stochastic dynamic programming, resource adequacy, optimal investments, market design.**

I. Introduction

This work is motivated by the on-going problems with sustainable value-based investments in the evolving electricity markets. Even the best functioning spot markets are challenged by the lack of signals for investment in generation and transmission capacity. While the reasons for this situation are multifold, one of the obvious questions concerns the management of physical uncertainties, such as demand variations and physical failures of equipment in the evolving electricity markets. Given that these are highly uncertain and multi-temporal, this brings up the basic question of managing and valuing uncertainties in these markets. It is our premise that failure to systematically manage these uncertainties is one of the major shortcomings of current spot market structure. This paper is also a starting point for enhancing such setups with well-defined and value-based new market structures.

While the overall problem of designing well-functioning electricity markets is very broad [1] in this paper we start by recognizing that different electricity market structures result in qualitatively different outcomes. However, this common-sense observation is hardly documented in the existing literature through systematic modeling and simulations. The paper illustrates the effects of different market structures in the electricity industry on the new generation investment decisions. Of particular interests are monetary incentives for inducing near-optimal capacity by means of long-term market mechanisms. We also investigate how these new investment decisions affect the economic performance of the long-run social welfare of the system as a whole, such as the average electricity prices and its volatility.

At present there are few liquid longer-term electricity markets, which are essential for ensuring both reliable service and sufficient capacity reserve to avoid boom-and-bust cycles in generation capacity. Determining near-optimal investments for long-run efficiency requires transparent signals for decision making under various physical and financial uncertainties. In this paper we introduce a set of coordinated sub-markets, each defined for a specific time horizon, ranging across day-, month-, season-, year-, five year-horizons, referred to as a Stratum Electricity Market (SEM). We evaluate the long-term effects of the SEM on the system reliability and efficiency. We also provide initial exploration of different market and regulatory rules which are essential for the long-term investments.

In Section II we briefly review generation planning problem and the existing modeling techniques. The newly proposed SEM is introduced in section III with a focus on its possible alternative solution to the resource adequacy problem. A generic generator investment problem in spot and forward two sub-markets SEM setup with short-term and long-term demand uncertainties is formulated as a stochastic dynamic programming problem in section IV. Detailed spot and forward energy market decision making processes are also modeled based on different decision criteria and driven by fundamental physical and economic signals in the markets. In Section V a simplified realization of the generic model is solved under different market structures. Preliminary results concerning the impacts of optimal investment decisions on investment boom-bust cycles under different scenarios are also discussed. Conclusions and further studies are summarized in Section V.

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II. Background

A. Decision criteria

The investment problem of physical electricity generation assets can be treated as an example of a more general asset investment and valuation problem. The conventional method of asset valuation is the net present value (NPV) approach [2]. The NPV is calculated by integrating the expected payoff ψ from the market, which is a spread between revenue received in the market and the cost of providing electricity, adjusted by the discount rate ρ over the period of evaluation T.

$$NPV = \int_t e^{-\rho t} E\{\psi_t\} dt$$

The NPV rule states that the firm should choose the investment option with the highest positive NPV. The revenue received in the market depends on the market rules and price predictions. One big challenge is to determine the appropriate discount rate, which must reflect the time value of money and the level of risk evolved in the investment.

The second approach is based on the mean-variance criteria. The firm can define its risk preference by stating its utility in terms of the tradeoff between the expectation and variance of the future return on the investment. Given the risk preference A_i, the investment option with the highest mean-variance utility would be chosen.

$$U(\sum_t \psi_t) = E\{\sum_t \psi_t\} - 0.5 A_i \times Var\{\sum_t \psi_t\}$$

The third approach is based on real option theory [3] which applies principles from financial option valuation for appraisal of investments in real assets. Its basic argument is that investment projects with uncertain future cash flows should be considered as options, if the decision is irreversible and the timing is flexible, which are often true for generation investment decisions. The optimal investment can be made when net cash flow from the project reaches V*, when the net present value of the project N(V) equals the value of having the option to invest in the future F(V), which is demonstrated in Fig II.1.

This paper utilizes all the above criteria in different sub-models.

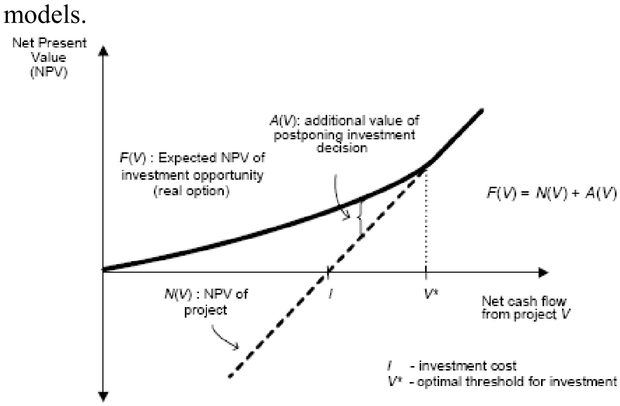

Fig. II.1 Illustration of real option criteria from [3]

B. Modeling electricity prices

The expected payoff of the investment depends on the forecasts of the electricity market prices and cleared quantities, which are driven by the underlying physical and financial factors, i.e. the load forecasts and market structure, as well as their inherent stochastic natures. Currently, there are a number of methods to model the price process. In statistical modeling [4], [5], the user attempts to find the lowest order model possible to describe the stochastic properties of the prices. In economic equilibrium based modeling [6], game theory based economic models like Cournot pricing are employed to solve the equilibrium solution. In agent based modeling [7], [8], depending on the objective function of each agent and observation of current price levels, agent updates his strategy using artificial intelligence methods. The market prices are the output of individual bids.

However, electricity markets are constantly evolving. All the above methods are static in the sense that they only apply to certain market setup and neglect the underlying drivers in the system. A fundamental modeling approach for the electricity markets is based on starting by modeling the dynamics of physical variables, such as load demand, generation capacity and fuel prices. This is followed by defining the economic variables, such as bidding strategies of market participants; and, finally, by defining the public policy variables, such as market structures and rules. Based on the dynamic interactions among all physical, economic and policy variables, financial outcomes such as electricity prices, individual participant's profits as well as total social welfares and their associated risks become the outputs of the overall model.

Examples of this approach can be found in [9] where electricity price was modeled for a spot market only structure with the aggregated stochastic system supply and demand processes. The applications of such approach on valuing generation assets are introduced in [10] [11].

In this paper, the fundamental modeling approach from [11] is further developed by combining the i) decision making by the Gencos considering the gaming in spot market; ii) decision making by the Gencos/LSEs in newly proposed long-term centralized energy market using the mean-variance criteria; and iii) investment decision making by investors using the real option theory and stochastic dynamic optimization techniques, as first introduced in [12] in regulated industry. Using this modeling approach, the financial outcomes seen by various market participants and the system as a whole become natural results of interactions between complex decision making processes. This modeling extension is critical for managing and valuing physical and financial risks over a variety of time horizons. It can be applied as a means of evaluating and making the investment decisions for a given market design. It can be further used to evaluate the effects of market structures and rules on various market attributes.

III. Stratum Energy Market Structure

A. Existing resource adequacy (RA) mechanism

In order to meet resource adequacy and reliability requirements, the Installed Capacity markets (ICAP) and other type of capacity markets are introduced to help recover the capacity costs by the North Eastern United States ISO/RTOs. The capacity market rules require that load serving entities (LSEs) must contract enough capacity from the generation companies (Gencos) to meet the "appropriate" ISO forecasted level of capacity for the future periods. When current installed capacity would not meet the forecasted peak load plus operating reserve requirement, the capacity price ($/MW-year) will be set by the annualized fixed cost of the cheapest new entry that could meet the administrative requirement. When current installed capacity exceeds the forecasted target, the price will fall to zero and the system would not attract any new investment assuming no market power in the capacity markets. The underlying argument of this approach is that there are two products in the electricity markets: energy and reliability. Energy should be settled on the spot market to ensure the short-term efficiency while the reliability should be achieved through capacity market design. Overall, recent studies found that the ability of financing capacity payments through the volatile ICAP markets is declining and that current ICAP payments alone are not sufficient to recover capital costs of power plants as discussed in [13] and [14]. The effectiveness of newly implemented long-term capacity market with a term of 3-5 years like the RPM model [15] by PJM is still remained to be seen.

B. The cause of RA problem

The RA problem is mainly due to the fact that there is no long-term risk management mechanism to reduce the risk/ uncertainties for investment projects. Consequentially, there is no long-term transparent price signals to guide the sensible investment decisions. The core of RA problem is risk sharing between different parties. In regulated industry, consumers take all the risks of generation expanding and the producers take zero risks after PUC approved the plan because of guaranteed rate-of-return. In liberalized electricity markets, the risks of new generation investment shift to the other end of spectrum. The investors bear all the risks. Due to the non-storability of electricity and the instantaneous balance of supply and demand at every second, the price and revenue volatility/uncertainties under the current spot market setup are too huge for generation companies and investors to take. How to distribute the risks fairly between different parties and align their economic incentives and desire to reduce risk with system's the short-term and long-term social welfare is the key to the problem.

Missing money [13] is another important exhibition of the problem. But the solution for missing money requires better market designs which provide good risk management tools to dampen the boom-bust investment cycles and improve the stability of power systems.

C. Proposed new market structure

In this paper, an alternative market structure focuses on a long-term energy supply rather than on the capacity availability is introduced. The Stratum Energy Market (SEM) structure proposed in this paper is motivated by the lack of transparent liquid long-term energy markets for power trading in current spot market. A large percentage of self-schedules in current day-ahead spot market indicates that most of power is traded through long-term bilateral contracts, however, current rules and regulations for such trading are insufficient in terms of their ability to create liquid active trading environment. Consequently, most of the existing forward and futures markets are not transparent, and, therefore, they may not provide the right information for investments.

The SEM structure comprises a sequentially clearing series of forward sub-markets of different duration. Forward sub-markets are designed for physical or financial energy trading with periodic bidding and clearing processes on daily, weekly, monthly, seasonal, annual and multi-annual basis. The short-term spot sub-market is designed to balance the deviations from real load pattern and forecasted load pattern. The SEM structure resembles ways in which the electric power capacity was planned and used in the regulated industry: large, base-load power plants were built and dispatched to supply a large portion of the base load; medium-size plants were turned on and off according to the seasonal variations, and small peaking plants were used to follow short-term high load demands. Fig.III.1 is an illustration of load partition for various sub-markets within the SEM.

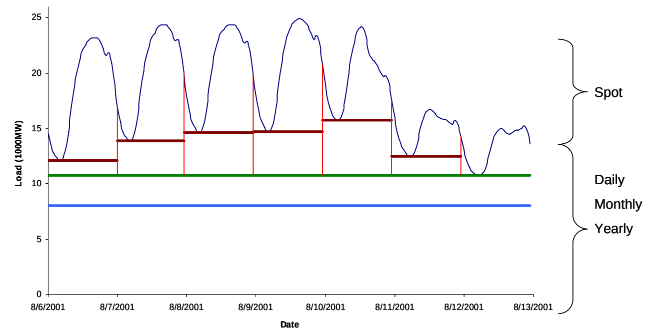

Fig.III.1 SEM structure

The forward markets can be subdivided into annual, seasonal, monthly, weekly or even daily markets according to the load cycles. All forward markets are cleared sequentially from longer-term to shorter-term. For example, at the end of year Y an annual forward auction for year Y+1 would be held and annual forward position and price are determined. Then the monthly forward auction for January Y+1 would be held successively.

The forward markets can be organized and monitored by the ISOs. The price in each submarket is determined by the uniform auction rule: the last offer that meets the demand if supply side opens only or by the equilibrium point of supply and demand if both sides are open. The market clearing quantities of these forward markets are financially binding and market participants are allowed to adjust their net position in the latter submarkets. For example if the expected market clearing price in spot market is lower than the already cleared forward price in the annual market, then the generator may choose to buy from the spot market instead of generating by itself to fulfill the annual market obligation. An optimal decision making model based on market equilibrium is introduced in the latter part of this paper.

Stratum Energy Market Model provides a good platform for all stake holders to interact through a centralized flexible market place to make their commitment decisions in both long-term as well as short-term balancing market level. The strata of energy markets with different lead time and terms provide both demand and supply sides to adjust their decisions in dynamic multi period according to their own risk preference levels to manage the volume risk (demand risk) and price risks as the forecast unfolds into reality. A good market structure should provide sufficient risk management tools to reduce short-term volatility and hedging physical and financial uncertainties. Multiple forward markets are perfectly designed instruments to hedge the spot market risks.

IV. Problem Formulation

In this section, a stochastic dynamic programming (SDP) problem similar to [11] is formulated for a profit-maximizing investor. This problem then can be solved using stochastic dynamic programming techniques, which automatically takes into account of the real option criteria: the value to invest in the future. The decision making processes of the short-term spot energy market and the long-term forward market under the proposed SEM structure are described and modeled as bilevel non-cooperative game and maximization of expectation and variance of expected profits respectively, taken into the consideration of long-term and short-term load uncertainties.

A. Investment problem

The investment problem is formulated over a planning period of T years with a granularity of one year. The optimal decision can be made at the beginning of each year. A backward SDP is used to solve the problem based on Bellman's principle. Detailed formulation is presented in (1)–(5).

$$J = \max_{u} \underset{l}{E} \sum_{k=1}^{T} \left[(1+r)^{-k} \Pi_k (x_k, l_k, l_{s,k}, u_k, \sigma_s, \sigma_l) \right] \tag{1}$$

$$x_{k+1} = x_k + u_{k-lt+1} \tag{2}$$

$$l_{k+1} = l_k + \kappa + \sigma_l z_k \tag{3}$$

$$l_{s+1,k} = (1-\alpha) l_{s,k} + \sigma_s z_s \tag{4}$$

$$\Pi_T (x_T, l_T, l_{s,T}, \sigma_s) = \Pi_T (x_T, l_T, l_{s,T}, \sigma_s \mid u_T = 0) \tag{5}$$

where

$J_0^*(x_0, l_0)$: max expected total profits at year 0
$\Pi_k(x_k, l_k, l_{s,k}, u_k, \sigma_s, \sigma_l)$: expected profits at year k
$\Pi_T(x_T, l_T, l_{s,T}, \sigma_s)$: expected profits at end year T
x_k: total installed capacity
u_k: investment decision at year k
l_k: long-term load mean at year k
$l_{s,k}$: short-term load deviation in day s of year k
σ_l: volatility of long-term load growth process
σ_s: volatility of short-term load deviation process
z_k: long-term load growth stochastic factor at year k
z_s: short-term load deviation stochastic factor at month s
r: discount rate
lt: construction lead time

The subscript l denotes the long-term process and s denotes short-term process. The load forecast process is decoupled into two stochastic processes; the long-term growth process of l_k with increase κ and volatility σ_l and short-term deviation process l_s with mean-reverse speed of α and volatility σ_s. Detailed demand modeling can be found in section IV.B. The state variable also includes the capacity x_k. A construction delay of lt is introduced in (2). The end condition is specified in (5) with no investment decision to make.

The expected total profits are a function of all the state variables $[x_k, l_k, l_{s,k}]$, disturbance $[\sigma_l, \sigma_s]$ and the control variable u_k. It includes the sum of expected profits from short-term spot market as well as long-term forward energy market.

$$\Pi_{k,i} = \sum_{s \in k} \pi_{s,i} + \pi_{k,i} - C_{invest,i} x_k \tag{6}$$

where

$\pi_{s,i}$ profit of generator i from spot market s
$\pi_{k,i}$ profit of generator i from forward market k
$C_{invest,i}$ the annualized capital cost of generator i

B. Short-term energy market

The expected profit in spot market s is the sum product of probability distribution function $Pr(z_s^j)$ and short-term market profit $\pi_{s,i}^j$ over all short-term load realizations:

$$\pi_{s,i} = \sum_{j} \Pr(z_s^j) \pi_{s,i}^j (x_k, l_k, l_{s,k}, \sigma_s, z_s^j) \tag{7}$$

The realized short-term market profit $\pi^j_{s,i}$ is a function of spot market cleared price λ_s and quantity $q_{s,i}$. Please note that the long-term uncertainty has been materialized and long-term decisions have been made at this stage. λ_s and $q_{s,i}$ in turn are determined by x_k, l_k, σ_s as well as investor i's own bidding strategy k_i in spot market and all the others' strategies k_{-i}. By introducing the bidding strategies, the model may explain why prices rise above cost-based levels and the decision making interactions between all the market participants. It is reasonable to assume the generator's marginal costs, capacities and load forecasts are public information since technical parameters of certain generator model can be obtained fairly easily. This problem then can be modeled as a bilevel non-cooperative game as described in [16].

$$\begin{aligned} &\max_{k_i} \pi(k_i, \lambda_s, q_{s,i}) \\ &s.t. \\ &g_i(k_i, q_{s,i}, q_{s,-i}) \ge 0 \\ &h_i(k_i, q_{s,i}, q_{s,-i}) = 0 \end{aligned} \tag{8}$$

$$q_{s,i} \text{ and } q_{s,-i} \text{ solves } \begin{cases} \min\limits_{q_{s,i}, q_{s,-i}} F(k_i, k_{-i}, q_{s,i}, q_{s,-i}) \\ s.t. \\ H(k_i, k_{-i}, q_{s,i}, q_{s,-i}) = 0 : \quad \lambda \\ G(k_i, k_{-i}, q_{s,i}, q_{s,-i}) \ge 0 : \quad \mu \end{cases} \tag{9}$$

The top level problem (8) is a generic formulation of the generator i's profit maximization in spot market s with k_i as bidding strategy. The lower level problem (9) is a generic formulation of ISO/RTO's market clearing process with the objective function of minimizing production costs/maximizing social welfare. Spot market price λ_s could be presented as a linear function of shadow prices λ and μ in the current LMP based ISO markets. If a pure Nash Equilibrium could be found, spot market cleared price λ_s and quantity $q_{s,i}$ as well as the realized short-term market profit $\pi_{s,i}^j$ in (7) could be calculated. A simplified model is explained in section V.

C. Long-term forward energy market

When making forward market decisions in year k, the spot price λ_s and position $q_{s,i}$ are random variables due to the uncertainties in short-term load process. Since supply and demand has to be balance instantaneously in spot market and no feasible storage method is available for electricity, the spot market prices are inherently volatile. Most market participants in energy industry are risk-averse, they may use the forward market not only to maximize the profit expectation but as a risk management tool to reduce the risk. The mean-variance criteria are chosen here as the object function for forward market. The generator i choose the optimal long-term position $q_{k,i}$ to maximize the expected total profits from both forward and spot markets while minimize its variance (risk) in year k. This formulation of forward market decision is first introduced in [17].

$$\max_{q_{k,i}} \; E(\sum_{s\in k}\pi_{s,i}+\pi_{k,i})-0.5A_i Var(\sum_{s\in k}\pi_{s,i}+\pi_{k,i}) \qquad (10)$$

The coefficient A_i is *risk-averse parameter* which implies the tradeoff between expected value and variance of long-term profits. We assume they are greater than zeros, which implies the risk is viewed negatively.

Profits for generator i in year k is the sum of profits in both spot and forward energy markets,

$$\sum_{s\in k}\pi_{s,i}+\pi_{k,i}=\sum_{s\in k}\lambda_s q_{s,i}+M\lambda_k q_{k,i}-\sum_{s\in k}C_i(q_{s,i}+q_{k,i})$$
$$=\sum_{s\in k}\rho_{s,i}+q_{k,i}(M\lambda_k-\sum_{s\in k}\lambda_s)$$

where

$q_{k,i}$: long-term position of generator i in forward market k

λ_k : price of forward market k

$C_i()$: production cost function of generator i

M: number of short-term periods in forward market k

$\rho_{s,i}=\lambda_s(q_{s,i}+q_{k,i})-C_i(q_{s,i}+q_{k,i})$: expected profits from spot market if the generator i clears all its position in spot market and leaves nothing for forward market. It is defined as *unhedged profit*.

The optimal forward position is obtained by applying first order condition on (10),

$$q_{k,i}=\frac{\lambda_k-E(X_k)}{A_i Var(X_k)}+\frac{Cov(X_k,Y_{k,i})}{Var(X_k)} \qquad (11)$$

where

$X_k=\lambda_s, s\in k$

$Y_{k,i}=\rho_{s,i}, s\in k$

X_k is the hourly spot price and $Y_{k,i}$ is the expected hourly unhedged profits from spot market in year k. After short-term load process are realized in year k, the expected value as well as variance and covariance of X_k and $Y_{k,i}$ can be calculated based on bilevel non-cooperative game formulation.

The equilibrium forward price λ_k can be derived from the long-term supply and demand balance condition,

$$\sum_i q_{k,i}=D_k \qquad (12)$$

where D_k is the forward market demand in year k.

Combining (11) and (12), λ_k can be expressed as following,

$$\lambda_k=E(X_k)-[-D_k Var(X_k)+\sum_i Cov(X_k,Y_{k,i})]/\sum_i(1/A_i) \qquad (13)$$
$$=E(X_k)+PREM$$

The forward price λ_k will converge to the average spot price if any of the Gencos' risk averse parameters A_i is zero or the number of Gencos approaches to infinite. The second term on the right side of (13) can be defined as a forward market premium *PREM*. Finally, the equilibrium forward position could be obtained by plugging (13) back to (11).

$$q_{k,i}=-\frac{PREM}{A_i Var(X_k)}+\frac{Cov(X_k,Y_{k,i})}{Var(X_k)} \qquad (14)$$

Intuitively, the forward market demand D_k can be express as a function of long-term load process l_k,

$D_k=f(l_k)$

where l_k follows the process in (3). Thus the long-term load uncertainty would impact the forward market price and positions. Note that short-term load uncertainties also influence the long-term decision making since they are implicitly considered when X_k and $Y_{k,i}$ are calculated.

$$\pi_{k,i}=\sum_j \Pr(z_k^j)\pi_{k,i}^j(x_k,l_k,\sigma_k,z_k^j,l_s,\sigma_s,z_s) \qquad (15)$$

Similarly to (6), the expected revenue in forward market k is the summation of probability distribution function $Pr(z_k^j)$ and realized forward market profit $\pi^j_{k,i}$ over all short-term load process random variable z_s realizations.

V. Numerical Example

A. Demand model

To observe the key characters for electricity demand, i.e. seasonality, mean reversion and stochastic growth, the demand model in [9] is adopted here. The daily load is modeled as a 24 hours vector $\boldsymbol{L_d}$ where each row represents an hourly load. This vector is defined as:

$$\vec{L}_d=\vec{\mu}_m+\vec{r}_d$$

where $\boldsymbol{\mu_m}$ is the monthly average hourly load and the stochastic component $\boldsymbol{r_d}$ are the deviation from the monthly mean, which has 24 hourly random variables. Because of high intra-daily correlations between these hours, Principal Component Analysis (PCA) was applied to reduce the number of variables. Only the first Principle Component (PC) and its associated weight w_d was kept in the model. Statistical analysis shows that the first PC could explain more than 90% of the total variance of the demand.

$$\vec{L}_d=\vec{\mu}_m+w_d\vec{v}_m$$

New vector $\boldsymbol{v_s}$ is the new Principle Components in each month m and w_d is its daily evolving score, which incorporates all the uncertainties.

$$w_d = l_k + l_s$$
$$l_{k+1} = l_k + \kappa + \sigma_l z_l$$
$$l_{s+1} = (1-\alpha) l_s + \sigma_s z_s$$

w_d is represents by the long-term growth component c and short-term mean-reverse deviation component l_s. The l_k process characterizes the long-term growth trend with expected value κ and stochastic component z_l on a monthly basis. The l_s process represents the short-term deviation from the monthly mean, which is mean-reverting at the rate α with stochastic component z_s. Both stochastic factors are assumed to follow normal distribution. Please notice that σ_l is constant and σ_s has twelve unique values, one for each month, and will not change between years.

Using the historic hourly load data from 1993 to 2003 on ISO New England website [18], the deterministic parameters [α κ σ_s σ_l] in the load model can be estimated. A more detailed description can be found in [9].

TABLE V.1
LOAD MODEL PARAMETERS

α	κ	$\bar{\sigma}_s$	σ_l
0.4696	1084	1792	7953

After all parameters were calibrated, the forecasted load samples used in the simulations were generated. The study period is set at 10 years.

In order to use the SDP technique to solve the problem, Markov transition probability need to be specified. The l_k process was transformed into a binomial tree with p=0.5 of high load growth ($k+0.43\sigma_l$) and p=0.5 of low load growth ($k-0.43\sigma_l$) for each year, where 0.43 is the value for standard normal distribution when CDF=2/3.

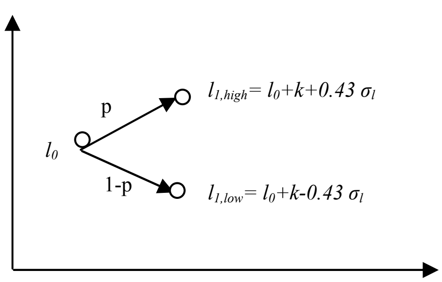

Fig.V.1 Long-term load growth transition probability in single stage

B. Simplified short-term energy market model

We adopt a simplified version of bilevel game formulation to calculate the short-term expected profits $\pi^j_{s,i}$. Under the following assumptions a pure Nash Equilibrium would always be obtained, as proved in [16].

- Linear marginal cost curve: $MC_i=a_i+b_iq_i$ where q_i is quantity and MC_i is marginal cost.
- Generator's bidding strategy is to adjust the interception a_i of the marginal cost curve. $Bid_i=k_i+a_i+b_iq_i$ where k_i is the decision variable.
- Ignore transmission network constraints as well as generator's physical constraints like ramping limits.

The lower level short term ISO market clearing problem can be simplified as:

$$\min_{q_{s,i}} \sum_i [(k_i + a_i) q_{s,i} + 0.5 b_i q_{s,i}^2]$$
$$s.t. \sum_i q_{s,i} = D_s^j : \lambda_s$$

where D_s^j is the realization j of load model in hour s.

The following solutions can be obtained by applying first order condition

$$\lambda_s = (D_s^j + \sum_i \frac{k_i + a_i}{b_i}) / \sum_i \frac{1}{b_i} \qquad (16)$$
$$q_{s,i} = \frac{\lambda_s - k_i - a_i}{b_i} \qquad (17)$$

where λ_s and $q_{s,i}$ represents is the cleared price and quantity in the spot market. The upper level problem is presented as

$$\max_{k_i} \pi_{s,i}^j = \lambda_s q_{s,i} - (a_i q_{s,i} + 0.5 b_i q_{s,i}^2) \qquad (18)$$

Plugging (16), (17) into (18) and applying first order condition, the closed form Nash Equilibrium solution of k_i could be found. In the interest of space, the detailed solutions are not presented here.

Solution (16)-(17) assumes that no capacity limits (Pmax) are considered in the system, due to the fact that response function may not be continuous after Pmax constraints are introduced and Pure Nash Equilibrium solution may not be found. However, Pmax are crucial for the capacity expansion problem. To overcome this dilemma we first obtained the optimal strategies without Pmax limits and then reinforce the limits and adjust λ_s and $q_{s,i}$ accordingly assuming the optimal strategies would not change.

When total installed capacity could not meet the demand in certain hour, a \$-100/MWh penalty price is set to represent the cost of blackouts to the units.

C. Dynamic Programming Formulation

The following assumptions are made in simulations:

1. Two submarkets in SEM: spot market and annual forward market.
2. Generator i is the only unit who is making investment decision in the system.
3. Demand in forward market is set at the minimum load within that year.
4. The risk-averse parameter A_i in long-term market is set dynamically so that the variance is always viewed as 50% of expected value.

For illustrative purposes, a small generation fleet of four units was used in simulations. Generator characteristics are summarized in Tables V.2. Unit #4 is making capacity expansion decisions described by (1)-(5).

TABLE V.2
GENERATOR TECHNOLOGY CHARACTERISTICS

unit #	Capital cost ($/KW)	Capacity (MW)	b	a
1	3000	1000	0.02	40
2	1200	400	0.04	40
3	500	300	0.2	20
4	350	300	0.5	20

The lead time *lt* for a new generator construction is three years and the problem (1)–(5) can be transformed into the following DP formulation.

$$J(x_k,l_k,l_s,k)=\max_{u_k}\{\underset{l_k}{E}\{\underset{l_s}{E}[\sum_{t=1}^{lt-1}\Pi_k(x_k,l_{k+t},l_s,u_k)$$
$$+J(x_k+u_k,l_{k+lt},l_s,k+lt)]\}\}$$

Additional assumptions are adopted here to reduce the curse of dimension problem: investment decisions are made every three years and at any given time no more than one new unit is under construction. All feasible states of unit's capacity are presented in Fig V.2. The end states were fixed with u_9=0 and the problem can be solved by backward SDP.

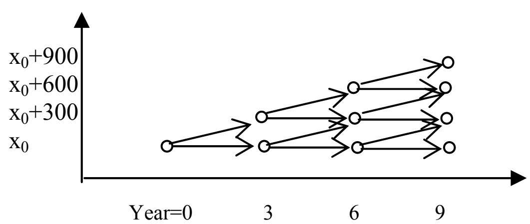

Fig.V.2 Feasible capacity expansion path

D. *Simulation results and discussions*

The optimal investment decisions for unit #4 under different market structures were studies here including the SEM market structure with spot market gaming, spot only market structure with gaming and spot only market with marginal cost bids. The results were presented in Table V.3.

TABLE V.3
GENERATOR TECHNOLOGY CHARACTERISTICS

Market Structure Scenarios	u_0	u_3	u_6	Expected Profits
SEM	300	300	0	2.30E+8
Spot Only	0	0	0	1.12E+8
Spot Only w/ MC bids	0	0	0	6.36E+7

The SEM market structure induced two new unit investment decision at year 0 and 3 while spot only market structure discouraged any investment decision with or without the consideration of gaming opportunities. This demonstrates that the day-ahead/real-time only energy markets without any long-term market mechanism like capacity markets or SEM are not sustainable and bust and boom cycles are inevitable. Also the unit obtained the highest expected profits under SEM. This is mainly due to the fact that without new capacity the system would frequently slip into blackouts emergencies when total demand is higher than installed capacity. The blackout penalty prices reduced the unit's profit margin substantially.

VI. CONCLUSIONS AND FUTURE RESEARCH

Given that today's measurement of market power in the spot market is classified as any bids higher than the SRMC cost, we suggest that it is essential to introduce other means to provide incentives of new generation capacity installation in a timely manner to supply the long-term demand growth. This can be done by designing longer-term physical and/or financial mechanisms for valuing future investments. In this paper we propose a Stratum Electricity Market (SEM) structure as an enhancement to the short-term spot market. This market would eliminate the need for various installed capacity and reliability markets currently under consideration. The SEM structure consists of several sequentially clearing sub-markets, ranging from a day-ahead-market, through month-, season-, year-, five year- and even ten year-forward sub-markets.

A fundamental modeling approach is further developed to model and simulate the SEM structure. A simple example was solved using the SDP method to demonstrate the importance of SEM structure.

Future research concerns:

1. Incorporating price-sensitive consumers into the demand model.
2. Developing stochastic fuel price model.
3. Simulating long-run capacity market mechanisms like the Reliability Provision Market (RPM) model proposed by PJM and comparing the results with SEM.
4. Including more realistic constraints into the power system, i.e. network constraints.

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