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**GENERATION ASSET PLANNING UNDER UNCERTAINTY**

**A Dissertation APPROVED FOR THE**
**SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING**

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# ABSTRACT

With the introduction of competition in the electric power industry, generation asset planning must change. In this changed environment, energy companies must be able to capture the extrinsic value of their asset operations and long-term managerial flexibility for sound planning decisions. This dissertation presents a new formulation for the generation asset planning problem under market uncertainty, in which short-term operational and long-term coupling constraints associated with investment decisions are simultaneously reflected in the planning process.

# CHAPTER 1

# INTRODUCTION

As the electricity market reform moves towards market competition in the United States and other countries, "generation expansion planning" has become "asset valuation". The challenges associated with asset valuation are related to the presence of a market that, even if partially liquid, introduces additional opportunities for possible interactions between operational and financial strategies.

Under regulation, market presence was not significant (or non-existent) and investment decisions made by generation companies were for the most part, passed on to the consumers through rate adjustments. In those times, the objective of generation expansion planning was to satisfy reliability requirements and then to find the most economical plan of adding generation capacity to the existing generation system. The term "economical" is understood here as minimization of investment, operational and maintenance costs. The methods of generation expansion analysis used then, whether deterministic or not, were always based on reliability and were a function of the future system demand, i.e,. load.

Early methods of generation planning [1] included reliability criteria such as the planning reserve margin and the capacity reserve margin. The planning reserve margin is defined as the difference between the installed capacity and the peak load divided by the peak load, while the capacity reserve margin is the difference between the installed capacity and the peak load divided by the installed capacity. The procedure then consists of finding the capacity addition plan that is most economical towards reaching the defined reliability criterion. In an alternate model, the definition of customer damage functions [2] allowed the capacity addition problem to be addressed as a more general economic problem [3]: the optimal reliability level is determined as a function of the generation investment and operational costs, and the economic cost of interruption. In a simpler version, a model in which cost characteristics are assumed for unserved energy (or unserved demand) can drive strategic decision planning: this type of model is also known as the unserved energy method.

When described as above, the generation capacity planning problem is usually presented as a one-stage decision-making problem. In reality, generation capacity planning must involve sequential time-related decisions that play a key role in determining the optimal planning strategy. For instance, when using a method that models customer damage function, one must remember that the costs of interruption are a function of the time of occurrence (time of day, season of year) and the duration of the interruption. Another example is that the lead-time required to have a potential new generation plant operational can result in choosing a more expensive alternative, given the reliability constraint target. Consequently, the capacity expansion problem should be formulated as a multi-stage mathematical programming problem. In that regard, the generation expansion usually takes the form of a dynamic programming problem, a formulation often very difficult to solve. Over the years, various techniques have been applied to suggest a more reasonable approach to this mathematical problem, amongst which are:

- state enumeration: the technique, consists of enumerating all the possible strategies and selecting the one with the best outcome. This technique proves efficient when used with small systems offering few candidate strategies;
- state tree truncation: based on the state enumeration techniques, heuristics are included to intentionally reduce the size of the decision space that must be searched, reducing the computation time for solution convergence;
- linear programming: the linear programming formulation is the first mathematical formulation of the generation expansion problem [33]. With this formulation, all the variables in the problem must be continuous, which sometimes results in suggesting that planners should purchase (or sell) fractions of generating capacity. This difficulty is generally solved by rounding up the affected variables into appropriate integers, possibly causing sub-optimality;
- decomposition algorithms such as Benders' decomposition or Lagrange multipliers are often used to address the dynamic programming formulation.

In long term planning, uncertainty should be reflected in the assessment of the planning strategies. Under regulation and no market, sources of uncertainty included demand growth, fuel costs and unplanned outages for installed capacity. Again here, there are four general approaches to that mathematical problem [4]:

- the deterministic equivalent approach: this approach assumes that the forecasted values of uncertain variables is 100% reliable,

- the scenario approach, where only ‘critical’ scenarios are built, each leading to a specific expansion plan. The challenge in this case is to find the plan which best satisfies all scenarios,
- the stochastic optimization approach, which recognizes the need of building the best plan on the average, given the random behavior of the uncertain variables [5],
- the simulation approach, which usually involves Monte Carlo runs [6].

The restructuring of electric power markets in recent years in the U.S and other countries has for main objective to improve efficiency through the introduction of competition. In a competitive environment, generation companies will look at capacity planning from a profit maximization perspective, rather than minimization of costs [7]. This change comes naturally as the role of central coordinator of regional planning to satisfy capacity adequacy and reliability would no longer be the primary responsibility of the generation companies. As a result, generation companies’ operational and investment strategies will be driven towards maximizing market opportunities [8]. Under competition, planning managers need to be aware of the various uncertainties that could affect the value of their potential investment strategies. These uncertainties include: market price of electricity (energy and ancillary services) and fuel, locational price caused by uncertainty in available transmission capacities, market structure and environmental constraints.

The presence of the market uncertainty, while a source of financial opportunity for asset owners and managers, introduces additional components of risk that strategic planning cannot ignore. Therefore, in determining the planning value of a generation plant, significant attention must be paid to market price uncertainty, or volatility as it is commonly known [9]. A brief description of the risk components that an energy company can face is found in [10]. The generation expansion problem under a market is also known as the generation valuation problem. Generation asset valuation efforts can be grouped in two categories:

- financial models [29]: these models use existing financial techniques to value physical generation assets. The solution often comes as a closed-form expression with assumed parametric distributions of market uncertainty. One advantage with these models is their simplicity of use. However, the complexity of the electricity market has shown that in general, the generation portfolio optimization problem cannot be solved via a closed-form expression. This limits the use of financial models, which can still be used for practical benchmark purposes,
- mathematical programming models [33],[40]: these models recognize the complex nature of generation portfolio optimization and try to adapt their proposed scheduling technique to the market uncertainty. While these models recognize the need for some scheduling method, they generally differ on how to model market uncertainty. The main difference between most of the methods in this category, aside of the portfolio coordination algorithm they may use, lies in the representation of market uncertainty.

Given the coming changes in market environment and the natural oligopolistic nature of the electrical power industry, some [11], [12] have looked at the generation capacity problem from a game theory or strategic behavior perspective. While these methods provide valuable insight on market structure impact, none explicitly takes into account the dynamic short-term constraints associated with generation plants operations, nor the long-term coupling constraints associated with possible changes in the make-up of the generation portfolio being managed during the planning horizon. In this dissertation, we quantify the impact of market price uncertainty in the planning value of a generation plant under competition, given the physical constraints of the plant and its strategic investment coupling constraints such as time-to-build and technology learning effect, when facing residual demand. Although out of the scope of the current work, it is the author's belief that the methodology presented in this dissertation can be included within a more systematic analysis of market strategic behavior as described in [11], where the planning value of each market participant (generation company) is determined via an iterative process.

Generation asset planning should be performed with models capable of reconciling the physical constraints associated with the energy delivery process. Unless these constraints are fully represented and considered, hedging and risk measures cannot be adequately assessed. The physical delivery requirements of electricity contracts represent the heaviest obstacle in modeling generation assets through standard financial valuation methods. Some of the important physical constraints include:

- minimum up-time: once a generation unit is brought on-line, it must stay on-line for at least a specified time,
- minimum down-time: once a generation unit is brought off-line, it must stay off-line for at least a specified time,

- startup/shutdown costs: bringing a generation unit on(off)-line causes additional costs, in terms of fuel and/or O&M costs,
- must-on, must-off periods: they represent time for which the hourly status of the generation unit is specified in advance, mainly because of electrical requirements and other maintenance constraints,
- transmission limitations: generation supply and end-users are connected through a physical network, which can be congested at times, adding additional constraints to the physical delivery process,
- time-varying incremental heat-rate and capacity/dispatch limits.

When coupled with the life cycle of a generation plant, the existence of market uncertainty offers asset management additional investment flexibility in terms of valuing that plant. In the management science literature, typical long term strategic alternatives [13] for a facility at some point in time are: selling the plant (or part of it), expanding the capacity of the plant, reducing the size of the plant, and keeping base-operations plan for the plant as is. When market interaction exists, financial alternatives such as long term forwards or option contracts should be included as well.

At this point, it is worth clarifying the terms 'strategic investment plan' and 'strategic alternative' as these will be used extensively throughout the rest of the dissertation:

- a strategic alternative is a unique (energy) portfolio configuration. Naturally, two strategic alternatives are different in the composition of their respective portfolio make-up;

- a strategic investment plan is defined as the time sequence of strategic alternatives within the planning horizon.

An example of strategic alternatives is the expansion of a generation plant capacity into a 2x1 plant: the expanded plant represents a new strategic alternative, when compared to the plant's size prior to the capacity expansion, which in turn is a different strategic alternative. The time sequence consisting of changing from a simple cycle installed capacity plant to a 2x1 combined cycle installed capacity plant is an example of a strategic investment plan. While mostly associated with some capital investment (e.g. expanding the generation plant capacity from a simple cycle to a 2x1 combined cycle) or reward (e.g. selling the plant to a third party), a strategic investment plan does not always incur capital costs/rewards when a change in strategic alternatives occurs. An example would be a strategic alternative described by a generation plant whose energy production can be directly sold into the energy market, compared to a strategic alternative in which part of the generation plant output could be sold through a 10-year forward contract. Finally let's note that although different in their portfolio configuration, it is possible for non identical strategic alternatives to return identical operational benefits over time as they could use identical operational strategies.

In an uncertain market, assets planners should understand how to value all strategic alternatives, and determine the risk profile associated with each of them. As the life of a generation plant represents a time line through which several strategic alternative decisions can be taken, additional value can come from the possible time combination of these strategic alternatives [14]; these state changes or regime switches are subject to long-term constraints such as investment costs, contract minimum execution period, delays from construction time, etc. Unfortunately, the impact of the interactions of the strategic alternatives over the lifetime of a generation plant under an uncertain market is not well documented in the competitive power industry literature. This shortcoming can be attributed to the absence of proper tools to undertake such analysis.

From a managerial/investment perspective, the problem of generation valuation/planning is two-fold:

1) understand and capture the value of each strategic alternative,
2) discover and quantify the managerial flexibility that could result from coupling these alternatives.

In the electric power industry, authors seem more interested in the first part of the planning problem, sometimes at the expense of not thoroughly addressing the second one, thus providing only part of the answer to this complex problem.

The major contribution of this research is the development of a new long-term generation planning method under uncertainty. This method departs from the existing ones in that the short-term operational and long-term strategic coupling constraints are simultaneously reflected in the planning mechanism, while uncertainty is captured through Monte Carlo simulation. The proposed method can be summarized as a two-step process for long term portfolio investment decisions. In the first step, a chronological operational portfolio optimization technique coupled with Monte Carlo simulation is used to determine the value of each of the considered strategic alternatives, given the strategic alternatives that have been defined. This valuation technique captures the short-term constraints associated with generation operations. Monte Carlo is used as an efficient technique to describe uncertainty and each scenario realization is associated with the operational flexibility of asset managers, as seen in practice. When compared to multinomial tree simulations, Monte Carlo simulation carries the advantage of being easily adaptable to various stochastic market price models and can generate simulated paths without too much computational burden. Then through a new planning problem formulation, the results from the previous step will be used towards the multi-stage coordination of existing strategic alternatives to determine the extrinsic value of the investment project. In the proposed long term planning algorithm, long term constraints associated with strategic changes are captured and help identify the optimal investment decisions.

The rest of this dissertation consists of three additional chapters. In Chapter 2, the problem of optimal portfolio execution is presented. The physical characteristics and time related constraints of the portfolio instruments (i.e. generators, energy forward contracts, and energy option contracts) play an important role in determining the optimal portfolio execution plan for a given strategic alternative. First, the energy portfolio execution problem will be presented as a deterministic unit commitment problem, and an algorithm will be described for a market-based problem. As future market conditions are subject to changes, the operational value of a strategic alternative becomes uncertain. Next, a method to assess the extrinsic operational value of a strategic alternative is described by effective combination of the Monte Carlo simulation and the robustness of the optimal operational portfolio algorithm. In Chapter 3, the problem of generation planning is presented. In its formulation, the time interactions of the various strategic alternatives along with the other long term constraints are included. Using a dynamic programming algorithm that reflects sequential time decisions and the operational results from the previous chapter, a methodology for the planning valuation of a generation plant is developed. The methodology presented in this chapter is first applied towards a deterministic market environment. Then following a Monte Carlo simulation, it is adjusted to represent the planning value under uncertainty. Finally, the conclusion and future recommendations on this research are presented in Chapter 4.

# CHAPTER 2

# STRATEGIC ALTERNATIVE OPTIMAL OPERATIONAL VALUATION

## II.1 Introduction

During the life cycle of a generation plant, strategic investment plans options can be exercised to improve its market profitability. By defining a strategic investment plan as a time combination of various strategic alternatives, the valuation of a given strategic investment plan is determined by the optimal execution of its strategic alternatives sequence. In other words, the value of this individual strategic investment plan is in direct correlation with that of its strategic alternatives, and the timing of their implementation.

Formally, the valuation of a strategic alternative is equivalent to solving for an operational energy portfolio optimization problem in which the portfolio configuration represents the strategic alternative, and for which the time horizon is the time period through which the strategic alternative is active. Unlike the load (or price) duration curve-based method used in long term analysis with traditional models, the strategic operational solution methodology outlined in this chapter uses a chronological-based problem formulation that takes into account the time-dependent physical constraints relative to generation plant operations. The problem of operational energy portfolio optimization is known in the literature as unit commitment problem. In the unit commitment problem, we seek to determine the optimal time sequence of bringing assets off-line and deactivating contracts, as well as the optimal time sequence of bringing assets on-line and exercising contracts, and determining at what level these resources should be allocated (or dispatched) to contribute to the optimal operational execution of the portfolio. While under regulated days the optimal operational execution of a portfolio was defined by minimizing total operational costs, it is defined as maximizing total operational profits under market environment. The latter definition of optimal operational portfolio execution will be used throughout this chapter. This chapter can be divided in two parts: a discussion of deterministic unit commitment and a presentation of operational valuation under uncertainty.

## II.2 Deterministic Strategic Operational Valuation

With the growing importance of optimal portfolio management in an evolving energy industry, the unit commitment problem has attracted significant interest within the last fifteen years or so. Under regulation and before market competition, the market structure and the natural monopolies created at the time did not encourage energy companies (electric utilities for the most part) to look at the unit commitment problem with scrutiny. At that time, the unit commitment problem in many electric utility companies was addressed through heuristics, or semi-heuristics methods. As the market evolved towards a more competitive structure, it became more obvious that generation asset optimization for operations would be key to remaining profitable within the industry. As a result, research in asset operational optimization generated significant interest both from the worlds of academia and the industry.

Aside from heuristics, research in deterministic operational asset optimization has essentially known three major development paths: the dynamic-programming based methods; the Lagrangian-based methods; and, the more recent sequential bidding-based methods. By viewing the short-term unit commitment problem as an optimal system state configuration problem to solve, the dynamic programming based approach consists of enumerating all system states (on/off combinations) over the short-term and finding the optimal path for the studied portfolio. The dynamic programming approach can be assimilated to a brute force method and suffers from "the curse of dimensionality", as the number of possible system states over the studied time window grows exponentially with the number of positions in the portfolio. In an effort to reduce the impact of the dimensionality problem, various schemes have been introduced to the original dynamic-programming based approach, leading to less computationally intensive methods, such as the dynamic-programming sequentially truncated (DP-SC) method [15]. However, truncation can not only result in sub-optimal solutions, it can also eliminate the path of feasible solutions. In the early 1980's, Merlin and Sandrin found that by decomposing the unit commitment problem into as many optimizing sub-problems as there are market instruments (or positions) in a portfolio, it becomes more efficient to coordinate the optimal portfolio execution through price signals [16]. This method, better known as the Lagrange Relaxation (LR) method, considerably improves the computational time required to solve a deterministic unit commitment problem. Unfortunately, the

Lagrangian relaxation method can suffer from oscillation problems when several option-like positions in the analyzed portfolio are identical. By the late 1980's, Fred Lee suggested a new approach to solving the unit commitment problem. By combining the strengths of both dynamic programming and Lagrangian relaxation methods, Lee proved that quality unit commitment solution could be found without carrying the burdens of extensive computation time found in dynamic programming methods, and by avoiding the oscillation traps of the Lagrangian relaxation method. This new approach called sequential bidding unit commitment, consists of given an initial solution, sequentially selecting positions and their optimal commitment strategy, through sound economic guidance, to fulfill in the most economic fashion the portfolio's target obligations and profit opportunities. In the publication where the sequential-based unit commitment method was first introduced [17], a complex algorithm is presented and describes the sequential selection process. Sequential based unit commitment is extensively used in the industry.

In the treatment of the unit commitment problem in this chapter, transmission congestion is ignored. Another assumption is that the only traded electricity product is the electrical energy, with no ancillary services products defined.

### II.2.1 Notation

Let us consider the following notation for the unit commitment problem

- t: time index (hour).
- T: time to horizon for the simulation period.

i, j, w, m: portfolio position index.

$\Omega$ : set of portfolio supply positions.

K : set of portfolio demand positions.

$u_i(t)$ : commitment status at time t for portfolio position i, $\forall i \in \Omega \cup K$.

$SUC_i$ : start-up cost for portfolio position i, $\forall i \in \Omega \cup K$.

$SDC_i$ : shut-down cost for portfolio position i, $\forall i \in \Omega \cup K$.

$\tau_i(t)$ : at the beginning of time t, $\tau_i(t)$ is read as the amount of time (number of hours) that portfolio position i has been on-line (>0), or off-line (<0), $\forall i \in \Omega \cup K$.

$Pmax_i(t)$ : maximum energy to be allocated at time t to portfolio position i, $\forall i \in \Omega \cup K$.

$Pmin_i(t)$ : minimum energy to be allocated at time t to portfolio position i, $\forall i \in \Omega \cup K$.

$P_i(t)$ : energy allocation for portfolio position i, at time t, $\forall i \in \Omega \cup K$.

$MUP_i$ : minimum-up time for portfolio position i, $\forall i \in \Omega \cup K$.

$MDN_i$ : minimum-down time for portfolio position i, $\forall i \in \Omega \cup K$.

$S_i(t)$ : cost incurred for a change in availability status between time t and (t-1), for portfolio position i, $\forall i \in \Omega \cup K$. $S_i(t)$ can be expressed as:

$$S_i(t) = u_i(t) \cdot [1 - u_i(t-1)] \cdot SUC_i + u_i(t-1) \cdot [1 - u_i(t)] \cdot SDC_i \qquad .\mathbf{(1)}$$

F(.): revenue/cost curve associated with a portfolio position. For a supply position, F(.) is a cost curve while for a demand position, F(.) is a revenue curve. For convexity purposes, the cost curve associated with a demand position is assumed to be convex, while that of a demand position is concave. In our presentation, we will use a quadratic function to represent a revenue/cost curve; that is, for any portfolio position i,

$$F_i[P_i(t)] = a_{0,i}(t) + a_{1,i}(t) \cdot P_i(t) + a_{2,i}(t) \cdot P_i^2(t) \quad , \qquad \textbf{(2)}$$

where: $a_{0,i}(t)$, $a_{1,i}(t)$ and $a_{2,i}(t)$ are parametric descriptors at time t for cost/revenue profile for portfolio position i, $\forall i \in \Omega \cup K$ .

II.2.2 Problem Formulation

The optimal operational portfolio execution problem over a time period T is equivalent to solving a unit commitment problem in which, operational decisions must be made at each time t, such that the total operational benefits over period T are maximized. This problem can be mathematically formulated as:

**Problem I**

$$\underset{\substack{u_i(t), P_i(t), \forall i \in \Omega, \forall t \in \{1,...,T\} \\ u_j(t), P_j(t), \forall j \in K, \forall t \in \{1,...,T\}}}{\text{Max}} \left\{ \sum_{t=1}^{T} \left[ \sum_{j \in K} \{u_j(t) \cdot F_j[P_j(t)] - S_j(t)\} - \sum_{i \in \Omega} \{u_i(t) \cdot F_i[P_i(t)] + S_i(t)\} \right] \right\} \qquad \textbf{(3)}$$

subject to:

$$\sum_{i \in \Omega} u_i(t) \cdot P_i(t) = \sum_{j \in K} u_j(t) \cdot P_j(t), \quad \forall t \in \{1,...,T\}, \qquad \textbf{(4)}$$

$$u_w(t) \cdot Pmin_w(t) \le P_w(t) \le u_w(t) \cdot Pmax_w(t), \quad \forall w \in \Omega \cup K, \quad \forall t \in \{1,...,T\}, \textbf{(5)}$$

$$\begin{cases} u_w(t) = 1, & \text{if} \quad 0 < \tau_w(t-1) < MUP_w - 1, \\ u_w(t) = 0, & \text{if} \quad -(MDN_w - 1) < \tau_w(t-1) < 0, \quad \forall w \in \Omega \cup K, \quad \forall t \in \{1,...,T\} \\ u_w(t) \in \{0,1\}, & \text{otherwise} \end{cases} \quad \textbf{(6)}$$

The objective function in Problem I can be reformulated in a way that gives it a more decomposable form. This is achieved by rewriting Problem I into Problem II as:

**Problem II**

$$\underset{\substack{u_i(t), P_i(t), \forall i \in \Omega, \forall t \in \{1,...,T\} \\ u_j(t), P_j(t), \forall j \in K, \forall t \in \{1,...,T\}}}{\text{Max}} \left\{ \sum_{j \in K} \left[ \sum_{t=1}^{T=1} \{ u_j(t) \cdot F_j[P_j(t)] - S_j(t) \} \right] - \sum_{i \in \Omega} \left[ \sum_{t=1}^{T=1} \{ u_i(t) \cdot F_i[P_i(t)] + S_i(t) \} \right] \right\} \quad \textbf{(7)}$$

subject to:

$$\sum_{i \in \Omega} u_i(t) \cdot P_i(t) = \sum_{j \in K} u_j(t) \cdot P_j(t), \quad \forall t \in \{1,...,T\}, \quad \textbf{(8)}$$

$$u_w(t) \cdot Pmin_w(t) \le P_w(t) \le u_w(t) \cdot Pmax_w(t), \quad \forall w \in \Omega \cup K, \quad \forall t \in \{1,...,T\}, \textbf{(9)}$$

$$\begin{cases} u_w(t) = 1, & \text{if} \quad 0 < \tau_w(t-1) < MUP_w - 1, \\ u_w(t) = 0, & \text{if} \quad -(MDN_w - 1) < \tau_w(t-1) < 0, \quad \forall w \in \Omega \cup K, \quad \forall t \in \{1,...,T\} \\ u_w(t) \in \{0,1\}, & \text{otherwise} \end{cases} \quad \textbf{(10)}$$

In sequential bidding based methods, the general algorithm procedure consists of determining an initial solution upon which each portfolio's position contribution is carefully evaluated. Once the evaluation has been performed, the most appropriate candidate position is selected, and the process is repeated until some convergence criterion is reached. In Tseng [18], the evaluation and candidate selection processes are performed through a downward commitment sequence. Our research [19] has shown that an upward commitment sequence when appropriately implemented, could produce a solution quality that is at least as good as that of the downward commitment sequence. In either case, the overall solution flow chart is the same as outlined in Figure 2.1.

Problem II (or Problem I) is a time varying optimization problem that involves continuous and integer variables. It can be viewed as a two-stage problem: the need to determine the optimal commitment status strategy for each portfolio position and, given the portfolio positions commitment status strategy adopted at each time interval t, the need to determine the optimal resources allocation strategy for each portfolio position committed at time t. In other words, Problem II consists of a commitment strategy sub-problem and a dispatch strategy sub-problem. In the next section, a detailed solution mechanism is presented.

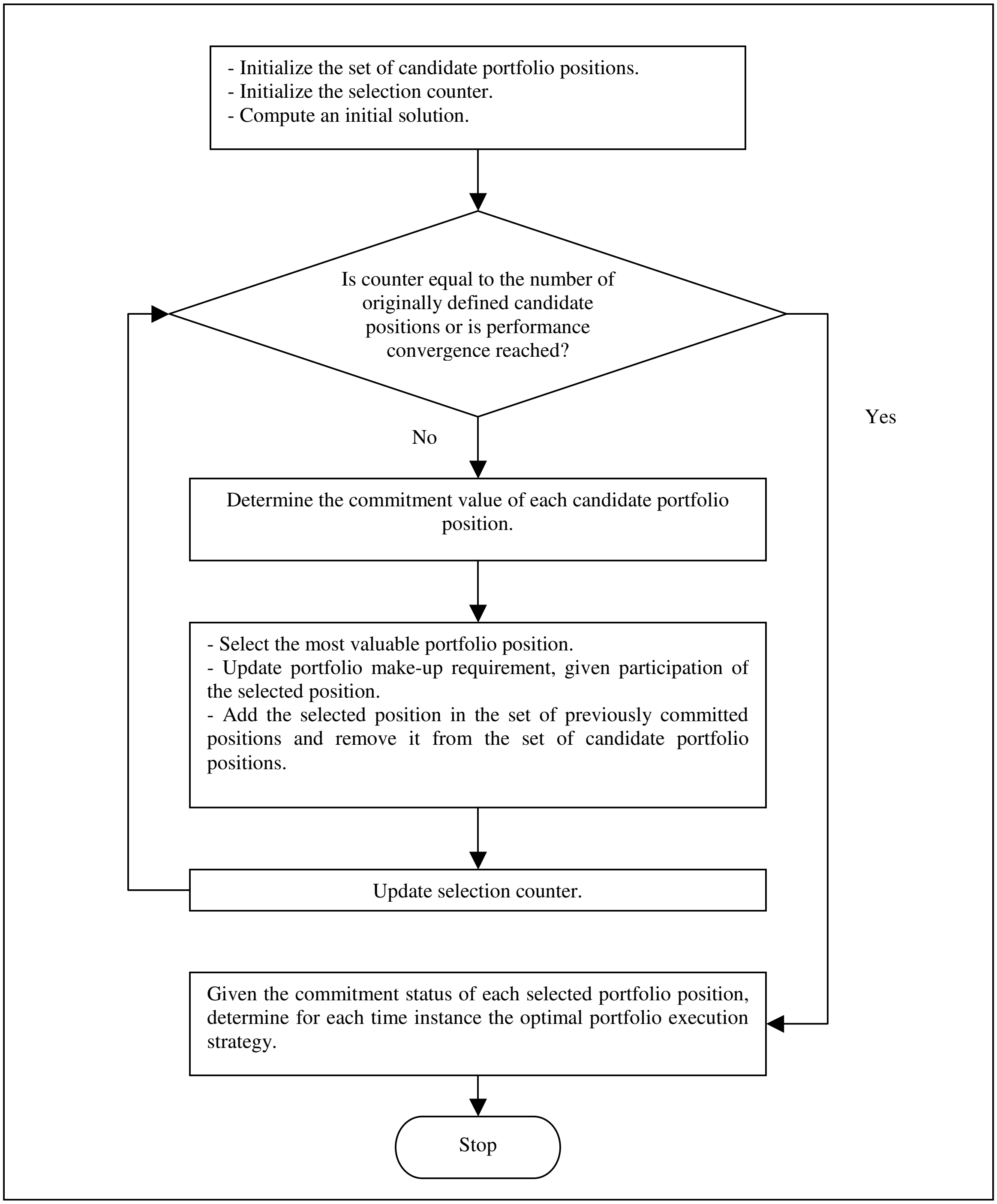


Figure 2.1: Flow Chart for Upward/Downward Unit Commitment Method.

The solution algorithm presented in the section below is designed towards a market-based optimization problem, where each asset commitment strategy can only be justified by market opportunity. The interested reader can refer to the above mentioned references for obligation-based problems.

### II.2.3 A Market-Based Deterministic Unit Commitment Method

For a market-based problem and, assuming a linear price curve response on the market sale opportunity, with no restricted hourly depth, and no minimum hourly sale requirement, the problem formulation can be further simplified. We can easily observe that the set of demand positions will be reduced to only one position (market sale) while the total hourly energy contribution from the supply positions will match the total hourly market energy sale. Under these conditions, constraint (8) needs not be explicitly mentioned in the constraint set, and Problem II is reformulated as:

**Problem III**

$$\underset{\substack{u_i(t), P_i(t), \forall i \in \Omega, \forall t \in \{1,...,T\} \\ u_j(t), P_j(t), \forall j \in K, \forall t \in \{1,...,T\}}}{\text{Max}} \left\{ \sum_{j \in K} \left[ \sum_{t=1}^{T=1} \{ u_j(t) \cdot F_j[\sum_{i \in \Omega} P_i(t)] \} \right] - \sum_{i \in \Omega} \left[ \sum_{t=1}^{T=1} \{ u_i(t) \cdot F_i[P_i(t)] + S_i(t) \} \right] \right\} \quad \textbf{(11)}$$

subject to:

$$u_i(t) \cdot Pmin_i(t) \le P_i(t) \le u_i(t) \cdot Pmax_i(t), \quad \forall i \in \Omega, \forall t \in \{1,...,T\}, \quad \textbf{(12)}$$

$$\begin{cases} u_i(t) = 1, \quad \text{if} \quad 0 < \tau_i(t-1) < MUP_w - 1, \\ u_i(t) = 0, \quad \text{if} \quad -(MDN_i - 1) < \tau_i(t-1) < 0, \quad \forall i \in \Omega, \quad \forall t \in \{1,...,T\} \\ u_i(t) \in \{0,1\}, \quad \text{otherwise} \end{cases} \tag{13}$$

$$u_j(t) = 1, \quad \forall j \in K, \forall t \in \{1,...,T\} \tag{14}$$

For notation clarity, we will use index j to represent the market sale from the demand position set K. Also, since in practice market sale revenue is represented through a revenue function in which $a_{0,j}(t)=0$, the objective function (11) under a linear market response curve can be rewritten as:

$$\underset{u_i(t),P_i(t),\forall i\in\Omega,\forall t\in\{1,...,T\}}{\text{Max}} \left\{ \sum_{t=1}^{T=1} \left[ a_{1,j}(t) \cdot \sum_{i\in\Omega} P_i(t) \right] - \sum_{i\in\Omega} \left[ \sum_{t=1}^{T=1} \{ u_i(t) \cdot F_i[P_i(t)] + S_i(t) \} \right] \right\} \tag{15}$$

where:

$a_{1,j}(t)$ represents the energy market price at time t

After re-arranging the terms in (15) and removing (14) accordingly, the open market-based unit commitment problem can be presented as:

**Problem IV**

$$\underset{\substack{u_i(t),P_i(t),\forall i\in\Omega,\forall t\in\{1,...,T\} \\ u_j(t),P_j(t),\forall j\in K,\forall t\in\{1,...,T\}}}{\text{Max}} \left\{ \sum_{i\in\Omega} \sum_{t=1}^{T=1} \left[ a_{1,j}(t) \cdot P_i(t) - \{ u_i(t) \cdot F_i[P_i(t)] + S_i(t) \} \right] \right\} \tag{16}$$

subject to:

$$u_i(t) \cdot Pmin_i(t) \le P_i(t) \le u_i(t) \cdot Pmax_i(t), \quad \forall i \in \Omega, \forall t \in \{1,...,T\}, \tag{17}$$

$$\begin{cases} u_i(t) = 1, & \text{if} \quad 0 < \tau_i(t-1) < MUP_w - 1, \\ u_i(t) = 0, & \text{if} \quad -(MDN_i - 1) < \tau_i(t-1) < 0, \quad \forall i \in \Omega, \quad \forall t \in \{1,...,T\} \\ u_i(t) \in \{0,1\}, & \text{otherwise} \end{cases} \tag{18}$$

The formulation of Problem IV contains no coupling constraints between the supply positions in $\Omega$. With the newly defined objective function (16), Problem IV is a set of individual commitment problems, each of them consisting of determining the optimal commitment/dispatch strategy for a given supply position in $\Omega$, when subject to a market revenue stream. For a given supply position $i \in \Omega$, the single commitment formulation is defined by:

**Problem V**

$$\underset{u_i(t), P_i(t), \forall t \in \{1,...,T\}}{\text{Max}} \left\{ \sum_{t=1}^{T=1} \left[ a_{1,j}(t) \cdot P_i(t) - \{u_i(t) \cdot F_i[P_i(t)] + S_i(t)\} \right] \right\} \tag{19}$$

subject to:

$$u_i(t) \cdot Pmin_i(t) \leq P_i(t) \leq u_i(t) \cdot Pmax_i(t), \quad \forall t \in \{1,...,T\}, \tag{20}$$

$$\begin{cases} u_i(t) = 1, & \text{if} \quad 0 < \tau_i(t-1) < MUP_w - 1, \\ u_i(t) = 0, & \text{if} \quad -(MDN_i - 1) < \tau_i(t-1) < 0, \quad \forall t \in \{1,...,T\} \\ u_i(t) \in \{0,1\}, & \text{otherwise} \end{cases} \tag{21}$$

Although it still carries a commitment decision and a dispatch problem schema, Problem V is a further reduced version of a network flow problem that must obey, for each supply position in $\Omega$, the state transition constraints defined in (21). The network flow optimal route can be determined by application of a dynamic programming algorithm for which the stage representation is the time index and the state representation at any stage is the set of possible on/off line hours that could be inherited from the previous stage. While the feasible commitment path can be addressed through the state transition diagram as a function of both the minimum-up and minimum-down times of the evaluated portfolio position [20], the dispatch problem is solved for each system state of positive on-line hours through the first-order derivation [21] of the argument of the objective function (19), leading to:

$$\begin{cases} \dfrac{d}{dP_i(t)}\left[a_{1,j}(t)\cdot P_i(t)-\{u_i(t)\cdot F_i[P_i(t)]+S_i(t)\}\right]=0 \\ P\min_i(t)\le P_i(t)\le P\max_i(t) \qquad\qquad ,\forall i\in\Omega,\quad \forall t\in\{1,\ldots,T\} \\ u_i(t)=1 \end{cases} \tag{22}$$

or

$$\begin{cases} P_i(t)=\max\left\{ P\min_i(t);\min\left\{P\max_i(t);\dfrac{a_{1,j}(t)-a_{1,i}(t)}{2\cdot a_{2,i}(t)}\right\}\right\} \quad ,\forall i\in\Omega,\quad \forall t\in\{1,\ldots,T\} \\ u_i(t)=1 \end{cases} \tag{23}$$

Once Problem V is solved for each supply position, the solution to the objective function of Problem IV is the sum of all the objective functions for each Problem V, as the final portfolio execution strategy in Problem IV is the collection of all the individual execution strategies determined in each Problem V. From that perspective, we can derive a solution flow chart in the case of a market-based optimization problem as a special case of the flow chart derived in Figure 2.1 as shown in Figure 2.2.

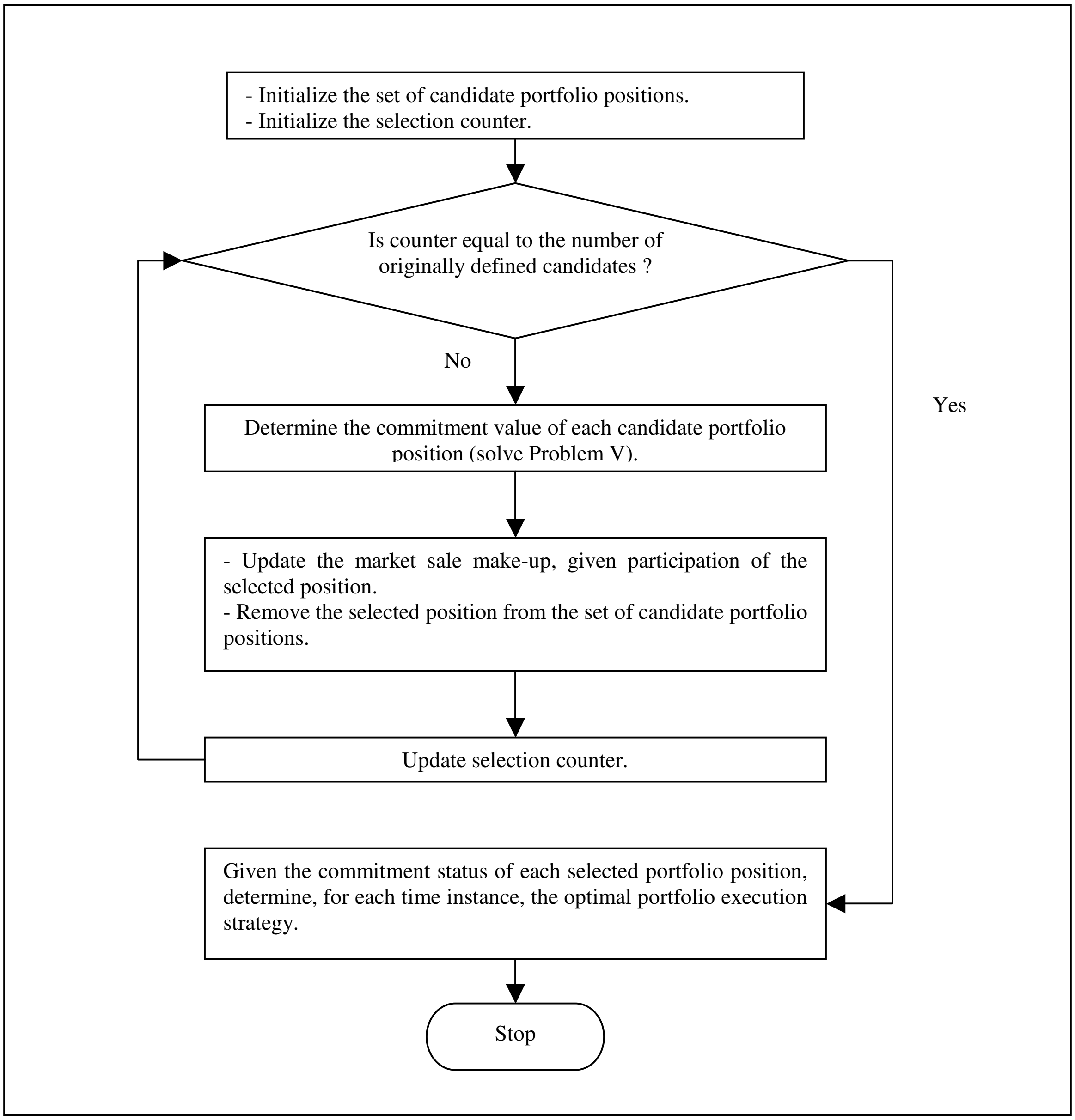


Figure 2.2: Flow Chart for a Market-Based Unit Commitment Problem.

### II.2.4 An Example

An asset manager, whose portfolio consists of 2 generation units, a simple cycle unit '150 Mw Gas' and baseload unit '400 Mw Coal', is interested in determining their optimal commitment and dispatch strategy for the upcoming week. Electricity and fuel market prices forecasts for that week are provided in Tables 2.4 and 2.5. The production fuel used by each asset is indexed to the corresponding fuel market. The operational constraints for each generating asset can be found in Tables 2.1 and 2.2.

| | **'150 Mw Gas' unit** | **'400 Mw Coal' unit** |
|---|---|---|
| **Pmin (Mw):** | 100 | 150 |
| **Pmax (Mw):** | 150 | 400 |
| **MUP (hrs):** | 8 | 72 |
| **MDN (hrs):** | 8 | 72 |
| $\tau(1)$ **(hrs):** | -50 | 124 |
| **Startup Cost ($):** | 4000 | 7000 |

Table 2.1: Generation Units Operating Characteristics.

| **'150 MW Gas' unit** | | | **'400 Mw Coal' unit** | | |
|---|---|---|---|---|---|
| Breakpoint ID | Mw | AHR (Mbtu/Mw) | Breakpoint ID | Mw | AHR (Mbtu/Mw) |
| 1 | 90 | 8.322 | 1 | 125 | 11.04 |
| 2 | 100 | 8.237 | 2 | 188 | 10.247 |
| 3 | 115 | 8.153 | 3 | 250 | 9.950 |
| 4 | 135 | 8.081 | 4 | 313 | 9.839 |
| 5 | 160 | 8.031 | 5 | 375 | 9.820 |
| | | | 6 | 437 | 9.856 |
| | | | 7 | 500 | 9.928 |

Table 2.2: Generation Units Average Heat Rate Information.

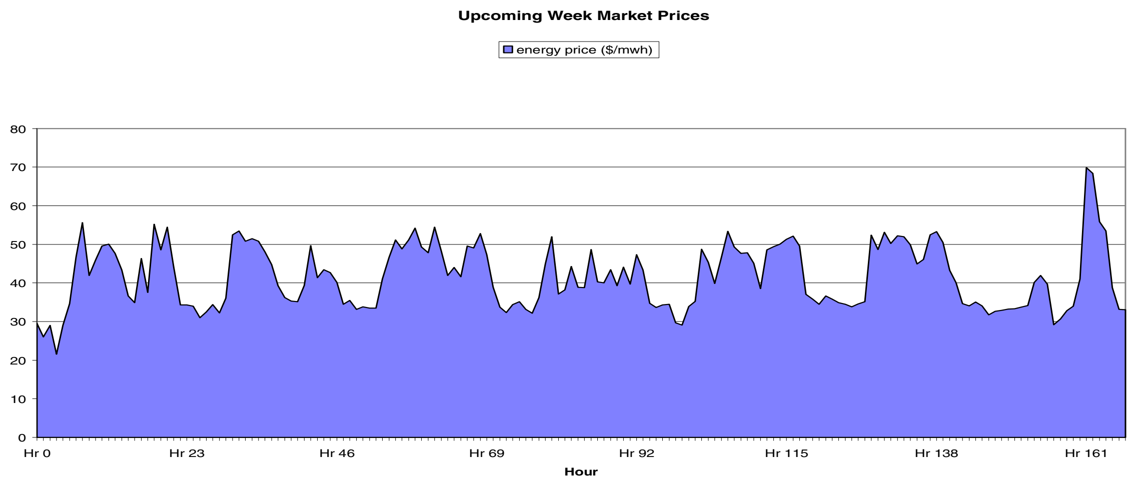


Figure 2.3: Upcoming Week Energy Market Prices.

After simulation, the optimal scheduling of the assets for the upcoming week leads to a portfolio performance of $90,197.39, summarized by portfolio instrument in Table 2.4.

| | Gas Market | Coal Market |
|---|---|---|
| Fuel Price ($/Mbtu): | 5.6 | 4.321 |

Table 2.3: Upcoming Week Fuel Market Prices.

| | Total Energy Allocation (Mwh) | Total Revenue ($) | Average Revenue ($/Mwh) |
|---|---|---|---|
| ‘150 Mw Gas’ unit: | 8,050 | -383,524.80 | -47.64 |
| ‘400 Mw Coal’ unit: | 40,758.8 | -1,760,708 | -43.20 |
| Market Sales: | 48,808.8 | 2,234,431 | 45.78 |

Table 2.4: Case Summary.

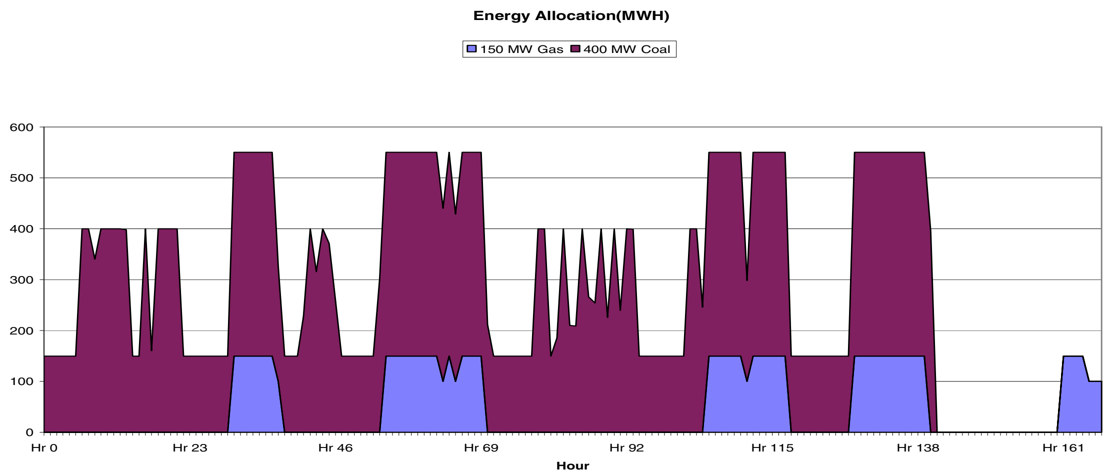


Figure 2.4: Optimal Generation Schedule for ‘150 MwGas’ and ‘400 Mw Coal’ Units.

| | HE01 | HE02 | HE03 | HE04 | HE05 | HE06 | HE07 | HE08 | HE09 | HE10 | HE11 | HE12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | 29.5 | 26.031 | 29.007 | 21.589 | 29.017 | 34.62 | 46.714 | 55.587 | 41.935 | 45.887 | 49.614 | 50.022 |
| **Tue.** | 34.004 | 30.998 | 32.465 | 34.363 | 32.229 | 36.087 | 52.514 | 53.514 | 50.757 | 51.493 | 50.849 | 48.133 |
| **Wed.** | 35.482 | 33.142 | 33.84 | 33.471 | 33.481 | 41.033 | 46.683 | 51.176 | 48.868 | 51.145 | 54.168 | 49.287 |
| **Thu.** | 32.362 | 34.353 | 35.164 | 33.132 | 32.167 | 36.231 | 44.886 | 52.024 | 37.177 | 38.188 | 44.243 | 38.852 |
| **Fri.** | 34.332 | 34.497 | 29.654 | 29.141 | 33.922 | 35.235 | 48.766 | 45.356 | 39.852 | 46.683 | 53.382 | 49.369 |
| **Sat.** | 34.497 | 36.682 | 35.81 | 34.866 | 34.497 | 33.819 | 34.589 | 35.174 | 52.412 | 48.677 | 53.099 | 50.216 |
| **Sun.** | 35.03 | 34.055 | 31.767 | 32.65 | 32.957 | 33.255 | 33.296 | 33.768 | 34.117 | 40.099 | 41.936 | 39.699 |

| | HE13 | HE14 | HE15 | HE16 | HE17 | HE18 | HE19 | HE20 | HE21 | HE22 | HE23 | HE24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | 47.653 | 43.334 | 36.646 | 34.931 | 46.346 | 37.575 | 55.199 | 48.613 | 54.454 | 44.172 | 34.332 | 34.322 |
| **Tue.** | 44.774 | 39.321 | 36.207 | 35.319 | 35.155 | 39.372 | 49.685 | 41.333 | 43.467 | 42.681 | 40.15 | 34.486 |
| **Wed.** | 47.868 | 54.413 | 48.235 | 41.925 | 44.049 | 41.649 | 49.553 | 49.062 | 52.789 | 47.357 | 38.909 | 33.748 |
| **Thu.** | 38.831 | 48.644 | 40.302 | 40.057 | 43.436 | 39.291 | 44.09 | 39.679 | 47.347 | 43.365 | 34.712 | 33.614 |
| **Fri.** | 47.674 | 47.796 | 45.06 | 38.535 | 48.583 | 49.399 | 50.012 | 51.319 | 52.136 | 49.522 | 37.01 | 35.82 |
| **Sat.** | 52.196 | 52.022 | 49.898 | 44.973 | 46.05 | 52.484 | 53.335 | 50.452 | 43.249 | 40.078 | 34.609 | 34.055 |
| **Sun.** | 29.212 | 30.649 | 32.845 | 33.973 | 40.981 | 69.886 | 68.429 | 55.859 | 53.428 | 38.827 | 33.204 | 33.04 |

Table 2.5: Upcoming Week Hourly Energy Market Prices.

| | HE01 | HE02 | HE03 | HE04 | HE05 | HE06 | HE07 | HE08 | HE09 | HE10 | HE11 | HE12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **Tue.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 |
| **Wed.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 |
| **Thu.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **Fri.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 150.00 | 150.00 | 150.00 |
| **Sat.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 150.00 | 150.00 | 150.00 | 150.00 |
| **Sun.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

| | HE13 | HE14 | HE15 | HE16 | HE17 | HE18 | HE19 | HE20 | HE21 | HE22 | HE23 | HE24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **Tue.** | 150.00 | 100.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **Wed.** | 150.00 | 150.00 | 150.00 | 100.00 | 150.00 | 100.00 | 150.00 | 150.00 | 150.00 | 150.00 | 0.00 | 0.00 |
| **Thu.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **Fri.** | 150.00 | 150.00 | 150.00 | 100.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 0.00 | 0.00 |
| **Sat.** | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **Sun.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 150.00 | 150.00 | 150.00 | 150.00 | 100.00 | 100.00 | 100.00 |

Table 2.6: Upcoming Week Optimal Schedule (Mw) for ‘150Mw Gas’.

| | HE01 | HE02 | HE03 | HE04 | HE05 | HE06 | HE07 | HE08 | HE09 | HE10 | HE11 | HE12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Tue.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -10,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 |
| **Wed.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -10,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 |
| **Thu.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Fri.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -10,759.9 | -6,759.9 | -6,759.9 |
| **Sat.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -10,759.9 | -6,759.9 | -6,759.9 | -6,759.9 |
| **Sun.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

| | HE13 | HE14 | HE15 | HE16 | HE17 | HE18 | HE19 | HE20 | HE21 | HE22 | HE23 | HE24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Tue.** | -6,759.9 | -4,612.7 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Wed.** | -6,759.9 | -6,759.9 | -6,759.9 | -4,612.7 | -6,759.9 | -4,612.7 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | 0.0 | 0.0 |
| **Thu.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Fri.** | -6,759.9 | -6,759.9 | -6,759.9 | -4,612.7 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | 0.0 | 0.0 |
| **Sat.** | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Sun.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -10,759.9 | -6,759.9 | -6,759.9 | -6,759.9 | -4,612.7 | -4,612.7 | -4,612.7 |

Table 2.7: ‘150 Mw Gas’ Hourly Total Operating Cost ($/hr).

| | HE01 | HE02 | HE03 | HE04 | HE05 | HE06 | HE07 | HE08 | HE09 | HE10 | HE11 | HE12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 400.00 | 400.00 | 340.37 | 400.00 | 400.00 | 400.00 |
| **Tue.** | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 400.00 | 400.00 | 400.00 | 400.00 | 400.00 | 400.00 |
| **Wed.** | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 301.62 | 400.00 | 400.00 | 400.00 | 400.00 | 400.00 | 400.00 |
| **Thu.** | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 400.00 | 400.00 | 150.00 | 185.76 | 400.00 | 209.89 |
| **Fri.** | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 400.00 | 400.00 | 245.75 | 400.00 | 400.00 | 400.00 |
| **Sat.** | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 150.00 | 400.00 | 400.00 | 400.00 | 400.00 |
| **Sun.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

| | HE13 | HE14 | HE15 | HE16 | HE17 | HE18 | HE19 | HE20 | HE21 | HE22 | HE23 | HE24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | 400.00 | 397.72 | 150.00 | 150.00 | 400.00 | 160.23 | 400.00 | 400.00 | 400.00 | 400.00 | 150.00 | 150.00 |
| **Tue.** | 400.00 | 226.69 | 150.00 | 150.00 | 150.00 | 228.53 | 400.00 | 315.70 | 400.00 | 370.95 | 258.72 | 150.00 |
| **Wed.** | 400.00 | 400.00 | 400.00 | 339.94 | 400.00 | 328.63 | 400.00 | 400.00 | 400.00 | 400.00 | 211.93 | 150.00 |
| **Thu.** | 209.13 | 400.00 | 266.11 | 254.20 | 400.00 | 225.63 | 400.00 | 239.55 | 400.00 | 398.99 | 150.00 | 150.00 |
| **Fri.** | 400.00 | 400.00 | 400.00 | 198.50 | 400.00 | 400.00 | 400.00 | 400.00 | 400.00 | 400.00 | 150.00 | 150.00 |
| **Sat.** | 400.00 | 400.00 | 400.00 | 400.00 | 400.00 | 400.00 | 400.00 | 400.00 | 394.23 | 0.00 | 0.00 | 0.00 |
| **Sun.** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table 2.8: Upcoming Week Optimal Schedule (Mw) for ‘400 Mw Coal’.

| | HE01 | HE02 | HE03 | HE04 | HE05 | HE06 | HE07 | HE08 | HE09 | HE10 | HE11 | HE12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -16,990.3 | -16,990.3 | -14,446.7 | -16,990.3 | -16,990.3 | -16,990.3 |
| **Tue.** | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 |
| **Wed.** | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -12,839.8 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 |
| **Thu.** | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -16,990.3 | -16,990.3 | -6,888.7 | -8,238.9 | -16,990.3 | -9,168.1 |
| **Fri.** | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -16,990.3 | -16,990.3 | -10,579.4 | -16,990.3 | -16,990.3 | -16,990.3 |
| **Sat.** | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -6,888.7 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 |
| **Sun.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

| | HE13 | HE14 | HE15 | HE16 | HE17 | HE18 | HE19 | HE20 | HE21 | HE22 | HE23 | HE24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | -16,990.3 | -16,891.3 | -6,888.7 | -6,888.7 | -16,990.3 | -7,271.8 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -6,888.7 | -6,888.7 |
| **Tue.** | -16,990.3 | -9,824.8 | -6,888.7 | -6,888.7 | -6,888.7 | -9,897.5 | -16,990.3 | -13,419.4 | -16,990.3 | -15,740.3 | -11,098.4 | -6,888.7 |
| **Wed.** | -16,990.3 | -16,990.3 | -16,990.3 | -14,428.7 | -16,990.3 | -13,956.0 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -9,247.6 | -6,888.7 |
| **Thu.** | -9,138.8 | -16,990.3 | -11,395.5 | -10,917.2 | -16,990.3 | -9,783.2 | -16,990.3 | -10,332.7 | -16,990.3 | -16,946.4 | -6,888.7 | -6,888.7 |
| **Fri.** | -16,990.3 | -16,990.3 | -16,990.3 | -8,727.5 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -6,888.7 | -6,888.7 |
| **Sat.** | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -16,990.3 | -16,740.5 | 0.0 | 0.0 | 0.0 |
| **Sun.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

Table 2.9: ‘400 Mw Coal’ Hourly Total Operating Cost ($/hr).

| | HE01 | HE02 | HE03 | HE04 | HE05 | HE06 | HE07 | HE08 | HE09 | HE10 | HE11 | HE12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | 4,407.2 | 3,884.6 | 4,333.3 | 3,234.2 | 4,377.2 | 5,193.4 | 18,698.8 | 22,190.5 | 14,265.9 | 18,372.3 | 19,840.7 | 20,003.2 |
| **Tue.** | 5,130.4 | 4,672.8 | 4,843.3 | 5,164.9 | 4,836.5 | 5,415.7 | 28,843.5 | 29,435.6 | 27,922.3 | 28,332.9 | 27,963.9 | 26,471.5 |
| **Wed.** | 5,326.0 | 4,972.0 | 5,070.7 | 5,012.5 | 5,050.1 | 12,405.6 | 25,692.7 | 28,148.5 | 26,879.6 | 28,167.1 | 29,741.3 | 27,105.9 |
| **Thu.** | 4,849.5 | 5,126.3 | 5,255.6 | 4,973.9 | 4,809.4 | 5,426.9 | 17,934.1 | 20,767.5 | 5,571.7 | 7,089.6 | 17,665.9 | 8,164.4 |
| **Fri.** | 5,143.6 | 5,205.1 | 4,441.3 | 4,359.1 | 5,120.6 | 5,280.9 | 19,477.7 | 18,111.7 | 9,772.9 | 25,692.7 | 29,313.0 | 27,147.3 |
| **Sat.** | 5,205.1 | 5,538.3 | 5,407.0 | 5,222.5 | 5,205.1 | 5,047.6 | 5,171.9 | 5,295.0 | 28,824.1 | 26,764.3 | 29,218.6 | 27,636.1 |
| **Sun.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

| | HE13 | HE14 | HE15 | HE16 | HE17 | HE18 | HE19 | HE20 | HE21 | HE22 | HE23 | HE24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mon.** | 19,031.7 | 17,207.9 | 5,524.7 | 5,254.9 | 18,548.9 | 6,034.6 | 22,132.3 | 19,457.4 | 21,793.4 | 17,671.4 | 5,143.6 | 5,160.0 |
| **Tue.** | 24,666.9 | 12,855.3 | 5,398.6 | 5,293.1 | 5,273.7 | 9,032.9 | 19,869.0 | 13,071.7 | 17,405.6 | 15,832.0 | 10,402.3 | 5,179.6 |
| **Wed.** | 26,291.2 | 29,884.8 | 26,550.9 | 18,448.1 | 24,188.9 | 17,873.8 | 27,268.8 | 27,001.3 | 29,005.1 | 26,042.8 | 8,254.0 | 5,062.9 |
| **Thu.** | 8,091.2 | 19,415.5 | 10,709.4 | 10,164.1 | 17,372.1 | 8,879.1 | 17,641.8 | 9,507.1 | 18,933.0 | 17,274.4 | 5,186.5 | 5,023.3 |
| **Fri.** | 26,226.4 | 26,286.7 | 24,758.1 | 11,507.3 | 26,718.1 | 27,127.9 | 27,513.7 | 28,189.3 | 28,700.0 | 27,189.9 | 5,548.7 | 5,362.5 |
| **Sat.** | 28,657.0 | 28,636.0 | 27,449.8 | 24,725.3 | 25,308.5 | 28,865.2 | 29,364.5 | 27,781.2 | 17,019.9 | 0.0 | 0.0 | 0.0 |
| **Sun.** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 10,491.7 | 10,232.9 | 8,327.3 | 7,971.5 | 3,878.4 | 3,350.8 | 3,286.2 |

Table 2.10: Market Sale Hourly Total Revenue ($/hr).

## II.3 Strategic Operational valuation under Uncertainty

Among the various drivers that can impact the operational value of a portfolio based on their random occurrence and evolution over time, the quantity and price (electricity and fuel) risks seem to be predominant over short- and long- term periods. Quantity risk is the risk that a specific contract quantity (purchase or sale) deviates from its expected forecast, and has been studied extensively in the power industry, with primary application in the analysis of avoided costs. In [22], Chiang performs the risk assessment on a load based energy portfolio performance, given load uncertainty. For its part, price risk and especially electricity price risk has only recently attracted interest in the power system literature. This is naturally explained by the fact that efforts towards market competition are recent. In the rest of this chapter and dissertation, market risk for electricity is considered as the most influential risk driver.

### II.3.1 Long Term Electricity Price Process

Unlike quantity risk, there is no strong historical pattern for electricity market prices. As a result, various price models have been proposed to describe their random behavior. One generally accepted representation that will be used in this work is the diffusion model following geometric Brownian motion (GBM). Under this assumption, electricity price movements can be described through the stochastic [23] differential equation:

$$d\,\mathrm{Price}(t) = a[\mathrm{Price}(t), t].dt + b[\mathrm{Price}(t), t].dw \qquad \textbf{(24)}$$

where:

$Price(t)$ is the price process as function of time,

$a[Price(t), t]$ is the drift of the market price process $Price(t)$,

w is the standard Brownian motion,

$b[Price(t), t]$ is the rate of change of the market price process $Price(t)$. This term describes the volatility of the market prices.

In order to model the electricity market price behavior described in (24), data estimates or forecasts for the drift and volatility terms need to be available, as well as the expected prices forecast. However, the absence of long term contracts and the low market liquidity make the estimation of these parameters a challenge for long term planning.

#### II.3.1.1 Volatility in Electricity Markets

Volatility can be estimated via two methods [24]: the implied volatility method and the historical-based volatility method. With the absence of a liquid market, the latter is usually preferred in the description of the electric energy price process. It is also important to notice that volatility in the electric power price process is more likely to be time dependent as it reflects the season of the year, day of the week, and even the peak hour of the day of electricity use. For instance, it is usual to see that the volatility of electrical energy price is smaller in off-peak hours than in peak hours. Similarly, energy price volatility on a shoulder (off-peak) month is usually smaller than in a peak month. The seasonality or time dependence of the volatility structure for electricity prices, also known as volatility term structure, is one of the unique characteristics of the electricity commodity [25]. The other parameter to estimate in our price model is the drift term in (24), which leads to the problem of long term electricity price forecast.

#### II.3.1.2 Long Term Price Forecast in Electricity Market: a Price Growth Model

As mentioned earlier, the electricity market is only fairly liquid from a mid-term perspective. Currently in the US, the electricity energy futures market does not trade for a time period longer than 18 months. In investment problems, the planning horizon can sometimes be more than 10 years, which requires that price forecast for that period be performed in order to undertake the analysis. In this section, we present a 2-phase price forecast process. The 2-phase price forecast process is a method through which historical prices are marked to futures prices, after forecast futures prices have been derived using a price growth model.

**Phase 1:** electricity futures market quotes are available through a small time window (18 months in the U.S). For long term planning purposes, market prices must be forecasted over the period through which market quotes are not available, namely the remaining planning horizon. In that regard, it is not unreasonable to use a price growth model to generate further yearly price profiles. A typical model to implement is a growth model for price projection in which future prices over a delivery period are characterized by a yearly total growth. In the case of a geometric growth model, such price model is described as follows:

$$\begin{cases} \text{Price}(t,k) = b_k \cdot \text{Price}(t,k-1) \quad \forall k, \forall t \\ \sum_t \text{Price}(t,k) = (1+\text{tpg}_k) \cdot \sum_t \text{Price}(t,k-1) \quad \forall k \end{cases} \tag{25}$$

where:

t is time (hour) index within a year,

k is the year index,

$b_k$ is the model parameter for price projection in year k,

$\text{tpg}_k$ is the estimated total price growth in year k .

Figure 2.5 shows a complete 25-year peak price projection for the month of January, using a yearly price growth of 2.54%. The projection schema is based upon the daily peak definition described in Table 2.11.

| Day of Week | On-Peak Period | Off-Peak Period |
|---|---|---|
| Mon through Fri: | HE07 through HE22 | HE01 through HE06, HE23, HE24 |
| Sat, Sun: | - | HE01 through HE24 |

Table 2.11: Daily Peak Definition.

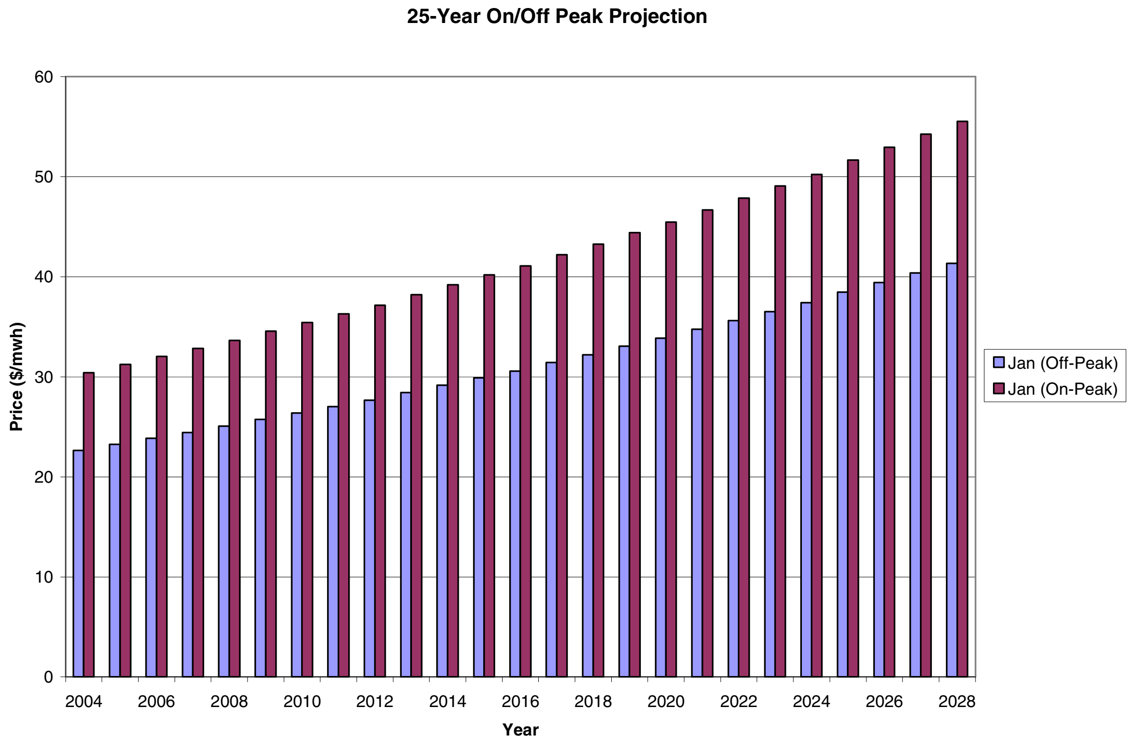


Figure 2.5: On/Off-Peak Price Forecast for January.

**Phase 2:** using historical prices and futures quotes (both available and forecasted), determine the projected futures prices over the quote horizon. One problem that arises is that the historical prices are known on an hourly base while the futures quotes are typically given on an average on-peak and/or off-peak format. To determine the projected hourly futures prices, the historical price information needs to be compiled on the same average on/off-peak format, and after same-day matching, the projected price is computed as:

$$\mathrm{Price}(t,y) = \frac{\overline{\mathrm{Price}(t,y)}}{\overline{\mathrm{Price}(t,x)}} \cdot \mathrm{Price}(t,x) \tag{26}$$

where:

t is the time index (hour)

x is the historical time horizon index

y is the projected time horizon index

$\Pr ice(t, y)$ is the projected price in time horizon y for time index t

$\Pr ice(t, x)$ is the historical price in time horizon x for time index t

$\overline{\Pr ice}(t, y)$ is the futures price for time horizon y for time index t

$\overline{\Pr ice}(t, x)$ is the average historical price for peak period at time t

As an example, let us consider NEPOOL market area and its historical market price data for January 2002. If we consider the futures prices information for January 2004 to be 22.64 $/mwh on off-peak hours and 30.41 $/mwh on on-peak hours, Figure 2.6 shows the projected price profile for January 2004, following the peak hours definition in Table 2.11.

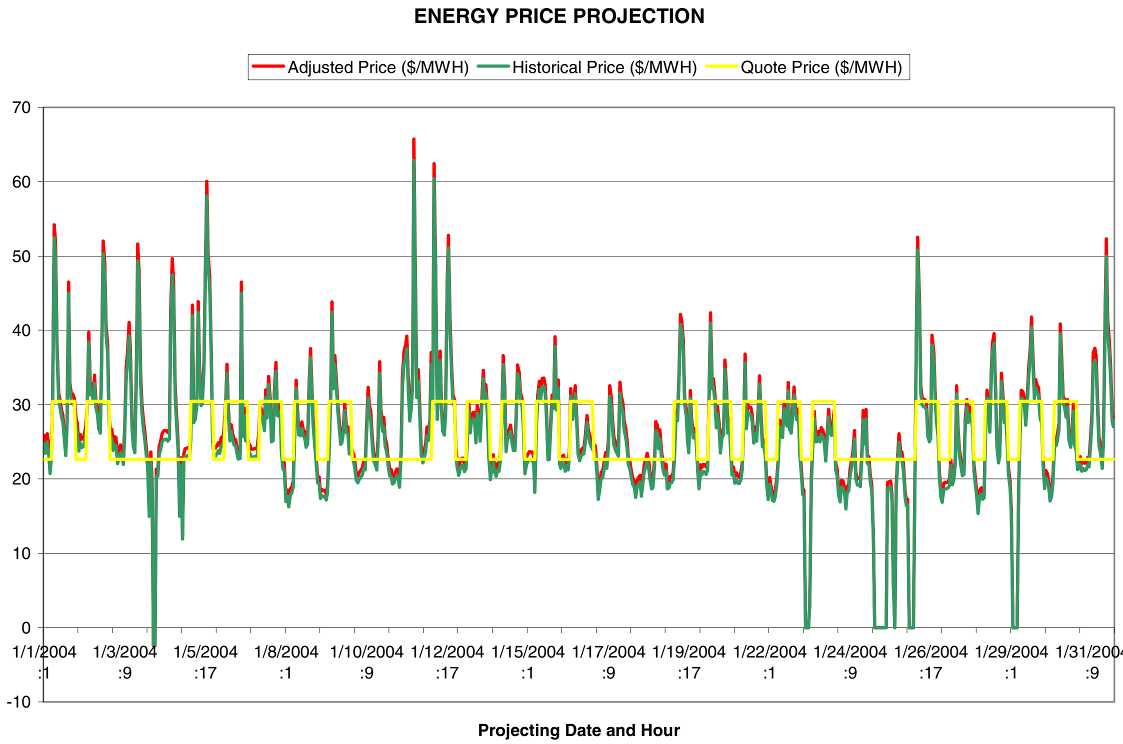


Figure 2.6: Hourly Marked-to-Market Price Projection for January 2004.

II.3.1.3 Price Growth Model and Supply-Demand Dynamics

The growth price model presented in (26) can be used in accordance with some general econometric parameters. While attractive, one inconvenience is that as defined, expression (26) does not capture the time related dynamics of capacity supply-demand relationship. For example, Figure 2.5 assumes a non-decreasing growth in prices while market dynamics suggest that the growth in prices, if caused by a deficient supply curve, would trigger additional capacity to be built and installed, further reducing the effective price growth, at least in the year following excess capacity installment. Rather than a shortcoming, this really suggests that the price growth model can be modified accordingly to include such market dynamics, if the data are available. Newbery [26] explicitly factors the impact of strategic behavior into the forecast of electricity market prices in the U.K. The approach which takes root in [27], uses the concept of supply function equilibrium and illustrates the oligopolistic nature of the electric power market. While these models provide insight to understanding the impact of the oligopolistic nature of the electric power industry in terms of pricing, they also for the most part assume that the various market participants (generation companies) exhibit identical supply curves, which is an unrealistic assumption.

### II.3.2 Strategic Operational Valuation: Limitations of Option Pricing Approach

Under market-based conditions, a generation power plant can be modeled as a call option: generate and sell power when price signals are strong, or shut-down otherwise. This explains why option pricing theory initially appeared to be an adequate valuation methodology for merchant plants and analysts. Under the assumption that the energy price process follows (24), the Black-Scholes closed-form solution [23] is sometimes suggested for market valuation of a generation plant. Unfortunately, the Black-Scholes solution does not recognize the very nature of a generation spark-spread capability, and when applied in circumstances where both fuel and electricity prices are uncertain, it would fail to recognize that a generation plant is really an option to exchange electric power for fuel, which itself is typically indexed to some market. The closest financial closed-form solution that integrates the spark-spread capability is attributed to Margrabe [28], who developed an extension of the Black-Scholes formula for spark-spread based derivatives.

Whether through the use of the Black-Scholes formula or other closed-form formulations, these valuation approaches fall short [29] from capturing the operational flexibility of a generation plant because they fail to consider the path-dependent nature of the asset to value. These shortcomings can lead to the overvaluation of generation plants, particularly for peaking plants. As presented earlier in this chapter, a generation asset's operations must be optimized within the full acknowledgment of its time variant parameters as well as its time dependent constraints. As such, the portfolio optimization problem under uncertainty, also known as stochastic unit commitment problem can only be efficiently addressed through simulation-based valuation methods rather than with financial based closed-form analytical expressions.

### II.3.3 Strategic Operational Valuation: a Simulation-Based Approach

For mid- and long-term purposes, the volatility of market prices requires that portfolio operational valuation be performed under uncertainty. The shortfalls of closed-form models and the complex nature of the physical delivery process associated with the performance of a generation plant make the valuation process more difficult. Takriti [30] relies on a discrete set of generated scenarios to perform portfolio optimization, with emphasis on non-anticipativity constraints. Using a tree-based architecture [31], Tseng extended a lattice formulation approach to solve the stochastic unit commitment problem, also with the enforcement of non-anticipativity constraints. A similar approach can be found in Gardner [32]. These methods bring some conceptual and practical challenges to analysts:

- non-anticipativity constraints are not of practical use in a long term operational problem. In fact, the flexibility in operations is what makes a generation asset attractive in a competitive environment. Thus, portfolio valuation should reflect the asset's capability to anticipate market price movements,
- the lattice structure is equivalent to a web whose size grows exponentially with time and become as multi-dimensional as there are price drivers to simulate. This makes the lattice approach not practical for real modeling situations in which several risk drivers often describe market uncertainty. It also limits the time horizon over which the analysis can be performed without unreasonable computation time. In Tseng's paper, the generation asset valuation is performed over a short term horizon (1 day).

Under market uncertainty, the portfolio operational optimization problem II can be reformulated as:

**Problem VI**

$$\underset{\substack{u_i(t),P_i(t),\forall i\in\Omega,\forall t\in\{1,...,T\} \\ u_j(t),P_j(t),\forall j\in K,\forall t\in\{1,...,T\}}}{\mathrm{Max}} E\left\{ \sum_{j\in K}\left[\sum_{t=1}^{T}\{u_j(t)\cdot F_j[P_j(t)]-S_j(t)\}\right]-\sum_{i\in\Omega}\left[\sum_{t=1}^{T}\{u_i(t)\cdot F_i[P_i(t)]+S_i(t)\}\right] \right\} \quad \textbf{(27)}$$

subject to:

$$\sum_{i\in\Omega}u_i(t)\cdot P_i(t)=\sum_{j\in K}u_j(t)\cdot P_j(t),\quad \forall t\in\{1,...,T\}, \quad \textbf{(28)}$$

$$u_w(t)\cdot \mathrm{Pmin}_w(t)\le P_w(t)\le u_w(t)\cdot \mathrm{Pmax}_w(t),\quad \forall w\in\Omega\cup K,\quad \forall t\in\{1,...,T\}, \quad \textbf{(29)}$$

$$\begin{cases} u_w(t) = 1, & \text{if} \quad 0 < \tau_w(t-1) < MUP_w - 1, \\ u_w(t) = 0, & \text{if} \quad -(MDN_w - 1) < \tau_w(t-1) < 0, \quad \forall w \in \Omega \cup K, \quad \forall t \in \{1,...,T\} \\ u_w(t) \in \{0,1\}, & \text{otherwise} \end{cases} \quad \textbf{(30)}$$

where:

$E\{.\}$ denotes the expected value operator.

To achieve modeling flexibility considering the set of possible multi-risk driving factors in a portfolio operational optimization problem, we propose a Monte Carlo based approach to solve Problem VII. Following the proposed Monte Carlo method, the derivation of the market risk drivers samples will lead to a decomposition of problem VII such that:

- the sample problem responds to the same algorithmic structure as developed in section II.2,
- the set of sample problems generated should cover most of the sample space in a more comprehensive way than lattice- or scenario analysis- based approaches would,
- the resulting sample distribution of portfolio performance offers insight towards the risk profile of the portfolio make-up, an information that proves more helpful for portfolio diversification purposes,
- the decomposition of Problem VI offers computational time advantage for multi-processing configurable computing structures and,

- the correlation between risk drivers (e.g. market fuel prices and energy fuel prices) can be easily implemented when generating sample states for each risk driver.

An implementation of the Monte Carlo based approach for stochastic portfolio optimization can be summarized in the flowchart below.

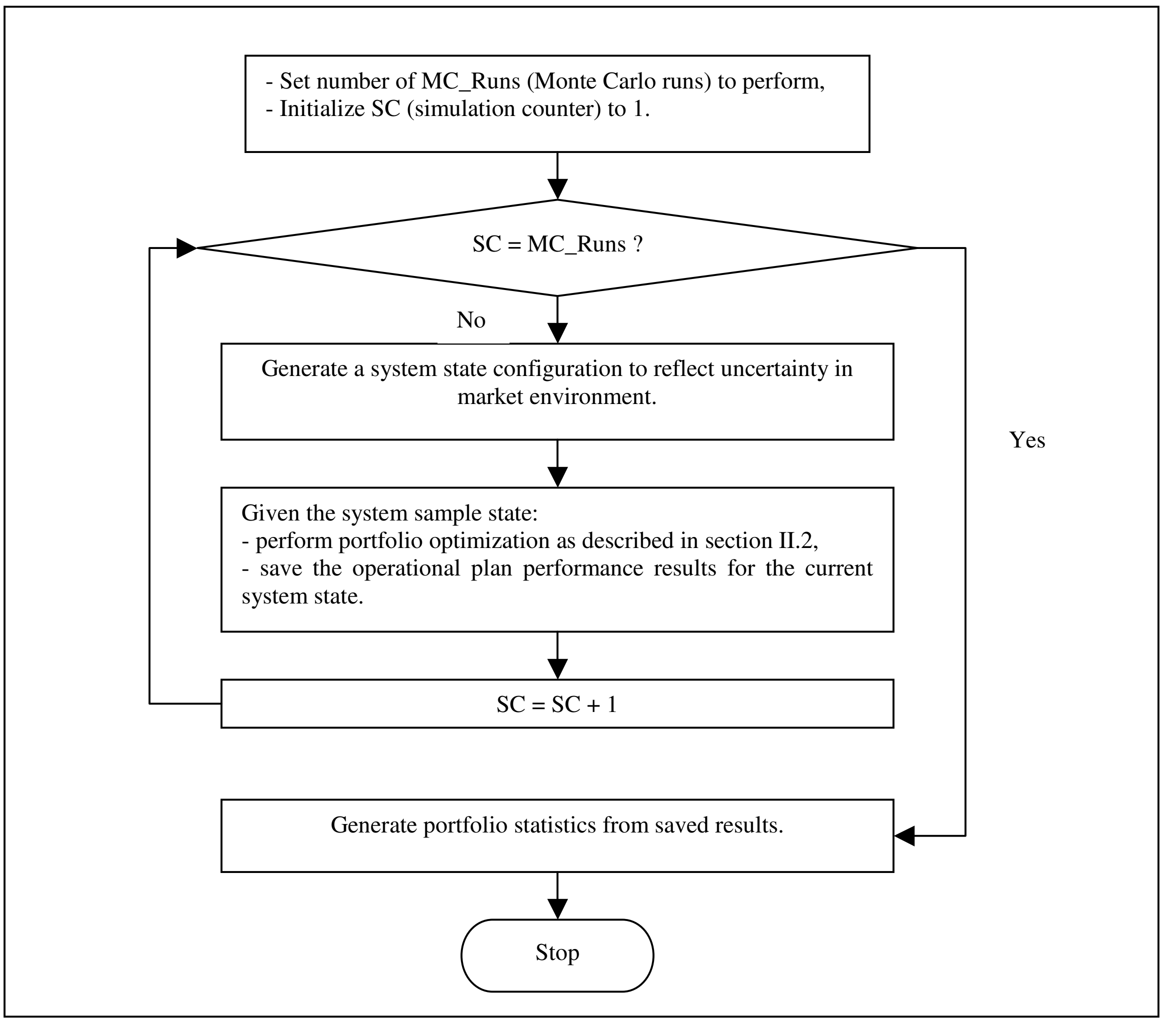


Figure 2.7: Flow Chart for Monte Carlo Based Portfolio Optimization Problem.

The example below illustrates the described methodology. The computational results were provided by the commercial software GenTrader®, courtesy of Power Costs, Inc.

## II.3.4 An Example

Consider the example in section II.2.4. The asset manager of the 2 generation units '150 Mw Gas' and '400 Mw Coal' wants to determine the operational market value of these assets for next year. The energy market prices and volatility data for next year are given in Tables 2.12 and 2.13, following the peak definition presented in Table 2.11. The market fuel prices are described in Table 2.14. The present value date and discount rate are respectively set to January 01, 2004 and 10%.

| | **Jan.** | **Feb.** | **Mar.** | **Apr.** | **May** | **Jun.** |
|---|---|---|---|---|---|---|
| **off-peak ($/mwh):** | 23.24 | 24.209 | 27.762 | 27.587 | 30.626 | 36.037 |
| **on-peak ($/mwh):** | 31.222 | 27.68 | 38.07 | 39.959 | 48.625 | 54.036 |
| | **Jul.** | **Aug.** | **Sep** | **Oct.** | **Nov.** | **Dec.** |
| **off-peak ($/mwh):** | 39.476 | 33.82 | 39.241 | 40.422 | 36.458 | 26.017 |
| **on-peak ($/mwh):** | 67.259 | 69.302 | 51.459 | 49.836 | 48.512 | 33.296 |

Table 2.12: Monthly Electricity Market Prices Forecast for 2005.

| | **Jan.** | **Feb.** | **Mar.** | **Apr.** | **May** | **Jun.** |
|---|---|---|---|---|---|---|
| **off-peak (%):** | 21 | 21 | 17.3 | 17.3 | 17.9 | 17.3 |
| **on-peak (%):** | 38.8 | 38.8 | 32 | 32 | 33 | 32 |

| | Jul. | Aug. | Sep | Oct. | Nov. | Dec. |
|---|---|---|---|---|---|---|
| **off-peak (%):** | 16.8 | 16.8 | 17.3 | 15.2 | 15.2 | 15.2 |
| **on-peak (%):** | 31 | 31 | 32 | 28.1 | 28.1 | 28.1 |

Table 2.13: Monthly Electricity Market Prices Volatility Forecast for 2005.

| | Jan. | Feb. | Mar. | Apr. | May | Jun. |
|---|---|---|---|---|---|---|
| **Gas Market ($/Mbtu):** | 6.89 | 6.83 | 6.66 | 6.03 | 5.88 | 5.895 |
| **Coal Market ($/Mbtu):** | 4.321 | 4.321 | 4.321 | 4.321 | 4.321 | 4.321 |
| | **Jul.** | **Aug.** | **Sep** | **Oct.** | **Nov.** | **Dec.** |
| **Gas Market ($/Mbtu):** | 5.93 | 5.94 | 5.91 | 5.92 | 6.095 | 6.26 |
| **Coal Market ($/Mbtu):** | 4.321 | 4.321 | 4.321 | 4.321 | 4.321 | 4.321 |

Table 2.14: Monthly Fuel Market Prices Forecast for 2005.

After a simulation of 1,000 market price sample paths, the expected market operational value of the assets' portfolio is $M 19.58, and is summarized by portfolio asset mark-to-market output in Table 2.15. The portfolio and individual assets P/L histograms are shown in Figure 2.8, 2.9 and 2.10. As expected, these figures show no negative P/L since the operational decisions for each asset are purely market based.

| | MTM P/L ($M) | MTM P/L Standard Deviation ($M) |
|---|---|---|
| **'150 Mw Gas' unit:** | 4.33 | 7.05 |
| **'400 Mw Coal' unit:** | 15.25 | 22.87 |
| **Total:** | 19.58 | 29.91 |

Table 2.15: Case Summary.

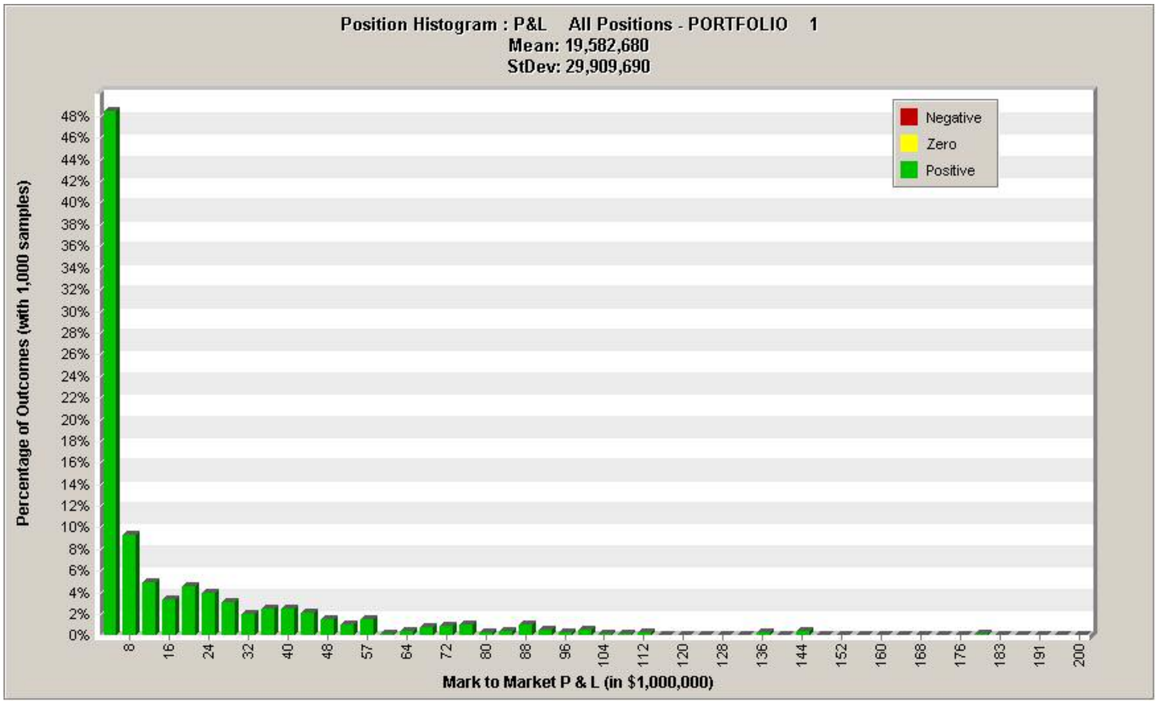


Figure 2.8: Portfolio P/L Histogram.

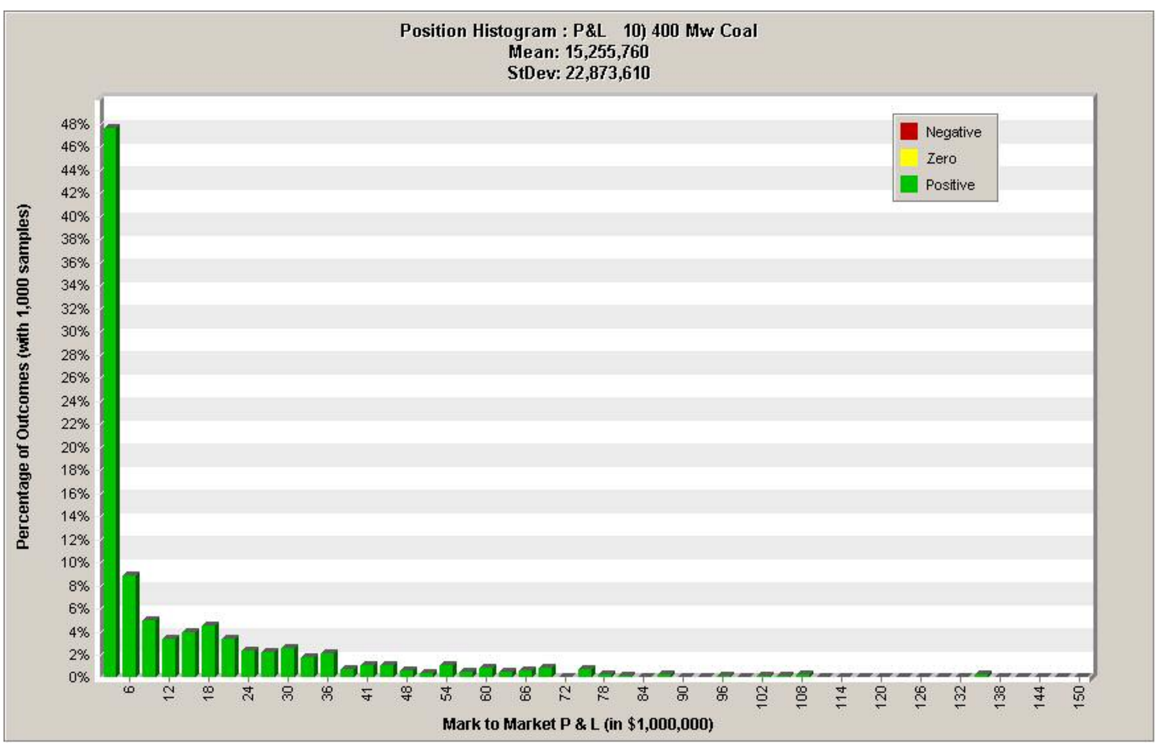


Figure 2.9: ‘400 Mw Coal’ P/L Histogram (courtesy of Power Costs, Inc.).

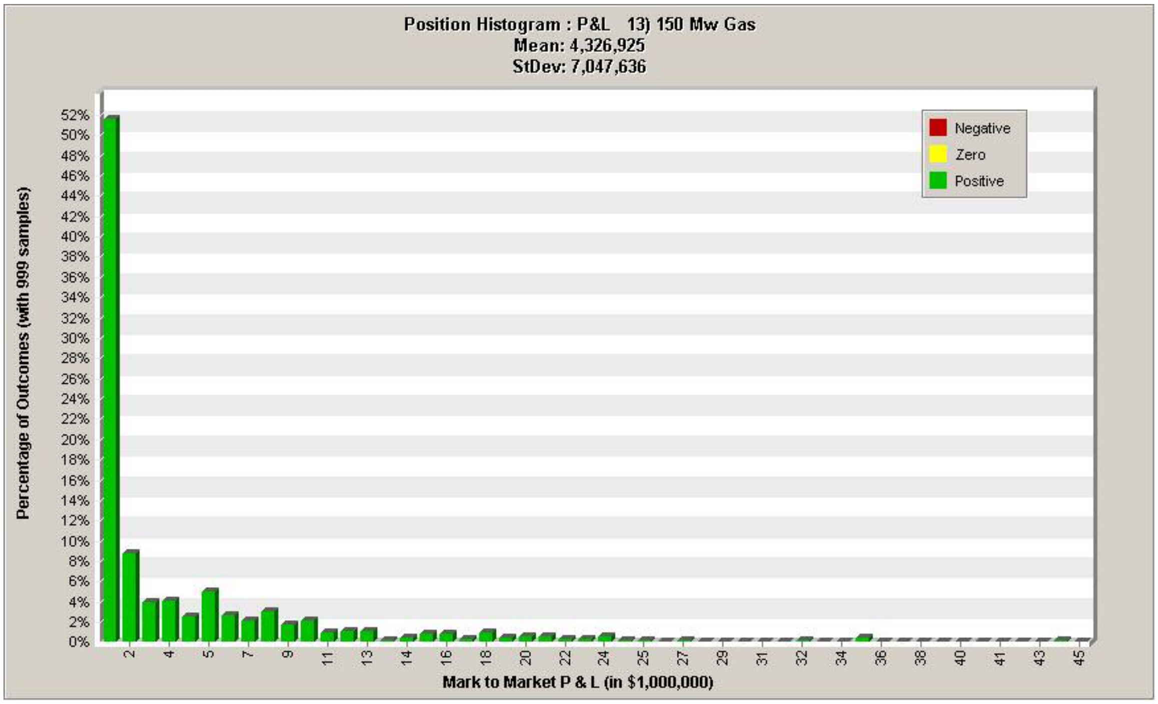


Figure 2.10: '150 Mw Gas' P/L Histogram (courtesy of Power Costs, Inc.).

## II.4 Conclusion

A strategic alternative that describes real asset operations should be valued with tools that reflect the constraints that impact its operational performance. In this chapter, we have presented a methodology that can be used to:

- value the deterministic optimal operational performance of any strategic alternative. A general algorithm for optimal operational valuation was presented, and a detailed description of the algorithm was presented for market-based operational valuation,

- build a more realistic assessment of a strategic alternative operational valuation under uncertainty. The described methodology reflects the operational choice available to the portfolio manager as market conditions evolve. Furthermore, it reflects the constraints associated with physical asset operations.

- determine the risk profile associated with a generation portfolio. This information, which is usually not available with closed-form models, provides asset managers with a better risk assessment picture of their asset portfolio.

In long term planning, strategic alternatives interact over time and the state changes associated with their implementation is usually subject to long-term constraints such as investment costs, time-to-build (for expansion plans), minimum time contract execution, etc. This added layer of complexity when combined with the short-term operational constraints of a generation asset portfolio, makes the problem of generation planning more difficult. In the next chapter, a long term planning methodology that addresses all these complexities is developed, and tested.

# CHAPTER 3

# STRATEGIC INVESTMENT PLANNING: A NEW MODEL

## III.1 Introduction

From a long term perspective, the time coupling of different strategic alternatives when possible, generates strategic investment plans. For example, the timeline consisting of keeping base operations for the initial 5 years of the plant's existence, then extending its capacity by turning it into a combined cycle on the 7$^{th}$ year, locking the plant revenues through an energy forward contract for the following 10 years and, selling the plant at the end of the 17$^{th}$ year, describes one of many possible strategic investment plans in the lifetime of a generation plant. Naturally, the planning value of a generation plant must reflect the interactions among the various strategic alternatives. Using the results from the operational valuation method described in the previous chapter, a mathematical problem formulation to quantify the planning value of generation plant will be derived in this chapter, thus capturing both the operational and long term coupling constraints associated with planning decisions. As with the previous chapter, this chapter can be divided in two parts: a discussion on the deterministic planning algorithm and a presentation of the planning valuation algorithm under uncertainty.

In the current literature, the problem of generation planning valuation is often posed as a capacity expansion problem, since inherited from regulation days. In that regard, the expression “generation expansion planning” is rather used. In early generation expansion problems, the objective consisted of meeting capacity requirements, i.e, reliability requirements, with minimum costs, by choice of the right type and/or timing of capacity addition. The problem of generation expansion planning is one of the most difficult to solve in the electric power industry: this difficulty comes from the complex nature of the problem, related to regional (single generator, plant, or service territory) and time scopes of the undertaken planning horizon.

The original mathematical problem formulation of the electric generation expansion planning is attributed to Masse [33]. In this traditional formulation, strategic alternatives are defined by capacity technology type (gas-fired plants, hydro plants, coal plants, nuclear plants, non-dispatchable plants, etc.) and their size, while strategic investment plans would represent their interactions over time. In his paper, Masse presents a linear programming solution to the problem of generation planning. Further research on the subject has put forth the non-linear mixed integer nature of the problem to solve, thus prompting for alternate problem formulations. Such formulations included dynamic programming [35] and more recently, decomposition-based approaches [34], [36].

In general, the generation expansion problem usually follows the generic formulation defined below:

$$\underset{\text{Over Planning Horizon}}{\text{Min}} \left[ \text{Investment Costs} + \text{Operational Costs} \right] \qquad \textbf{(40)}$$

subject to:

$$\text{Total Used Capacity} \leq \text{Installed Capacity}, \quad \text{for all time periods, for all technologies} \; \textbf{(41)}$$

Total Produced Energy = Energy Demand, for all time periods **(42)**

In the generation expansion problem (40)-(42), market uncertainty is non-existent as the problem formulation is posed from the perspective of a regulated environment. With this typical problem formulation, it is not unusual to recognize the following characteristics with the models currently in use:

- uncertainty is defined in the model as a function of unplanned outages , whether on generation plants or transmission lines. It can also be defined as a finite discrete probability function on the energy demand [38],
- the minimum time-step resolution for the planning horizon in the problem formulation is typically a year. With this time-step resolution, the energy demand constraint (42) is addressed by solving a load duration curve dispatch problem. An allocation solution often used for this problem relies on the optimal-mix algorithm devised by Levin [37]. The algorithm builds a merit-order loading procedure of the generation units to meet the energy demand at any time period. However, the use of a load (or price) duration based solution fails to reflect the impact of the time dependent operational constraints of generation plants and/or contracts, thus eventually preventing the correct investment signals to be captured,
- for simplification of the problem formulation, the time dependency of strategic alternatives is often not considered in the problem statement. Here also, the failure to capture the appropriate timing for strategic state changes can result in poor planning value estimation and bad investment decisions.

## III.2 Generation Asset Planning: a New Formulation

In a competitive environment, the generation expansion problem formulation must change as generation companies must look at planning from a profit maximization perspective. For clarity purposes in the rest of this chapter, the problem of generation expansion is presented from the perspective of a single plant. When the market is liquid, the results can be easily extended to a multiple plants system due to the fact that the market decouples the planning decisions as each plant expansion problem can be analyzed independently of any other. When the market is not liquid, the planning decision for a multiple plants system can still rely on an adaptive schema that would guide its optimality on the capability of valuing each individual plant expansion. The newly proposed planning valuation problem formulation differs from the existing formulations in the following:

1) the strategic alternatives available to planners under market environment are no longer restricted to simple additions or divestiture of capacity. The market environment offers further flexibility such as the leasing of the plant, entering into more bilateral contracts, etc. Such non-capacity related strategic alternatives must be modeled accordingly. Moreover, some of these alternatives have distinct and specific characteristics, i.e. a generation plant merchant can enter into a long term electric power forward contract with a 5-year duration period only, or a minimum 5-year duration period, etc,
2) the number of possible strategic alternatives that can be implemented during the life cycle of a generation plant is by far much smaller. Consequently, the

coordination of the strategic alternatives over time becomes a more traceable problem,

3) strategic alternatives are interrelated by time dependency constraints, further complicating the optimal decision that defines the time-sequence of their implementation. An example of such constraints can be that the implementation of alternative A should occur only after alternative B has been in activity for least k years. Since the plant expansion problem is a more traceable problem, the time dependency constraints between strategic alternatives can be included in the problem formulation, in contrast to the more general capacity expansion formulation in which they are often excluded,
4) while the objective function in the general capacity expansion problem is to minimize both the investment and operational costs over the planning horizon, the objective value in a generation plant expansion plan problem is to maximize the market value of the plant, regardless of the implemented strategy(ies).

In earlier generation expansion problems, the emphasis was put on the type and the timing of possible investment in a specific generation technology. At that time, uncertainty was more a function of load growth and inflation. With the absence of a market, the strategic alternatives and their coupling over time could be addressed within a simplified analysis framework [39]**.** With a market, more strategic alternatives become available to planners. As the number of strategic alternatives grows, the time-sequence of their possible interactions becomes more elaborate and intricate. Consequently, the planning value of a generation plant can be affected by these parameters both in terms of its expected results and risk profile.

In determining the operational value for each strategic alternative in Chapter 2, we used a one-hour time increment as the time index, and the valuation process was carried out all through the planning period. This time index resolution carries the advantage of reflecting the operational constraints of a generation unit when compared to average operational estimates. However, the time index resolution is often a year in the case of planning strategies. To remain coherent within the problem formulation, it is enough to aggregate the hourly operational results and present them in a yearly format, making them available in the appropriate format for the planning value problem to be solved. The rest of this chapter is divided in two parts: a discussion of generation planning under a deterministic environment and a presentation of a planning algorithm under uncertainty. Both discussions are take root within the new paradigm described earlier in this section.

## III.3 Generation Asset Planning: a New Deterministic Method

### III.3.1 Notation

For better clarity in the problem formulation, let us define the following notation:

t: time index (year).

$T$: planning period.

$i, j, k$: strategic alternative indices.

$u_i(t)$: status of strategic alternative i during time period t (0:inactive, 1:active).

$w_{i,j}(t)$: state change flag to indicate feasibility to move from strategic alternative i to strategic alternative j at time t (0: infeasible switching; 1: feasible switching). Two or more strategic alternative cannot be simultaneously active within the same year.

$\tau_i(t)$: number of time periods (years) that strategic alternative i has been active at the beginning of time period t,.

$LagPeriod_{i,j}$: consecutive number of time periods (years) that strategic alternative i has to be active before switching to strategic alternative j.

$OperValue_i(t)$: present value of the operational profits associated with strategic alternative i during time period t.

$ICosts_{i,j}(t)$: present value of the lumped capital costs incurred when changing from strategic alternative i active until time period (t-1), to strategic alternative j, active at time period t.

$RecovLife_j$: when a state change activates strategic alternative j, $RecovLife_j$ represents the estimated life cycle of the given alternative. This parameter is used to evaluate the effective transitional cost/benefit effect distributed over the remaining planning period.

$MinUP_j$: minimum number of active periods required for strategic alternative j, whenever selected. An example is a 5-year minimum power sale agreement contracted with an energy merchant.

$\text{MaxUP}_j$: maximum number of active periods defined for strategic alternative j, whenever selected. An example is a power sale agreement with an energy merchant, for a maximum 10-year activation period.

$\Omega$: set of defined strategic alternatives for the studied generation plant.

### III.3.2 Problem Formulation

We can formulate the planning valuation problem of a generation plant as:

**Problem VII**

$$\underset{\substack{u_k(t),u_j(t)\\ \text{OperValue}_k(t)\\ k\in\Omega,j\in\Omega,t\in\{1,\ldots,T\}}}{\text{Max}} \left\{ \sum_{t=1}^{T}\sum_{k\in\Omega}\left[u_k(t)\cdot \text{OperValue}_k(t)\right] - \sum_{t=1}^{T}\sum_{k\in\Omega}\left[u_k(t)\cdot[1-u_k(t-1)]\cdot \sum_{\substack{j\in\Omega\\ j\neq k}}\left[u_j(t-1)\cdot \text{ICosts}_{j,k}(t))\right]\right]\right\} \quad \textbf{(43)}$$

subject to:

$$\sum_{k\in\Omega} u_k(t) = 1, \quad \forall t \in \{1,\ldots,T\} \quad \textbf{(44)}$$

$$\begin{cases} u_k(t)\cdot[1-u_k(t-1)]\cdot u_j(t-1) = 0 \\ \text{if } w_{j,k}(t) = 0, \forall\ j \neq k, \forall t \in \{1\ldots T\}, \forall (j,k) \in \Omega x \Omega \end{cases} \quad \textbf{(45)}$$

$$\begin{cases} u_k(t)\cdot[1-u_k(t-1)]\cdot u_j(t-1) = 0 \\ \text{if } u_j(t-1) = 1 \text{ and } \tau_j(t-1) < \text{LagPeriod}_{j,k}, \forall j \neq k, \forall t \in \{1,\ldots,T\}, \forall (j,k) \in \Omega x \Omega \end{cases} \quad \textbf{(46)}$$

$$\begin{cases} u_k(t) = 1 \\ \text{if } u_k(t-1) = 1 \text{ and } \tau_k(t-1) + 1 < \text{MinUP}_k, \forall k \in \Omega, \forall t \in \{1,\ldots,T\} \end{cases} \quad \textbf{(47)}$$

$$\begin{cases} u_k(t) = 0 \\ \text{if } u_k(t-1) = 1 \text{ and } \tau_k(t-1) + 1 = \mathrm{MaxUP}_k, \forall k \in \Omega, \forall t \in \{1,...,T\} \end{cases} \quad \textbf{(48)}$$

$$u_k(t) \in \{0,1\} \quad \forall k \in \Omega, \forall t \in \{0...T\} \quad \textbf{(49)}$$

In the formulation of Problem VII, the objective function captures the time sequence of yearly market operational values along with the capital costs over the planning horizon for the implemented strategic alternatives. From the problem's constraint set, constraint (44) states that at any time t, there is only one strategic alternative active. Constraint (45) prevents infeasible transition between two different strategic alternatives. In constraint (46), assuming that a strategy transition from j to k is feasible, this transition will not take place until alternative j has been active for a minimum of $\mathrm{LagPeriod}_{j,k}$ time periods. Constraint (47) indicates that any decision to de-activate strategic alternative j at time t must not violate its minimum active period $\mathrm{MinUP}_j$, while constraint (48) indicates that the active period for strategic alternative j should not exceed its maximum activation period, $\mathrm{MaxUP}_j$. These last two constraints are more likely to be encountered when considering long term bilateral contracts for a generation plant.

III.3.3 A Dynamic Programming Based Solution

As presented above, the generation planning problem formulation resembles a unit commitment problem. However, the presence of constraint (46) linking the implementation of a given strategic alternative to another strategic alternative gives the problem a non-decomposable form. From that perspective, Problem VII can be compared to the commitment problem of a complex generation unit in which the configuration states are equivalent to strategic alternatives with inter-temporal constraints. Following that mathematical formulation, the number of possible configuration states is a function of the number of strategic alternatives. A network flow problem representation of the problem will still prove useful and a dynamic-programming (DP) solution approach can be implemented to find the optimal planning value of the generation plant. The proposed dynamic programming structure will consist of states and stages defined such that:

- a stage represents a distinct time period t. For example, a 15-year planning horizon will result in a DP structure with 15 stages,
- a state, also called node, represents a strategic alternative implementation along with its current activation period. This definition for a state in this DP structure allows the algorithm to easily manage constraints (47) and (48), which are often encountered with long-term forward contracts. This particular definition for a state representation departs from the traditional definition [40], where a state would consist of a strategic alternative (for instance, a 2x1 capacity addition) with no use of the activation period. In the proposed DP structure, a state at time t also contains information about the operational value of the corresponding strategic alternative at time t,
- within a given stage, there is no possible arc transition between the defined states, in accordance with constraint (44),
- the arc transition between any two states in consecutive stages is possible only if constraints (45), (46) and (47) are met. The transition arc represents a

continuation link if the two states represent the same strategic alternative. Otherwise, it represents the transition costs/revenues associated with state change.

It should also be noted that the objective function of the planning valuation problem as defined in (43) favors a lumped sum representation of the transition costs/revenues, in contrast with the annually distributed transition cost/benefit allocation encountered in a typical capacity expansion problem. In order to avoid the end effects that the lumped sum representation can cause for state changes in time periods when the remaining planning horizon is less than the estimated life cycle of the candidate strategic alternative, it is not unreasonable to define the lumped transitional costs/benefit as a function of the remaining planning horizon. By doing so, Problem VII is rewritten as:

**Problem VIII**

$$\underset{\substack{u_k(t),u_j(t)\\ \text{OperValue}_k(t)\\ k\in\Omega,\, j\in\Omega,\, t\in\{1,\ldots,T\}}}{\text{Max}} \left\{ \sum_{t=1}^{T}\sum_{k\in\Omega}\left[u_k(t)\cdot \text{OperValue}_k(t)\right] - \sum_{t=1}^{T}\sum_{k\in\Omega}\left[u_k(t)\cdot[1-u_k(t-1)]\cdot \sum_{\substack{j\in\Omega\\ j\neq k}}\left[u_j(t-1)\cdot \text{RICosts}_{j,k}(t))\right]\right]\right\}$$

**(50)**

subject to:

$$\sum_{k\in\Omega} u_k(t) = 1, \quad \forall t \in \{1,\ldots,T\} \qquad \textbf{(51)}$$

$$\begin{cases} u_k(t)\cdot[1-u_k(t-1)]\cdot u_j(t-1) = 0 \\ \text{if } w_{j,k}(t) = 0,\ \forall t\in\{1\ldots T\},\ \forall j\neq k,\ (j,k)\in \Omega \text{x} \Omega \end{cases} \qquad \textbf{(52)}$$

$$\begin{cases} u_k(t)\cdot[1-u_k(t-1)]\cdot u_j(t-1) = 0 \\ \text{if } u_j(t-1) = 1 \text{ and } \tau_j(t-1) < \text{LagPeriod}_{j,k}, \forall t\in\{1,\ldots,T\}, \forall j\neq k,\ (j,k)\in \Omega \text{x} \Omega \end{cases}$$

**(53)**

$$\begin{cases} u_k(t) = 1 \\ \text{if } u_k(t-1) = 1 \text{ and } \tau_k(t-1) + 1 < \text{MinUP}_k, \forall k \in \Omega, \forall t \in \{1,...,T\} \end{cases} \quad \textbf{(54)}$$

$$\begin{cases} u_k(t) = 0 \\ \text{if } u_k(t-1) = 1 \text{ and } \tau_k(t-1) + 1 = \text{MaxUP}_k, \forall k \in \Omega, \forall t \in \{1,...,T\} \end{cases} \quad \textbf{(55)}$$

$$u_k(t) \in \{0,1\} \quad \forall k \in \Omega, \forall t \in \{0...T\} \quad \textbf{(56)}$$

where:

$$\text{RICosts}_{j,k}(t) = \frac{\text{ICosts}_{j,k}(t)}{\text{RecovLife}_k} \cdot \text{Max}\{0\,;\min\{\text{RecovLife}_k\,;T - t + 1\}\} \quad \textbf{(57)}$$

So far, none of the problem formulations presented above explicitly represent (42) in the constraints' set. In contrast to the traditional formulation, the supply-demand equilibrium requirement will be passed on to the objective function, and is embedded within the term $\text{OperValue}_k(t)$. In reality, the term $\text{OperValue}_k(t)$ is indicative of the operational performance of any strategic alternative k during year t, in which the operational performance is determined through an optimization layer similar to the process described in Chapter 2. As such, the computed operational performance is a better assessment of the operational value of any given strategic alternative k as it takes into consideration the physical constraints that determine the optimal scheduling of a generation plant in a short-term horizon. This value reflects the optimal equilibrium point on the supply-demand curve. Consequently, there is no need to explicitly mention constraint (42) in our problem formulation.

A flowchart that describes the solution methodology discussed above is presented in Figure 3.1.

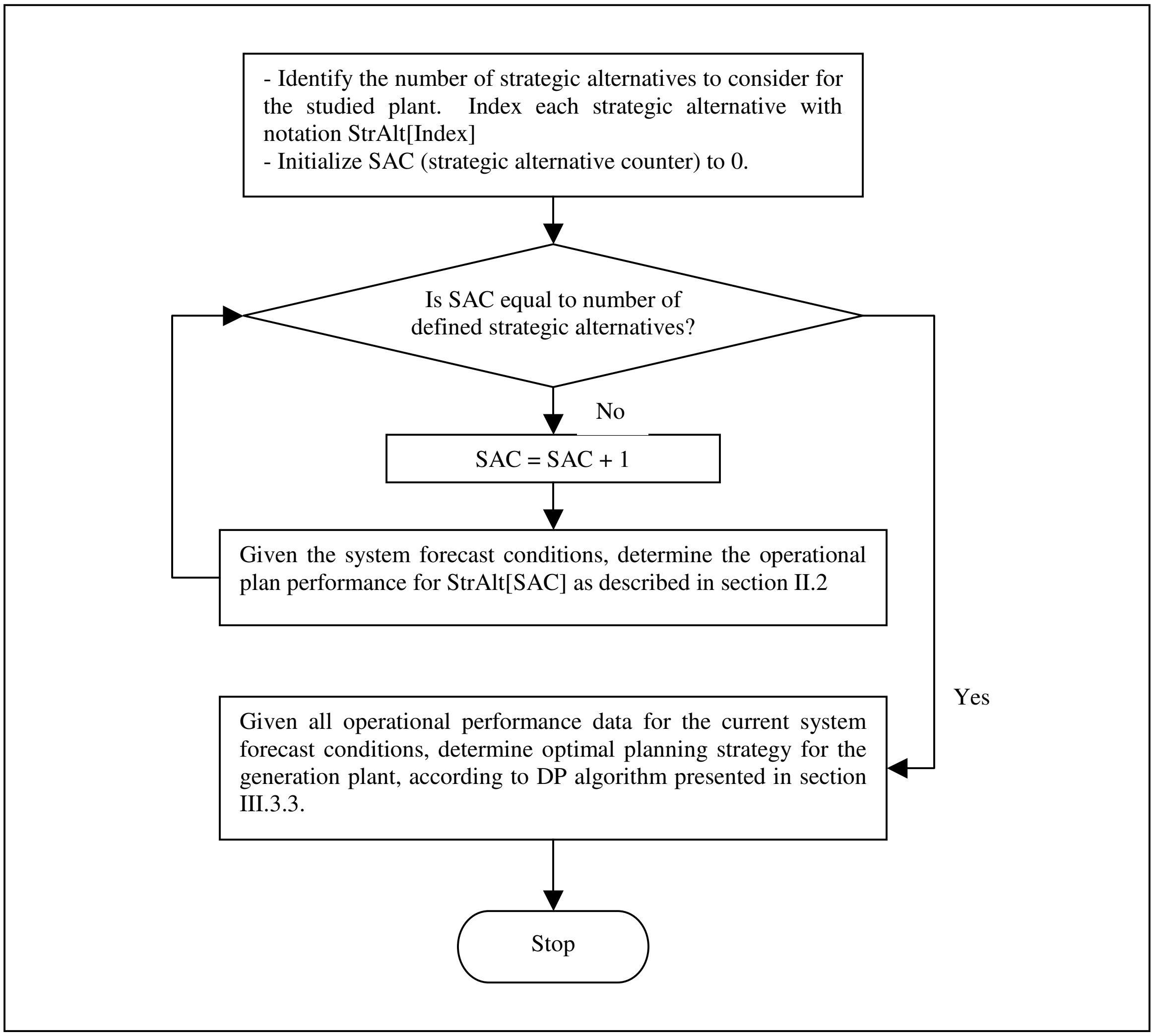


Figure 3.1: Deterministic Planning Algorithm Flow Chart.

### III.3.4 An Example

A generation manager is interested in planning alternatives over a 20-year planning period, starting in 2005 for a 1-unit generation plant. The forecast of yearly market average prices for electricity is shown in Figure 3.2, while the weekly price forecast for July 2014 is shown Figure 3.3. At any given time, the asset manger can decide sell the generator's output forward to the market, and if forecasted market prices are favorable, expand the plant's capacity. Once the capacity expansion has been realized, there is no investment strategy associated with capacity reduction. The capital cost involved with the expansion is $ 559/Kw and the investment life time is 15 years. For simplification purposes, we will assume that when the decision to expand has been made, the expanded capacity becomes available at the beginning of the expansion year. Whether operating in its current capacity or in the extended capacity mode, the production fuel of the generation unit is assumed to be directly indexed to the gas market. Finally, the discount rate for the expansion cost is 10% and the present value date is January 01, 2004.

If in a given year no expansion decision has been made, the following year is subject to two possible strategic alternatives, as below.

**strategy 1** or [**1x1**] - keep the current plant capacity and capture market opportunity,

**strategy 2** or [**2x1**] – expand the plant capacity and capture market opportunity.

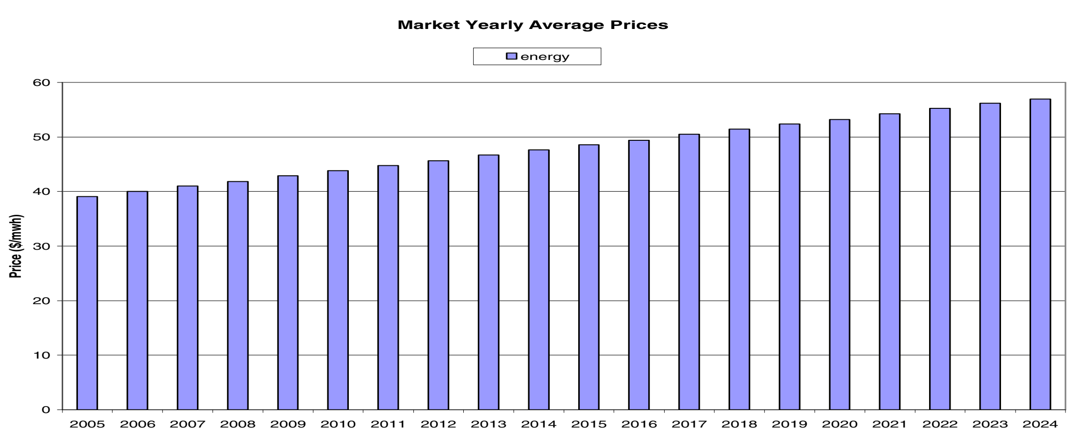


Figure 3.2: Average Energy Market Prices for 2005-2024.


Figure 3.3: Average Gas Market Prices for 2005-2024.

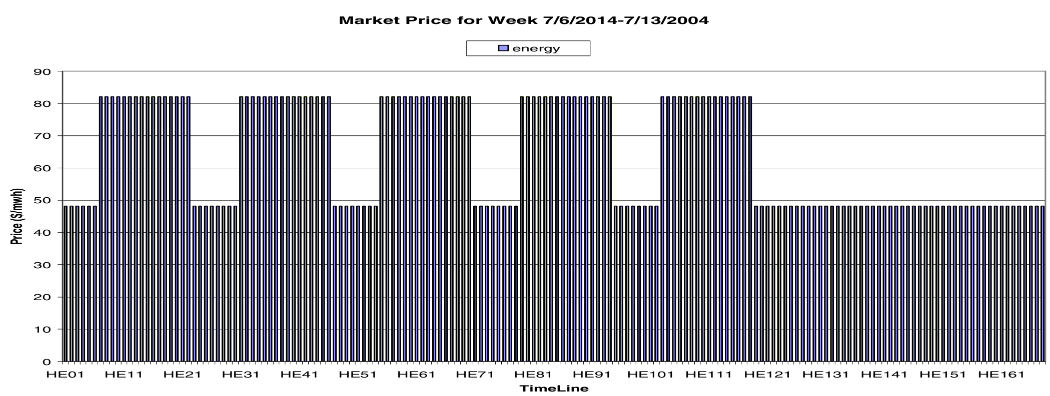


Figure 3.4: Energy Weekly On/Off-Peak Prices Forecast for July 2014.

In its current capacity mode (1x1), the generation unit can be described as in Table 3.1.

| **Operational Data** | | **Average Heat Rate Data** | | |
|---|---|---|---|---|
| | | Breakpoint ID | Mw | AHR (Mbtu/Mw) |
| Pmin (Mw): | 100 | | | |
| Pmax (Mw): | 230 | 1 | 90 | 15.33 |
| MUP (hrs): | 8 | 2 | 130 | 12.529 |
| MDN (hrs): | 8 | 3 | 187 | 10.614 |
| Initial status (hrs): | -50 | 4 | 235 | 9.733 |
| Startup Cost ($): | 4000 | | | |
| Var. O&M ($/mwh): | 2 | | | |

Table 3.1: Operational and Average Heat Rate Information for [1x1] Mode.

When expanded, the plant can actually be operated either in its initial capacity mode (with 1 turbine), or in its extended capacity mode (with 2 turbines). In the extended capacity mode, the generation unit operational data can be described as in Table 3.2.

| **Operational Data** | | **Average Heat Rate Data** | | |
|---|---|---|---|---|
| | | Breakpoint ID | Mw | AHR (Mbtu/Mw) |
| Pmin (Mw): | 220 | 1 | 210 | 12.6 |
| Pmax (Mw): | 450 | 2 | 300 | 10.724 |
| MUP (hrs): | 8 | 3 | 375 | 9.856 |
| MDN (hrs): | 8 | 4 | 470 | 9.177 |
| Initial status (hrs): | -50 | | | |
| Startup Cost ($): | 4000 | | | |
| Var. O&M ($/Mwh): | 2 | | | |

Table 3.2: Operational and Average Heat Rate Information for [2x1] Extended Mode.

Using the commercial software GenTrader®, courtesy of PCI, the yearly operational value stream for each strategic alternative is determined as shown in Figure 3.5.

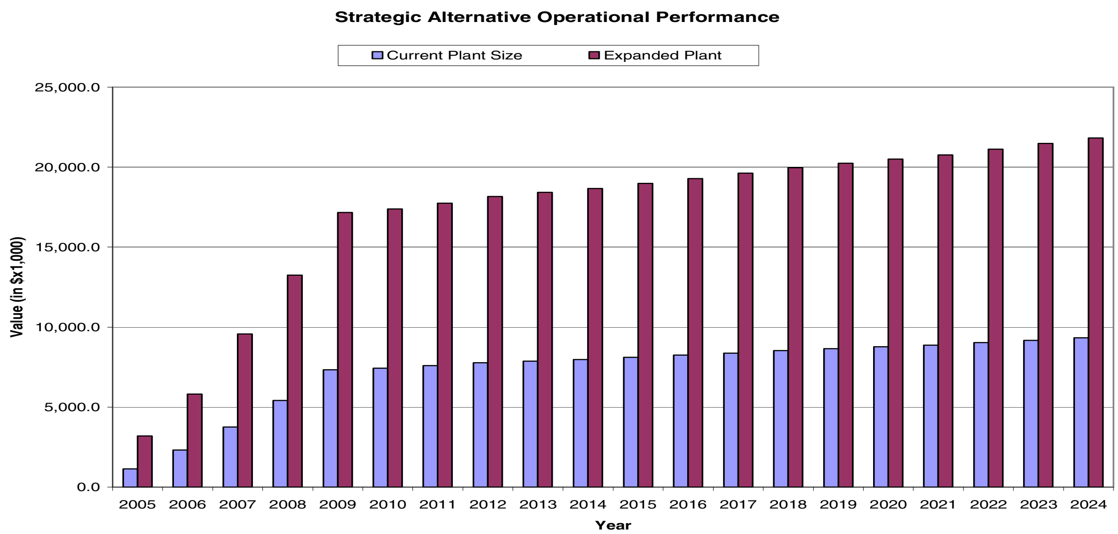


Figure 3.5: Optimal Strategic Operational Value Chart (not discounted).

After simulation of the algorithm described in Figure 3.1, the optimal planning present value of the generation unit is computed as $ 47,743,572. Furthermore, the algorithm advises not to expand the plant before January 1, 2020. The optimal strategic sequence details are shown in Table 3.5, where the monetary data are in present value terms.

| **Year:** | **2005** | **2006** | **2007** | **2008** | **2009** |
|---|---|---|---|---|---|
| **Alternative:** | [1x1] | [1x1] | [1x1] | [1x1] | [1x1] |
| **Transition Value ($):** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Oper. Value ($):** | 942,542.1 | 1,728,740.1 | 2,537,384.8 | 3,320,233.0 | 4,067,626.8 |
| **Total Value ($):** | 942,542.1 | 1,728,740.1 | 2537,384.8 | 3,320,233.0 | 4,067,626.8 |

| **Year:** | **2010** | **2011** | **2012** | **2013** | **2014** |
|---|---|---|---|---|---|
| **Alternative:** | [1x1] | [1x1] | [1x1] | [1x1] | [1x1] |
| **Transition Value ($):** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Oper. Value ($):** | 3,736,346.8 | 3,450,923.5 | 3,197,506.0 | 2,933,033.3 | 2,692,755.5 |
| **Total Value ($):** | 3,736,346.8 | 3,450,923.5 | 3,197,506.0 | 2,933,033.3 | 2,692,755.5 |

| Year: | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|
| Alternative: | [1x1] | [1x1] | [1x1] | [1x1] | [1x1] |
| Transition Value ($): | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Oper. Value ($): | 2,478,433.3 | 2,280,440.0 | 2,097,313.0 | 1,932,822.9 | 1,775,621.9 |
| Total Value ($): | 2,478,433.3 | 2,280,440.0 | 2,097,313.0 | 1,932,822.9 | 1,775,621.9 |
| Year: | 2020 | 2021 | 2022 | 2023 | 2024 |
| Alternative: | [2x1] | [2x1] | [2x1] | [2x1] | [2x1] |
| Transition Value ($): | -7,605,800.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Oper. Value ($): | 3,804,991.3 | 3,486,285.3 | 3,211,905.0 | 2,955,851.5 | 2,718,617.5 |
| Total Value ($): | -3,800,808.5 | 3,486,285.3 | 3,211,905.0 | 2,955,851.5 | 2,718,617.5 |

Table 3.3: Deterministic Optimal Strategic Investment Plan.

Table 3.4 shows the results of planning value for various planning scenarios. As can be seen, an earlier or later expansion than 2020 returns a lower planning value.

| Planning Scenario | Available Strategic Alternatives | Planning Value ($) |
|---|---|---|
| 1 | No choice of strategy 2 at any time | 46,088,544 |
| 2 | Forced choice of strategy 2 in 2009 | 28,127,250 |
| 3 | Forced choice of strategy 2 in 2022 | 47,438,260 |
| 4 | Yearly choice of strategy 1 or 2 | 47,743,572 |

Table 3.4: Planning Scenarios Expected Values (present value).

The example above shows how the proposed algorithm helps detect what the best strategic alternatives are and when to implement them. As will be shown later, the proposed algorithm can also be used to perform a relative comparison of the contribution of a given strategic alternative to the investment plan P/L.

## III.4 Generation Asset Planning Under Uncertainty

### III.4.1 A Monte Carlo based Algorithm: a Screening Method

In a deterministic market environment, the optimal planning of a generation plant can be derived by solving Problem VIII with the dynamic programming technique discussed in section III.3.3. The procedure is relatively simple and effective. Under market uncertainty, it becomes important to identify how market price volatility can impact the profitability of a portfolio investment strategy, let alone to determine an optimal investment strategy. Our treatment of market price uncertainty and its impact on strategic alternatives operational performance was presented in Chapter 2. Aware of the limitations of closed forms solutions for physical assets portfolio optimization, we have described how through simulation, it is possible to derive the optimal expected operational value of any given strategic alternative. It was argued that through Monte Carlo simulation, the adaptive operational flexibility could be captured in the expected operational value. Similarly, the same argument on long-term optionality could be made from a planning perspective.

Under uncertainty, the generation planning problem presented in Problem VIII must be reformulated. The new formulation essentially affects the objective function as seen below.

## Problem IX

$$\underset{\substack{u_k(t),u_j(t)\\ \text{OperValue}_k(t)\\ k\in\Omega, j\in\Omega, t\in\{1,...,T\}}}{\text{Max}} \quad E\left\{\sum_{t=1}^{T}\sum_{k\in\Omega}\left[u_k(t)\cdot \text{OperValue}_k(t)\right]-\sum_{t=1}^{T}\sum_{k\in\Omega}\left[u_k(t)\cdot[1-u_k(t-1)]\cdot\sum_{\substack{j\in\Omega\\ j\neq k}}\left[u_j(t-1)\cdot \text{RICosts}_{j,k}(t))\right]\right]\right\}$$

**(59)**

subject to:

$$\sum_{k\in\Omega} u_k(t)=1, \quad \forall t\in\{1,...,T\} \qquad \textbf{(60)}$$

$$\begin{cases} u_k(t)\cdot[1-u_k(t-1)]\cdot u_j(t-1)=0 \\ \text{if } w_{j,k}(t)=0,\ \forall t\in\{1...T\}, \forall j\neq k,\ (j,k)\in\Omega x\Omega \end{cases} \qquad \textbf{(61)}$$

$$\begin{cases} u_k(t)\cdot[1-u_k(t-1)]\cdot u_j(t-1)=0 \\ \text{if } u_j(t-1)=1 \text{ and } \tau_j(t-1)<\text{LagPeriod}_{j,k}, \forall t\in\{1,...,T\}, \forall j\neq k,\ (j,k)\in\Omega x\Omega \end{cases}$$

**(62)**

$$\begin{cases} u_k(t)=1 \\ \text{if } u_k(t-1)=1 \text{ and } \tau_k(t-1)+1<\text{MinUP}_k, \forall k\in\Omega, \forall t\in\{1,...,T\} \end{cases} \qquad \textbf{(63)}$$

$$\begin{cases} u_k(t)=0 \\ \text{if } u_k(t-1)=1 \text{ and } \tau_k(t-1)+1=\text{MaxUP}_k, \forall k\in\Omega, \forall t\in\{1,...,T\} \end{cases} \qquad \textbf{(64)}$$

$$u_k(t)\in\{0,1\} \quad \forall k\in\Omega, \forall t\in\{0...T\} \qquad \textbf{(65)}$$

where:

$$\text{RICosts}_{j,k}(t)=\frac{\text{ICosts}_{j,k}(t)}{\text{RecovLife}_k}\cdot \text{Max}\left\{0\,;\min\left\{\text{RecovLife}_k\,;T-t+1\right\}\right\} \qquad \textbf{(66)}$$

$E\{.\}$ denotes the expected value operator.

In Chapter 2, market price uncertainty was described through the derivation of multiple scenarios using Monte Carlo technique. Through the Monte Carlo decomposition technique, one could compute the expected operational value of any strategic alternative, and subsequently its standard deviation, after detailed simulation in each market price path. That same approach will be implemented for the investment valuation and derivation of the planning value of a generation plant described in Problem IX's formulation. In the proposed approach, the planning value of a generation plant is determined through the following sequence:

- enumerate the strategic alternatives that represent the possible changes over the long term,
- identify the market risk drivers susceptible of impacting the operational value of the above mentioned alternatives,
- using Monte Carlo technique, generate the system (market) sample states that represent the market uncertainty,
- for each system sample state, perform a long term operational valuation for each strategic alternative as described in section II.2,
- given the long term operational valuation results above, derive the plant optimal investment plan for each system sample state as described in section III.3.3,
- given all the system sample states optimal investment plans, determine the planning value of the generation plant.

The sequence described above is summarized in Figure 3.6. In that flowchart, note how the methodologies implemented to capture the impact of uncertainty and the hourly portfolio optimization schema outlined in Chapter 2 both integrate the building block of the proposed algorithm. This algorithm inherently captures the constraints associated with the implementation of a strategic alternative as much as it captures the physical operational constraints associated with the hourly operational economics of the various strategic alternatives, all of which in an uncertain market environment. The combination of these short term operational and long term planning constraints in the proposed algorithm allows us to appropriately determine the strategic planning value of a generation plant. The underlined valuation methodology is flexible enough to perform a robust analysis in the presence of multiple risk drivers.

### III.4.2 A Formulation Including Capacity Payments

The term $\mathrm{OperValue}_k(t)$ is a function of the electricity price structure used during time period t. If the electricity market prices used to determine $\mathrm{OperValue}_k(t)$ include an energy and a capacity components, the term $\mathrm{OperValue}_k(t)$ represents the rewards associated with capacity built up until year t. However, the electricity price structure used to determine $\mathrm{OperValue}_k(t)$ does not always include a capacity component. In that case, the generation planning problem described in Problem IX might not favor changes towards capital-required strategic alternatives. This is explained by the fact that the stream of $\mathrm{OperValue}_k(t)$ data that such alternatives would generate over the planning horizon could not be sufficient to recover investment costs. A broader discussion on the subject of justifying capacity payments or markets can be found in [41]. Further discussion on the subject is outside the scope of the current work: in this section, the latest generation planning problem formulation is appropriately modified when the electricity price structure is characterized by an energy and a capacity components.

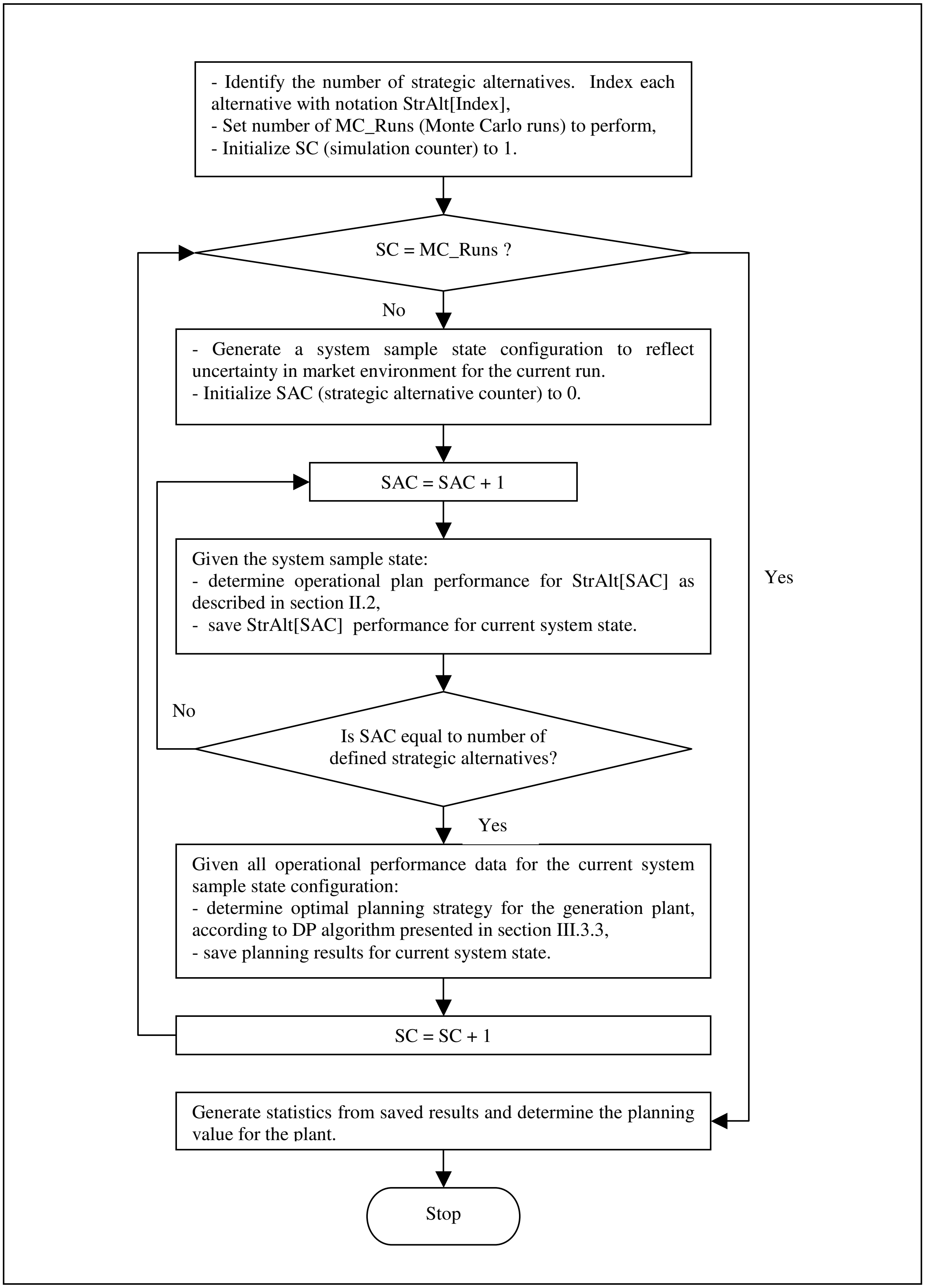


Figure 3.6: Flow Chart for Planning Algorithm Under Uncertainty.

In practice, the capacity component of the electricity market price which is reflective of the eventual capacity deficiency in the market environment would mostly exhibit a seasonal pattern. A reasonable assumption is that there exists a monthly shape for capacity prices: for example, in markets where the installed capacity is close to the predicted demand, capacity prices are non-zero during peak months, and are rather negligible in other months. By using a monthly capacity reward in the problem statement, Problem IX can be rewritten as:

**Problem X**

$$\underset{\substack{u_k(t), u_j(t) \\ \text{OperValue}_k(t) \\ k\in\Omega, j\in\Omega, t\in\{1,...,T\}}}{\text{Max}} \quad E\left\{ \begin{array}{l} \sum_{t=1}^{T}\sum_{k\in\Omega}\left[ u_k(t)\cdot[\text{OperValue}_k(t) + \sum_{m=1}^{12} c_k \cdot \text{CapValue}_k(m)] \right] \\ -\sum_{t=1}^{T}\sum_{k\in\Omega}\left[ u_k(t)\cdot[1-u_k(t-1)]\cdot \sum_{\substack{j\in\Omega \\ j\neq k}}\left[ u_j(t-1)\cdot \text{RICosts}_{j,k})\right] \right] \end{array} \right\} \tag{67}$$

subject to:

$$\sum_{k\in\Omega} u_k(t) = 1, \quad \forall t \in \{1,...,T\} \tag{68}$$

$$\begin{cases} u_k(t)\cdot[1 - u_k(t-1)]\cdot u_j(t-1) = 0 \\ \text{if } w_{j,k} = 0, \ \forall t \in \{1...T\}, \forall j \neq k, \ (j,k) \in \Omega x \Omega \end{cases} \tag{69}$$

$$\begin{cases} u_k(t)\cdot[1 - u_k(t-1)]\cdot u_j(t-1) = 0 \\ \text{if } u_j(t-1) = 1 \text{ and } \tau_j(t-1) < \text{LagPeriod}_{j,k}, \forall t \in \{1,...,T\}, \forall j \neq k, \ (j,k) \in \Omega x \Omega \end{cases} \tag{70}$$

$$\begin{cases} u_k(t) = 1 \\ \text{if } u_k(t-1) = 1 \text{ and } \tau_k(t-1) + 1 < \text{Min}UP_k, \forall k \in \Omega, \forall t \in \{1,...,T\} \end{cases} \tag{71}$$

$$\begin{cases} u_k(t) = 0 \\ \text{if } u_k(t-1) = 1 \text{ and } \tau_k(t-1) + 1 = \text{MaxUP}_k, \forall k \in \Omega, \forall t \in \{1,...,T\} \end{cases} \tag{72}$$

$$u_k(t) \in \{0,1\} \quad \forall k \in \Omega, \forall t \in \{0...T\} \quad \textbf{(73)}$$

where:

$$RICosts_{j,k}(t) = \frac{ICosts_{j,k}(t)}{RecovLife_k} \cdot Max\{0\,; \min\{RecovLife_k\,; T - t + 1\}\} \quad \textbf{(74)}$$

$E\{.\}$ denotes the expected value operator,

m is the month index in year t,

$c_k$ is the flag that indicates that strategic alternative k is a capacity based alternative,

$CapValue_k(m)$ is the capacity reward for strategic alternative k during month m and is a function of the monthly capacity price $CapPrice(m)$, the relative capacity size addition $CapMW_k$ caused by its implementation and how long it applies for during the month $NumHours_m$. We can write:

$$CapValue_k(m) = CapPrice(m) \cdot CapMW_k \cdot NumHours_m \quad \textbf{(75)}$$

By modifying the objective function as in (67), it was shown that the capacity adequacy problem can be included in the general planning formulation without changing the structure of the solution flow process. The solution flow process flexibility can also be extended towards a multi-commodity electricity market, where several products (energy, responsive reserves, regulation, etc) play a more important role in determining the operational benefits of a given strategic alternative.

III.4.3 Generation Planning Under Uncertainty with a Non-Adaptive Price Model

This section presents the results of the planning methodology presented in Figure 3.6 when the price process follows a GBM model, assuming there is no anticipation of price movements given the current information. In other words, the planning problem is looked at from the perspective that the price process follows a yearly GBM process and the prices occurrence for a given year does not impact the uncertainty for the following year. This assumption is often used in a simplified framework. When that is the case, the solution to the stochastic differential equation (24) is described as:

$$\ln(\Pr_t) = [\mu - \frac{1}{2} \cdot \sigma_t{}^2] \cdot t + z_t \qquad \textbf{(76)}$$

where:

t is the time index,

ln(.) is the logarithm operator,

$\Pr_t$ is the energy price value at time t,

$\mu$ is the mean of energy price in the ln(.) domain,

$\sigma_t$ is the volatility of price at time t,

$x_t$ is a random variable that follows N(0,1),

$z_t = \sigma_t \cdot \sqrt{t} \cdot x_t$

Expression (76) is itself a random variable that follows $N([\mu - \frac{1}{2} \cdot \sigma_t{}^2] \cdot t, \ \sigma_t \cdot \sqrt{t})$, with N(.) describing a normal process.

To say that prices are independently generated from one year to the next means that the $z_t$ variables are independently generated for each year t. If n is the total number of price paths to be constructed through the Monte Carlo based algorithm described in section III.4.1, the $z_t$ variables will be generated according to the following procedure:

**Step 1**: for each time index t, generate independently random values $x_t$ where $x_t$ follows N(0,1).

**Step 2**: for each generated $x_t$ at time t, multiply $x_t$ by $\sigma_t \cdot \sqrt{t}$ so that

$$z_t = \sigma_t \cdot \sqrt{t} \cdot x_t \qquad \textbf{(77)}$$

III.4.3.1 An Example

Let us consider the planning problem presented in III.3.4. After consulting with a third party, the asset manager is told that electricity prices over the next 20 years will follow a GBM process with the volatility data as shown in Table 3.5. The on/off-peak time periods are defined according to Table 2.10. Again, If in a given year no expansion decision has been made, the following year is subject to six possible strategic alternatives, as below.

**strategy 1** or [**1x1**] - keep the current plant capacity and play the market,

**strategy 2** or [**2x1**] – expand the plant capacity and play the market.

| | Jan. | Feb. | Mar. | Apr. | May | Jun. |
|---|---|---|---|---|---|---|
| **off-peak (%):** | 21 | 21 | 17.3 | 17.3 | 17.9 | 17.3 |
| **on-peak (%):** | 38.8 | 38.8 | 32 | 32 | 33 | 32 |
| | **Jul.** | **Aug.** | **Sep** | **Oct.** | **Nov.** | **Dec.** |
| **off-peak (%):** | 16.8 | 16.8 | 17.3 | 15.2 | 15.2 | 15.2 |
| **on-peak (%):** | 31 | 31 | 32 | 28.1 | 28.1 | 28.1 |

Table 3.5: Electricity Market prices Volatility Structure.

The Monte Carlo simulation is carried over 1,000 market price paths (the detailed samples outputs are too voluminous to be included in this dissertation). Using the commercial software GenTrader®, the operational performance over the planning horizon for each strategy can be computed, as shown in the P/L histograms in Figure 3.7 and 3.9.

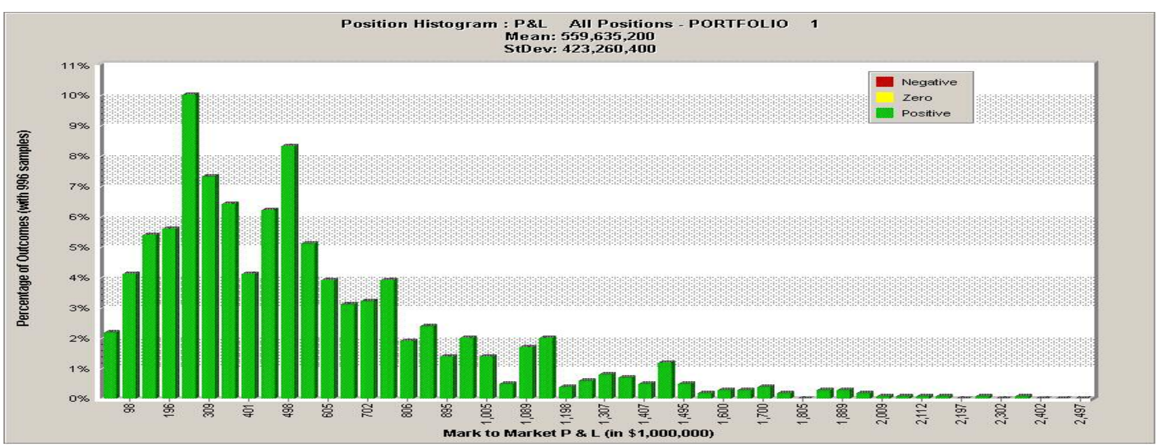


Figure 3.7: [1x1] Strategic Operational P/L (face value) Histogram.

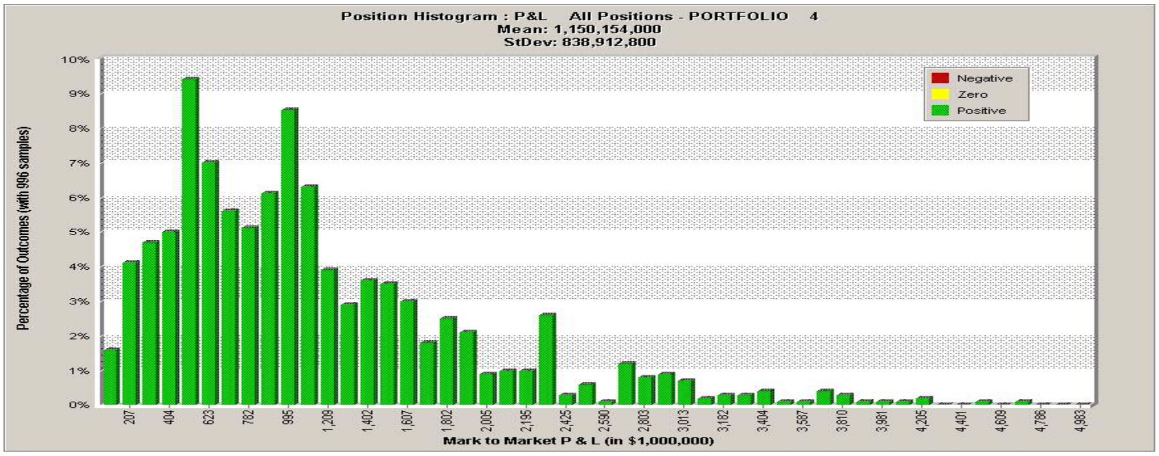


Figure 3.8: [2x1] Strategic Operational P/L (face value) Histogram.

Using the results of the strategic operational performances as inputs to the algorithm described in Figure 3.6, the optimal expected planning value for the generation unit is determined to be $ 267,449,657. The planning value P/L histogram distribution is shown in Figure 3.9. Note that there is no negative P/L as the study case is purely market based, even though expanding the plant requires some capital investment, such decision would only be taken when the overall benefits exceed the required investment.

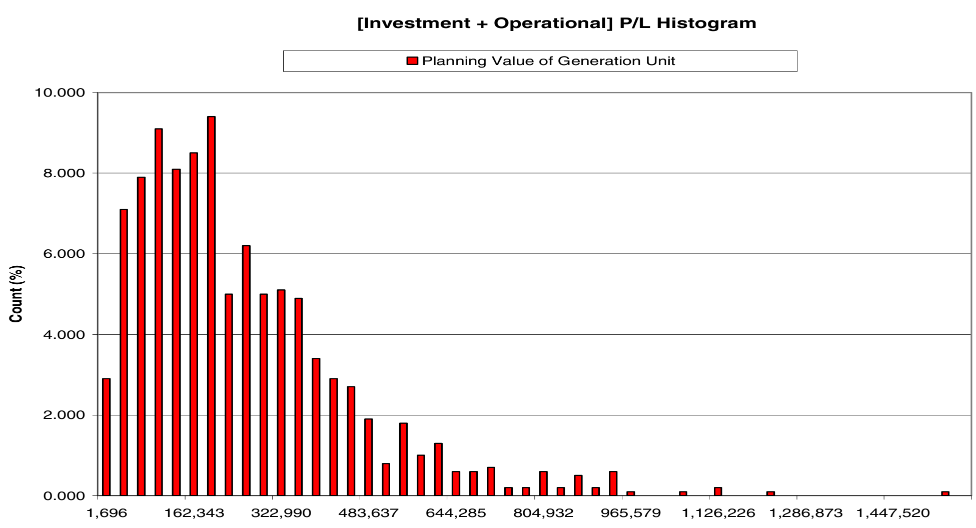


Figure 3.9: Planning (present value) P/L Histogram.

In addition to the P/L distribution histogram, it is possible for the asset manager to obtain the frequency of the recommended expansion plan during the planning period. According to Figure 3.10, the most recommended years of expansion are 2006, 2007 and 2008.

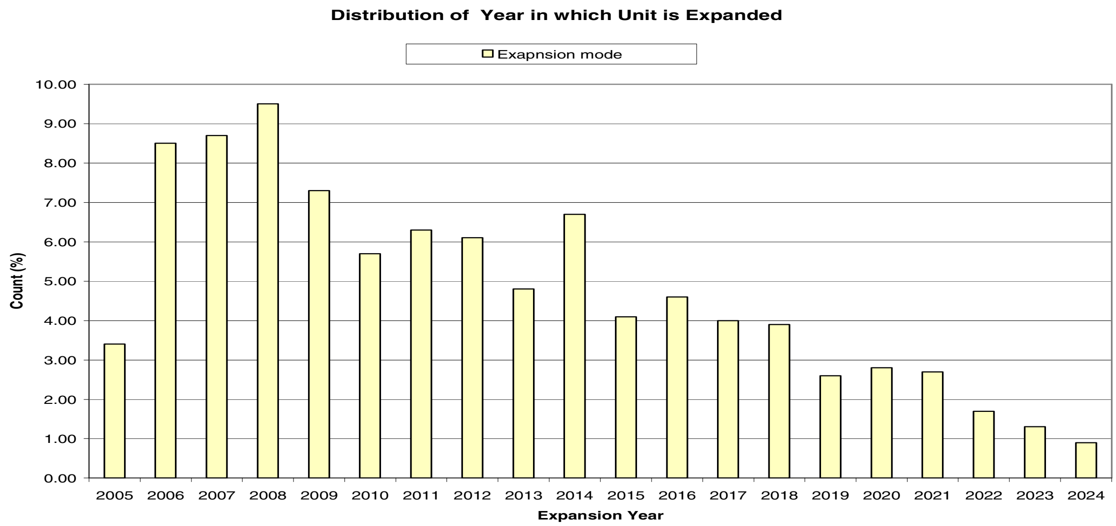


Figure 3.10: Expansion Plan Recommendation Histogram.

The results of the simulation under various planning scenarios are summarized in Table 3.6.

| Planning Scenario | Available Strategic Alternatives | Planning Value ($M) | Standard Deviation ($M) |
|---|---|---|---|
| 1 | No choice of strategy 2 at any time | 162.48 | 104.17 |
| 2 | Forced choice of strategy 2 in 2009 | 237.65 | 199.25 |
| 3 | Forced choice of strategy 2 in 2022 | 177.17 | 121.81 |
| 4 | Yearly choice of strategy 1 or 2 | 267.45 | 198.65 |

Table 3.6: Planning Scenarios Expected Values (present value).

III.4.4 Planning Under Uncertainty with an Adaptive Price Model

In the results presented in the previous section, the planning results suffer from the non-anticipation of price movements. As presented, these results are not in accordance with results that a price decision tree would produce. The obvious disadvantage is due to the assumption of having time-uncorrelated sample paths. In reality, a reasonable decision maker would factor in the current price information to adjust for future forecast. In other words, a decision maker would like to think of a price process as being close to that of a decision tree (Figure 3.11). Unfortunately, a planning analysis based upon a decision tree can be computationally prohibitive. For instance, a 20-year planning problem with one risk driver in a 3-branch tree translates into generating 3,486,784,401(=$3^{20}$) price scenarios overall.

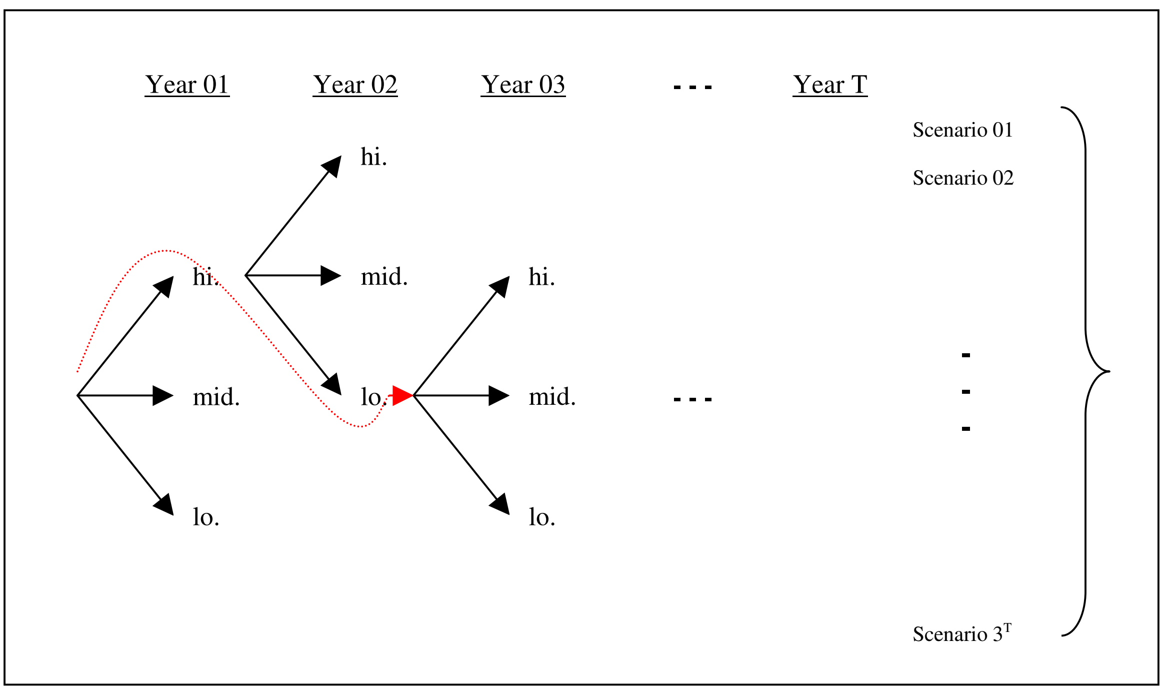


Figure 3.11: A 3-Branch Tree Scenario Generation with one Risk Driver.

In order to keep the computational time reasonable, it is possible to use a Monte Carlo based schema as described in the previous chapters and sections, and still capture the natural time-correlation dependency required in the price process.

When the Brownian process is correlated over time, it means $z_t$ variables are correlated over time. In that case, expression (76) needs to be adjusted to reflect conditional expectation and variance in the price model, as suggested below.

$$\ln(\mathrm{Pr}_t) - \ln(\mathrm{Pr}_{t-1}) = [\mu - \frac{1}{2} \cdot \sigma_{t|t-1}{}^2] \cdot t + z_{t|t-1} \qquad \textbf{(78)}$$

where:

t is the time index,

ln(.) is the logarithm operator,

$\mathrm{Pr}_t$ is the energy price value at time t,

$\mu$ is the mean of electricity price in the ln(.) domain,

$\sigma_{t|t-1}$ is the conditional volatility of price at time t, given the expected volatitilty at time t-1,

$x_t$ is a random variable that follows N(0,1),

$z_{t|t-1}$ is the conditional movement of price at time t, given the observed price movement at time t

$z_t = \sigma_t \cdot \sqrt{t} \cdot x_t$

In order to reproduce what would happen with a binomial tree price model, $z_t$ over time must be defined through its conditional mean and variance:

a) mean $_{z_t|z_{t-1}} = z_{t-1}$,

b) conditional variance$_{t|t-1}$ = estimated variance$_t$ − estimated variance$_{t-1}$.

This way, the sample variance of $z_t$ will always remain [$\sigma_t^2 \cdot t$].

The $z_t$ variables are generated following the procedure below.

**Step 1**: for each time index t, generate independently random values $x_t$ where $x_t$ follows N(0,1).

**Step 2**: at t=1, create $z_t$ such that it follows $N(0,\ \sigma_t \cdot \sqrt{t})$. This is done by applying

$$\begin{cases} z_t = \sigma_t \cdot \sqrt{t} \cdot x_t \\ t = 1 \end{cases} \tag{79}$$

**Step 3**: for subsequent time indices ($t \neq 1$), create the conditional realizations of $z_t$. This is done by applying

$$\begin{cases} z_t = z_{t-1} + \sqrt{(\sigma_t^{\ 2} \cdot t) - (\sigma_{t-1}^{\ 2} \cdot (t-1))} \cdot x_t \\ t \neq 1 \end{cases} \tag{80}$$

Note: the analytical correlation between two consecutive time realizations of $z_t$ is given by:

$$\rho_{z_t, z_{t-1}} = \frac{\sigma_{t-1} \cdot \sqrt{t-1}}{\sigma_t \cdot \sqrt{t}} \tag{81}$$

III.4.4.1 An Example

A generation plant must serve a 20-year forward sale obligation, starting in 2005. The forecasted market depth over that period is estimated to 100 Mw and 500 Mw for hourly purchase and sale respectfully: as shown in Figure 3.12, the market depth is not enough to compensate for the growing energy requirement over that period, namely after 2014. In the original contract negotiation, a clause stipulates that any load interruption is subject to a \$/Mwh 600 penalty. After research, the new management team believes that electricity market over the 20-year period follow a GBM process as shown in Table 3.5. Furthermore, these prices are correlated over time according to (81). To minimize the penalty associated with load interruption, the asset management team is presented with the two following planning options:

- a 150 Mw capacity addition. This capacity addition can be effective within a year. The capital cost and life time for that investment are estimated to be \$/Kw 559 and 15 years respectfully,
- 3 incremental additions of '60 MW CT GAS' each. Although the first addition can be implemented without any time delay restriction, management fears that any additional capacity addition would be effective only 2 years after the previous

one, due to permit allocation and other budget restrictions. Each 60 Mw capacity addition capital cost is valued over a 5-year life time, while the estimated investment cost is $/Kw 700. A standard description of a '60MW CT GAS' can be found in Table 3.7.

| **Operational Data** | | **Average Heat Rate Data** | | |
|---|---|---|---|---|
| | | Breakpoint ID | Mw | AHR (Mbtu/Mw) |
| Pmin (Mw): | 40 | 1 | 30 | 11.667 |
| Pmax (Mw): | 60 | 2 | 35 | 11.096 |
| MUP (hrs): | 6 | 3 | 40 | 10.696 |
| MDN (hrs): | 4 | 4 | 45 | 10.399 |
| Initial status (hrs): | -5000 | 5 | 50 | 10.167 |
| Startup Cost ($): | 2500 | 6 | 55 | 9.991 |
| Var. O&M ($/Mwh): | 2 | 7 | 60 | 9.861 |

Table 3.7: Operational and Average Heat Rate Information for '60 MW CT GAS'.

Note that the production fuel for generation operations is indexed to the gas market. The asset manager is only interested in choosing one of these investment policies. The discount rate and present value date for the analysis are 10% and January 01, 2004 respectfully. If no expansion decision has been made in a given year, the following year is subject to the following strategic alternatives:

**strategy 1** or [**Base Plan**] – keep the plant as 1x1 (see section III.3.4 for operational and heat rate information),

**strategy 2** or [**Base Plan as CC**] – expand the plant capacity by turning it into a 2x1 (see section III.3.4 for operational and heat rate information),

**strategy 3** or [**Base Plan + 60 Mw**] – add 60 Mw capacity to the current plant capacity,

**strategy 4** or [**Base Plan + 120 Mw**] – add 120 Mw capacity to the current plant capacity,

**strategy 5** or [**Base Plan + 180 Mw**] – add 180 Mw capacity to the current plant capacity.

The Monte Carlo simulation is carried over 1,000 market price paths. As with the previous example, the detailed samples outputs are too voluminous to be included in this dissertation. If the management team decides not to consider any investment option over the 20-year period, the planning value of the generation plant is determined by the plant's operational flexibility: the expected planning P/L is $M 162.5. Similarly, if the management team decides to consider the combined cycle plant expansion as its only investment option over the 20-year period, the planning value of the generation plant is determined by both the operational flexibility (whether using 1CT or 2CTs) and the long term flexibility on the expansion decision: the expected planning P/L is $M 256.4. Finally, if the management team decides to consider one or more incremental capacity additions as well as the combined cycle expansion as investment options over the 20-year planning period, the planning value of the plant is determined by the operational flexibility of each of the then selected strategic alternatives as well as their optimal implementation time sequence: in the case of 3 incremental capacity additions, the expected planning P/L is $M 269.7. The results of all these planning scenarios, through a detailed application of the algorithm described in Figure 3.6 are summarized in Table 3.8.

| Planning Scenario | Yearly Available Strategic Alternatives | Planning Value ($M) | Intrinsic Value ($M) | Standard Deviation ($M) |
|---|---|---|---|---|
| 1 | strategy 1 only | 162.54 | 101.06 | 129.21 |
| 2 | strategies 1 or 2 | 256.36 | 110.55 | 280.38 |
| 3 | strategies 1, 2 or 3 | 261.11 | 111.76 | 279.13 |
| 4 | strategies 1, 2, 3 or 4 | 269.66 | 112.90 | 276.83 |
| 5 | strategies 1, 2, 3, 4 or 5 | 278.81 | 112.90 | 300.38 |

Table 3.8: Expected Planning Values (present value).

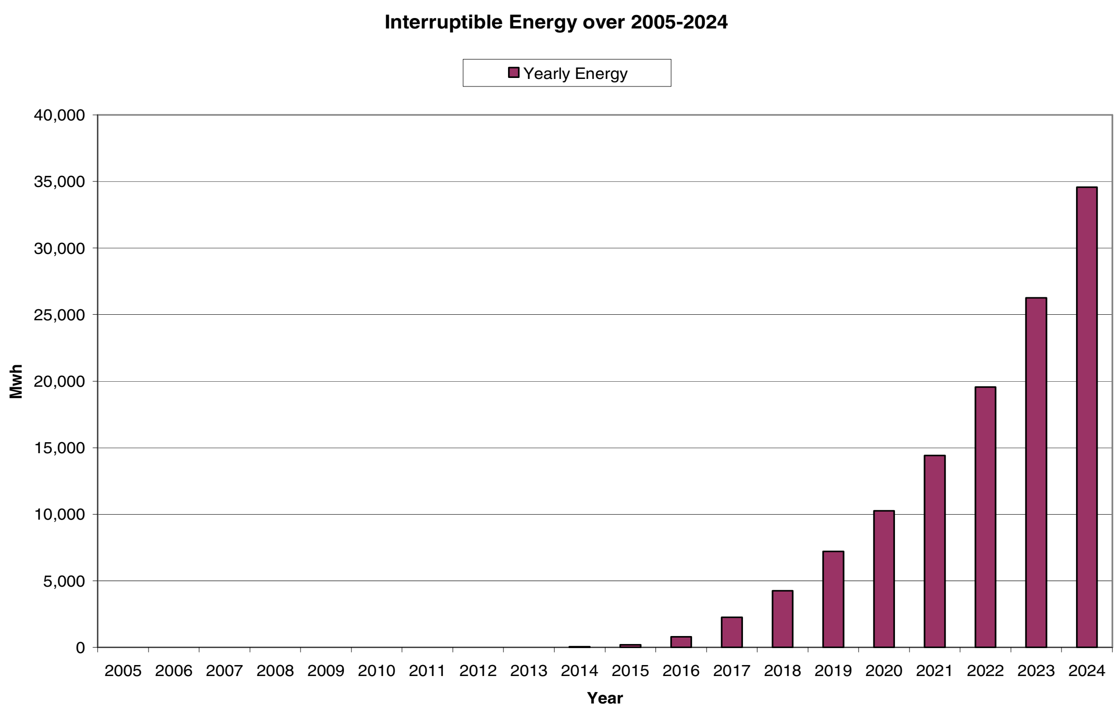


Figure 3.12: Expected Interruptible Energy in Case of no Expansion.

Although the results in Table 3.8 reflect the long-term flexibility associated with the time interactions of several investment options, the expected planning P/L does not provide an insight as to the recommended expansion year(s), nor does it expose the sensitivities associated with choosing one alternative over another. In fact, such information can only be obtained by further analysis of the detailed outputs from the considered planning scenario.

Table 3.9 shows the relative recommendations on implementing incremental capacity additions rather than expanding the plant into a combined cycle plant at once. As can be seen, it is recommended to use incremental capacity additions once the total capacity addition is at least 120 MW. For instance, if the management team decides to consider 2 incremental capacity additions as well as the combined cycle expansion as investment options over the 20-year planning period, at least 67% of the recommended investment plans will involve 1 incremental capacity addition, in contrast to 47% when only a 60 MW incremental addition is considered. This difference is explained by the additional benefits that another 60 MW capacity addition would provide (at least 63% of the investment plans involve 2 incremental capacity additions), thus reducing the frequency on the combined cycle recommendation (25% in planning scenario 4 rather than 44% in planning scenario 3). In Table 3.10, the P/L contribution of each strategic alternative is assessed in each planning scenario.

| | Planning Scenario 2 | Planning Scenario 3 | Planning Scenario 4 | Planning Scenario 5 |
|---|---|---|---|---|
| **BasePlan as CC:** | 91.30% | 44.50% | 25.60% | 5.50% |
| **BasePlan + 60 MW:** | - | 47.40% | 67.30% | 90.90% |
| **BasePlan + 120 MW:** | - | - | 63.40% | 87.00% |
| **BasePlan + 180 MW:** | - | - | - | 38.60% |

Table 3.9: Capacity Addition Recommendation Frequency.

| | Planning Scenario 2 | Planning Scenario 3 | Planning Scenario 4 | Planning Scenario 5 |
|---|---|---|---|---|
| **BasePlan as CC:** | 75.14% | 56.10% | 44.58% | 5.35% |
| **BasePlan + 60 MW:** | - | 34.59% | 8.44% | 6.87% |
| **BasePlan + 120 MW:** | - | - | 42.01% | 40.70% |
| **BasePlan + 180 MW:** | - | - | - | 43.86% |

Table 3.10: Strategic Alternatives Contribution to the Expected Planning P/L.

The information provided in Tables 3.9 and 3.10 is not enough to determine the appropriate schedule for the expansion timeline: we need to look at the detailed outputs from the various results. When no incremental capacity addition is considered as an investment option, the combined cycle expansion recommendation favors three expansion periods: 2005-2008, 2012-2014, and 2019 through 2022. When one or more incremental capacity additions are considered as investment options, the combined cycle expansion is recommended mostly during the 2005-2008 period. On the other hand, the first incremental capacity addition (BasePlan + 60 MW) is recommended during the 2005-2006 period, and more specifically by 2006. The second incremental capacity addition (BasePlan + 120 MW) is recommended during 2007, 2008 and 2010. Finally, the third incremental capacity addition (BasePlan + 180 MW) is recommended during 2009-2010. Figures 3.13 through 3.16 show when each recommended strategic alternative is initially activated, for each planning scenario.

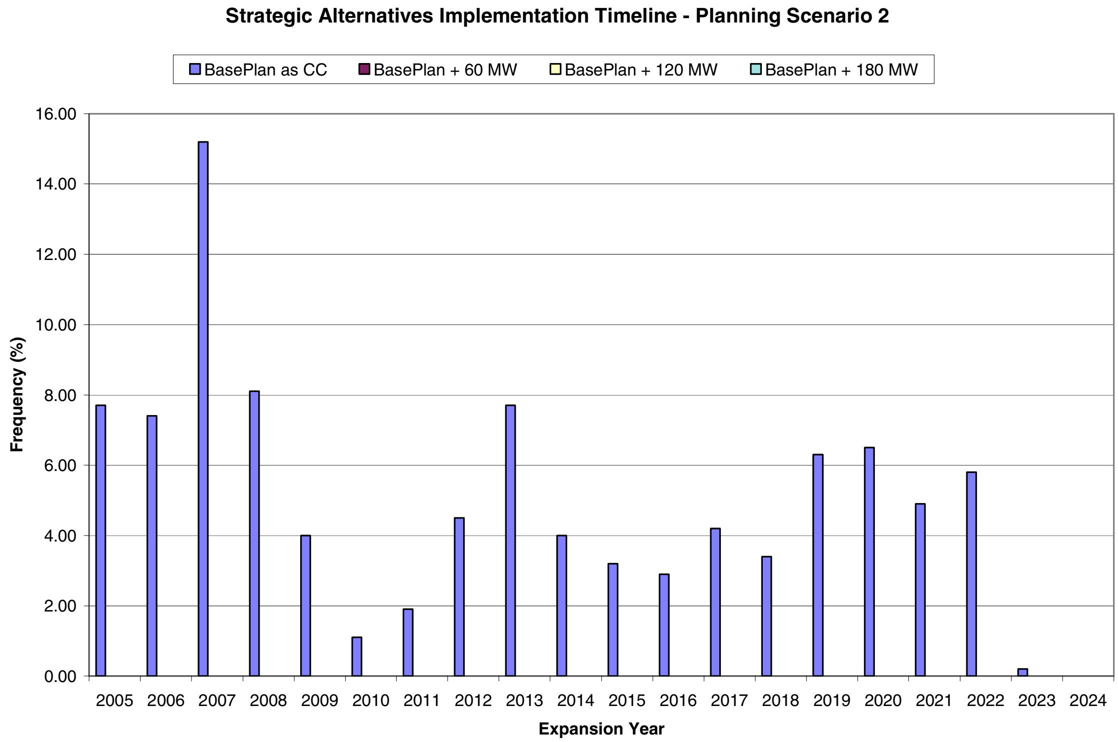


Figure 3.13: Recommended Expansion Timeline for Planning Scenario 2.

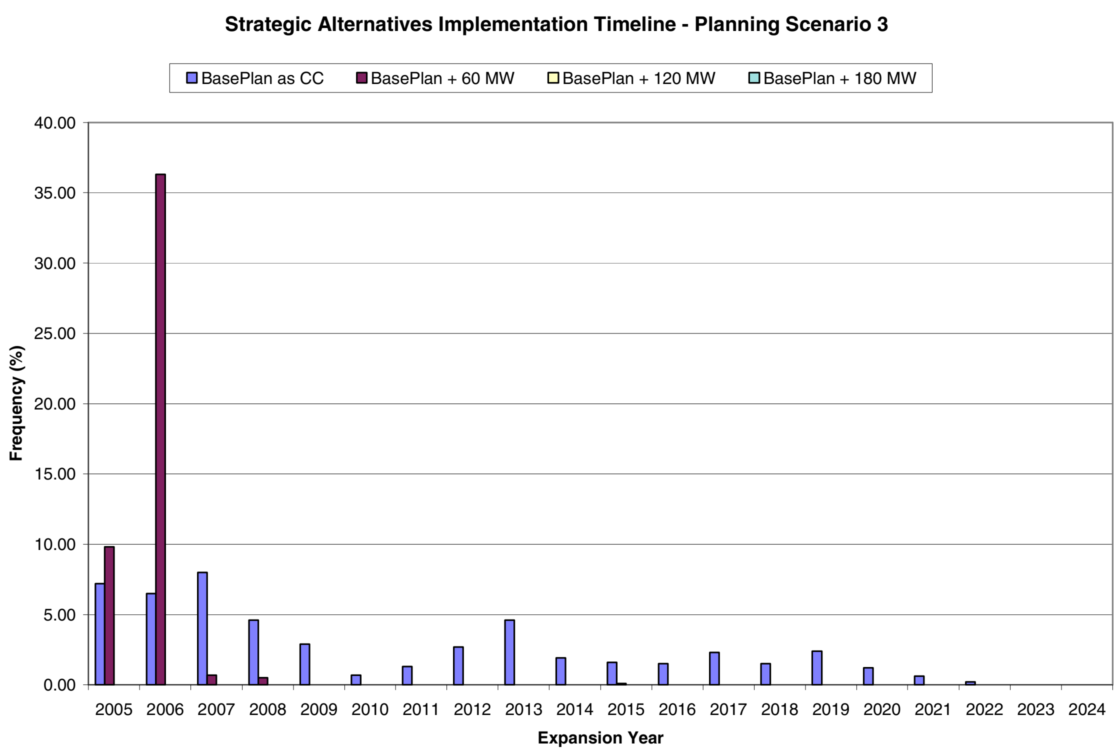


Figure 3.14: Recommended Expansion Timeline for Planning Scenario 3.

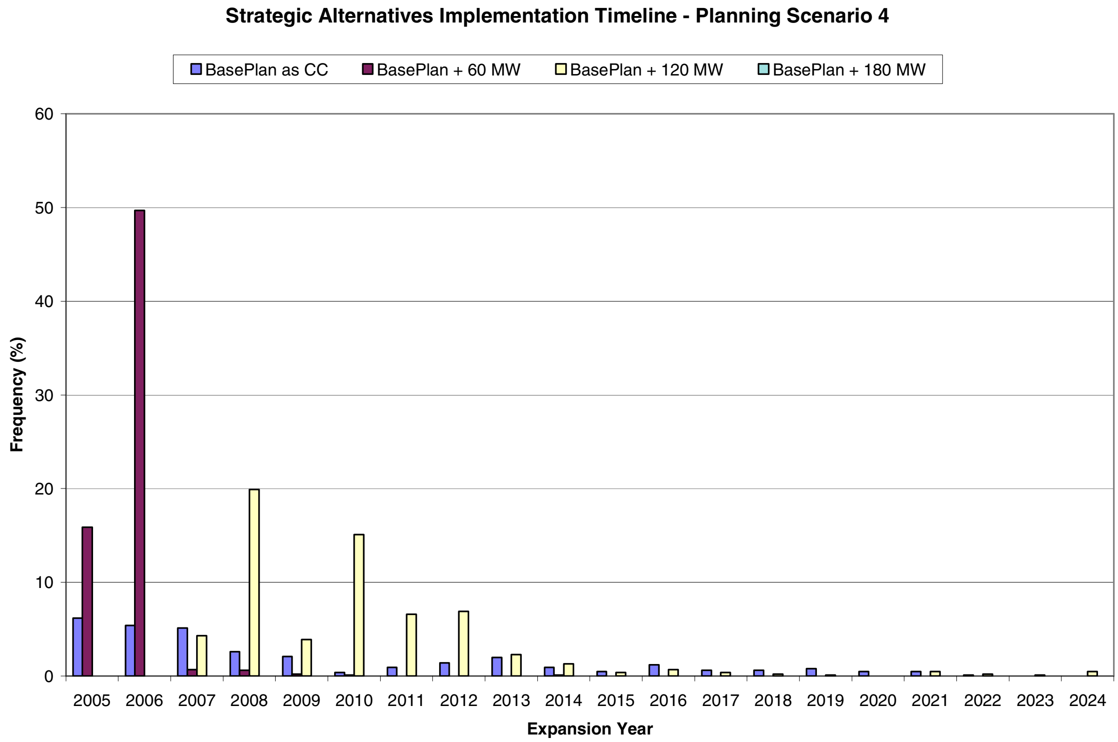


Figure 3.15: Recommended Expansion Timeline for Planning Scenario 4.

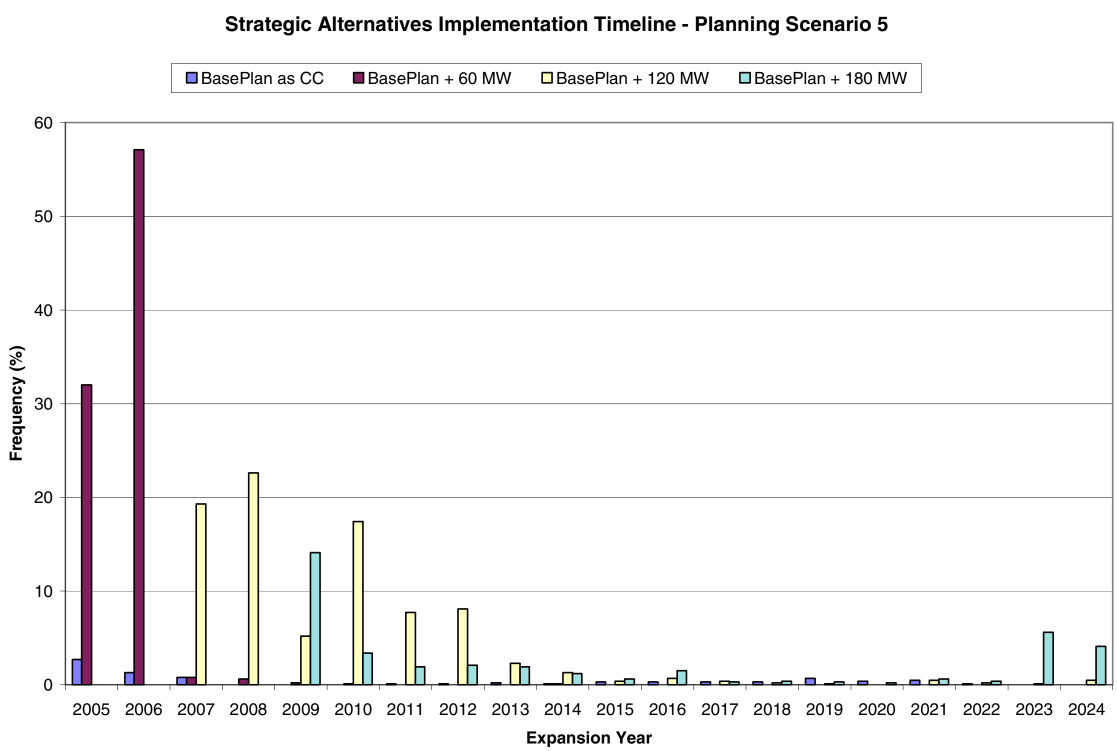


Figure 3.16: Recommended Expansion Timeline for Planning Scenario 5.

As illustrated through the above example, the planning valuation methodology developed in this chapter can help compute the expected long term value of a generation portfolio. This value helps capture the extrinsic value associated with planning as shown in Table 3.8. The model can also serve as an efficient tool to determine the adequate timeline for optimal investment planning.

# CHAPTER 4

# CONCLUSION

In the United States, the electrical sector is not the first to undergo market reform. Telecommunications and natural gas are examples of industries that have been restructured towards market openness. Market models, financial instruments and methods of valuing commodities related to the specific industries are known and available. However, their application to the electrical energy industry in planning studies has produced mixed results. This can essentially be attributed to the following characteristics of the underlying commodity:

- Electricity is an essential commodity for most customers and it cannot be stored, at least not for the quantities at which it is traded in the market,
- Due to the physical delivery requirements associated with the traded contracts, electricity derivatives must be priced through a fair assessment of the physical production process, a non-feasible task with current financial models.

On the other hand, the traditional engineering planning models are not suited to value market based asset portfolios, and like their financial counterparts they do not capture the short-term operational constraints associated with strategic valuation, nor do these models take into consideration the time dependencies that often characterize long term strategic changes.

In this dissertation, a new approach to electric generation planning is proposed, formulated and implemented. The proposed method copes with uncertainty by acknowledging the adaptive nature of the decision makers as uncertainty unfolds. Also, it simultaneously captures the impact of the short-term operational and long-term dynamic coupling constraints of the candidate strategic alternatives in determining the optimal strategic investment plan while uncertainty unfolds. Thus, the method captures the extrinsic value due to operational flexibility and long term adaptive decision making. Through its innovative formulation, the proposed method can be used to address generation planning under various market structure environments such as pure competition, partial competition or total regulation. From a technical standpoint, the proposed method is conceived as a simulation model that intricately combines a two-layer interdependent optimization schema, each solved by a different algorithmic approach.

In the first part of this dissertation, a review of generation planning is presented and the shortcomings of the currently available methods are described. Amongst others, these shortcomings include the failure to thoroughly reflect assets short-term operational constraints in overall operational valuations, the inability to capture the flexibility associated with changing the course of action (whether in operations and/or planning decisions) as uncertainty unfolds, and the inability to handle the time dependencies that couple the implementation sequence of multiple strategic alternatives. Furthermore, the introduction of market competition brings an additional level of complexity in the problem formulation. All these inadequacies require that the generation planning problem be studied under a new paradigm.

In the second part of this dissertation, the problems of strategic optimal operational valuation and market uncertainty formulation are presented and addressed. After a detailed formulation of the strategic operational valuation problem also known as the unit commitment problem, a general solution algorithm based on the upward commitment method is discussed, with specific implementation for a market-based strategic alternative operational problem, where each market instrument is valued individually. The 2-generation unit deterministic case study in Chapter 2 shows how the short-term operational time dependent constraints drive the optimal decision of the commitment sequence while the static constraints affect the optimal dispatch level of each generation asset. In the later part of the chapter, the problem of market uncertainty is presented. Since decision makers should be able to adjust their course of action as uncertainty unfolds, it appears appropriate to describe market uncertainty through Monte Carlo sampling. Contrary to standard financial models, the stochastic strategic alternative operational valuation method presented in this dissertation reflects the short-term constraints associated with assets operations, thus providing a more realistic operational value. Building on the results of the deterministic strategic operational valuation algorithm, a Monte Carlo based algorithm is presented and tested on the previous study case. In addition to the flexibility in adding multiple risk drivers without hindrance to the structure or the efficiency of the solution algorithm, the proposed methodology allows computing additional statistics otherwise not available with standard financial models, further providing decision makers with a better representation of their strategic alternatives risk profiles.

In the third part of this dissertation, the problem of long term strategic decision is addressed under a new formulation for generation planning. The new formulation departs from the traditional engineering models in that it poses the problem from a market opportunities maximization perspective, embeds the supply-demand constraint within the objective function argument, and includes the time dependencies associated with the strategic alternatives implementation within its general framework. Afterwards, a dynamic programming (DP) based solution algorithm is developed, and initially tested against a deterministic long term problem formulation in Chapter 3. The introduction of the time dependencies within the stages/states structure of the DP algorithm allows an efficient coordination of the time dependent strategic alternatives coupling constraints, when they exist. Furthermore, the computed operational value of each strategic alternative in the DP algorithm reflects the short term operational constraints of the studied assets as the valuation is performed dynamically through the hourly chronological unit commitment algorithm described in Chapter 2. With the effective combination of the short and long term constraints, the planning value obtained through the deterministic planning algorithm provides decision makers with adequate investment signals, as shown in the deterministic planning example presented in Chapter 3. Taking advantage of the modularity structure of the derived DP algorithm, a Monte Carlo sampling technique is added to the initial DP planning algorithm in order to address the generation planning problem under uncertainty. As argued earlier, the flexibility in changing the course of action as uncertainty unfolds should provide decision makers with better decision signals between the competing strategic alternatives. In addition to the expected, intrinsic and extrinsic planning values, the Monte Carlo based planning algorithm also provides decision makers with other statistics such as the standard deviation, the histogram of the planning profits, the cumulative distribution of the planning profits, and the relative frequency of implementation timing for the different competing strategic alternatives.

As competition and further deregulation become more effective in the United States and elsewhere, generation asset planning must be studied with new tools. While these tools need to adapt to the new market environment, they must also factor in the operational and long term constraints associated with realistic generation asset planning. This dissertation has presented a generation planning model that can be used towards such realistic assets planning in the new market structure as seen in developed countries. The proposed model is also flexible enough to have practical applications in emerging and developing energy markets, and the initial results are encouraging. While the proposed model has put emphasis on a single-plant planning problem, it is the author's belief that it can be extended towards a more systematic planning tool. If pursued, the extended research should provide system planners with a comprehensive and coherent model that can undertake the true valuation of generation assets from operations to planning, all within a unified framework.

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